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ABSTRACT

This dissertation explores three issues regarding mutual funds. The first chapter examines the ability of government bond fund managers to time the market, based on their holdings of Treasury securities during the period 1997-2006. We find that, on average, government bond fund managers exhibit significantly positive timing ability at the one-month horizon, under a holdings-based timing measure. In particular, fund managers specializing in Treasury securities are more likely to better time the market than general government bond fund managers. We also find that more successful market timers tend to have relatively higher Morningstar ratings, larger fund flows, lower expense ratios, higher Sharpe ratios, and higher concentrations of holdings of Treasury securities.

In the second chapter, we study whether mutual fund managers successfully time market liquidity. Using a model assuming that fund managers attempt to maximize fund shareholders' utility by timing market exposure, we motivate liquidity timing from the fund manager's perspective. Fund managers reduce market exposure in illiquid markets and increase market exposure in liquid markets. Relative to survivors, the negative performance of non-surviving funds is emphasized when the model includes market wide liquidity indicating that liquidity timing is an important component in evaluating the performance of active fund managers.

In the third chapter, we study the dynamic relation between aggregate mutual fund flow and market-wide volatility. Using daily flow data and a VAR approach, we find that market volatility is negatively related to concurrent and lagged flow. A structural VAR impulse response analysis suggests that shock in flow has a negative impact on market volatility: An inflow (outflow) shock predicts a decline (an increase) in volatility. From the perspective of volatility–flow relation, we find evidence of volatility timing for recent period of 1998–2003. Finally, we document a differential impact of daily inflow versus outflow on intraday volatility. The relation between intraday volatility and inflow (outflow) becomes weaker (stronger) from morning to afternoon.

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Chapter 1

Timing Ability of Government Bond Fund Managers: Evidence from Portfolio Holdings

1.1 Introduction

The market timing ability of equity fund managers has been extensively discussed in the literature.[1] Yet little attention has been paid so far to the same ability of bond fund managers.[2] The discrepancy is even more striking if we take into consideration the increasingly important status which bond funds enjoy in the investors' portfolios. According to the *2007 Investment Company Fact Book*, the total net assets under management by non-municipal bond funds have almost tripled from $392 billion to $1.1 trillion during the 1997 to 2006 period. And at the end of 2006, these funds accounted for 11% of total mutual fund assets, as compared to 54% for equity funds. As such, it is interesting to take a close look at whether bond fund managers possess market timing skills that deliver superior risk-adjusted performance.

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[1] Empirical evidence on the timing ability of equity fund managers is mixed so far. Studies that find no timing ability include Treynor and Mazuy (1966), Chang and Lewellen (1984), Henriksson (1984), Graham and Harvey (1996), Ferson and Schadt (1996), and Becker, Ferson, Myers, and Schill (1999). However, Bollen and Busse (2001) document significant timing ability using daily fund returns, and Wermers (2000) and Jiang, Yao, and Yu (2007) find similar results using holdings-based performance analysis.

[2] In fact, the literature on the performance of bond fund managers is also thin. Cornell and Green (1991), Blake, Elton, and Gruber (1993), Elton, Gruber, and Blake (1995), and Ferson, Henry, and Kisgen (2005), for example, document that, in general, bond funds under-perform the relevant indices, factors, or benchmarks used to measure performance.

There has been anecdotal evidence suggesting that bond fund managers time the market or base asset allocation decisions on their views of future market conditions. For instance, in a 2006 Bloomberg article, two top government bond fund managers discuss their views about future interest rate changes and the portfolio rebalances they have done in anticipation of the fluctuations.[3] Nonetheless, the available empirical evidence on the timing ability of bond fund managers is inconclusive so far. Chen, Ferson, and Peters (2006), for example, adopt a return-based nine-factor model and document overall neutral timing ability among non-municipal bond funds during the 1962-2002 period. Based on annual sector weights, Comer (2006) finds that general government bond fund managers have neutral sector timing ability during the period of 1998 to 2004. Using return-based style analysis, Boney, Comer, and Kelly (2005) even find evidence of negative timing ability by high quality corporate bond fund managers over the period 1994-2003.

These existing studies either use the return-based timing measures (Chen, et al. (2006) and Boney, et al. (2005)) or a return attribution approach based on sector weights with very limited frequency (Comer (2006)). These measures, however, might lack sufficient power to detect the market timing ability among bond funds. For example, the return-based timing measures using monthly returns are known to have limited power in detecting the timing ability among equity funds (see, e.g., Jiang, et al. (2007)). Comer

[3] Bill Gross, who oversees the world's largest bond fund at Pacific Investment Management Co., forecasts the central bank will lower interest rates in 2007 and Treasuries maturing in less than two years will lead a market rally. As a result, he increased his holdings of short-term U.S. Treasury and agency debt in September 2006 to its highest level in nine months. George Fischer, a bond fund manager at Fidelity Investments Inc., the world's largest mutual fund company, however, predicts the Federal Reserve will keep rates unchanged, possibly through 2007 and short-term U.S. government debt will lose the most. Accordingly, he avoided two-year notes in his portfolio. See "What Fidelity knows about Bernanke that Gross doesn't," *by* Michael McDonald, Bloomberg (10/23/2006).

(2006) argues that the return attribution approach is more powerful than the return-based timing measures, but with only annual sector weights, he cannot fully disentangle asset selection ability from market timing ability.

An alternative and arguably more accurate way of measuring the market timing ability is to examine the detailed portfolio holdings of bond funds at quarterly or higher frequencies, and this is the focus of this paper. In particular, we use the holdings-based timing measures developed by Jiang, et al. (2007). As shown in Jiang, et al. (2007), such measures are free from potential biases associated with interim trading and passive timing effects. These measures also have increased statistical power compared to their return-based counterparts since they can take advantage of return observations of individual securities at a higher frequency (e.g., daily) and over extended time periods.

For the purpose of this study, we investigate the market timing performance of government bond funds, based on their holdings of Treasury securities during the period 1997-2006. We focus on Treasury security holdings of government bond funds for two reasons. First, a manager of such funds is primarily concerned with the interest rate risk, since these funds hold mainly Treasury securities. This is different from a manager of other types of bond funds (e.g. corporate bond funds) whose returns are also subject to other market risks such as the default risk. Secondly, as the returns of individual Treasuries are highly correlated, the main mechanism by which government bond fund managers can deliver superior performance is to engage in market timing rather than asset selection activities. Unlike other studies, we focus on a more homogenous sample of bond funds most likely to time the market by shifting assets across various maturities within the Treasury security sector. Therefore, it is easier to detect market timing ability in this sample if the managers do possess superior timing ability.

Our main finding, using a sample of 146 government bond funds, is that, on average, government bond fund managers possess significantly positive timing ability at the one-month forecasting horizon, based on a bootstrapping approach to statistical inference. At the three- and six-month horizons, however, government bond fund managers generally do not time the market.

We also estimate the economic values of market timing to be 0.16% and 0.14% per year, respectively, for an average and median government bond fund, assuming continuous trading and no transaction costs. These values are economically large given that the average annual excess return of government bond funds in our sample is about 1.7%. This implies that, on average, market-timing performance explains 9.4% of annual excess returns of government bond funds. The ratio is comparable to what is documented in the literature on equity fund performance. For example, Jiang, et al. (2007) find that roughly 9% of the average annual excess return of equity funds in their sample can be attributed to market timing. In addition, the economic values documented in this paper might still be achievable even after controlling for transaction costs, which are estimated to be around 1-3 bps for Treasury securities. The result indicates the importance of market-timing strategies for government bond fund managers.

We further document that certain fund characteristics help identify successful market timers. For instance, fund managers specializing in Treasury securities exhibit significantly positive timing ability compared to general government fund managers who invest in a combination of Treasury, Mortgage-backed, and agency securities.

Government short-maturity bond funds are found to be the most successful market timers, followed by government intermediate-maturity and government general bond funds. In addition, market timing funds tend to be those with relatively higher Morningstar ratings, larger fund flows, lower expense ratios, higher Sharpe ratios, and higher concentrations of holdings of Treasury securities. Given that the Morningstar rating and the Sharpe ratio are measures of a fund's risk-adjusted returns, the results suggest that government bond fund managers generate higher returns by timing the market.

Finally, we find that government bond fund managers adjust their portfolio betas in response to public information, especially historical bond betas. However, average market timing performance becomes insignificant after controlling for the pre-determined macroeconomic variables, suggesting that private information appears to play little role in managers' market-timing decisions.

The remainder of the paper is organized as follows. Section 1.2 describes the sample of government bond mutual funds used in our empirical analysis. Section 1.3 discusses the empirical methodology, and in particular, the holdings-based timing measures and the bootstrapping approach to statistical inference. Section 1.4 presents empirical results. Concluding remarks appear in Section 1.5.

1.2 Data

This paper merges two mutual fund databases. The first is the Morningstar Principia Pro Plus for Mutual Funds dataset (hereafter referred to as Morningstar), which contains stock and bond holdings for all mutual funds existing at any time between January 1997 and December 2006.[4] Morningstar also provides prospectus objectives, Morningstar ratings, duration, and the total number of holdings for each fund.[5] The second is the CRSP survivor-bias-free mutual fund database (hereafter referred to as CRSP), which contains fund characteristics such as total net assets (TNA), expense ratios, and turnover rates at an annual frequency for the years 1962 to 2006, and fund holdings data of quarterly or higher frequencies from July 2003 to December 2006.

We manually match two datasets by ticker symbols and fund names. In order for a fund to be included in the sample, it must be classified by both CRSP and Morningstar as a government bond fund. Specifically, we include funds with the CRSP S&P investment objectives of government general (GGN), government intermediate-maturity (GIM), and government short-maturity (GSM) bond funds, and funds with the Morningstar prospectus objectives of general government and Treasury bond funds.[6,7] When a fund

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[4] Morningstar obtains the holdings data from the mutual funds on a mandatory or voluntary basis. Before 2004, by law, funds were required to disclose their holdings twice every calendar year. Effective May 2004, SEC increased the mandatory disclosure frequency from semiannual to quarterly. Many funds, however, voluntarily disclose their holdings at higher frequencies. For example, Yacktman group provides monthly updates on its holdings to Morningstar.

[5] Morningstar bases a fund's prospectus objective on the wording in the prospectus sent by the mutual fund's distributor or underwriter.

[6] According to CRSP, GGN funds invest in securities backed by the Federal Government including U.S. Treasury bonds, federally guaranteed mortgage-backed securities, and other Government notes with average maturities above ten years. GIM funds invest in securities backed by the Federal Government, its

has multiple share classes, we calculate the fund level TNA as the sum of the TNAs across different share classes. We also compute the annual return, the expense ratio, and the turnover rate of the fund as the TNA-weighted averages across multiple share classes. We further exclude index funds, index enhanced funds, inflation-linked funds, mortgage-backed bond funds, and funds of funds.

We then obtain the government bond fund holdings data from CRSP from July 2003 to December 2006, and complement the dataset with the holdings information from Morningstar from 1997 to 2006. For the purpose of this paper, we only retain the fund holdings consisting of Treasury bills, notes, and bonds.[8] To ensure robust statistical inference, we require a fund to have a minimum of 20 holding observations to be included in the sample.[9]

The final sample includes 146 unique government bond funds with their holdings of Treasury securities. Panels A and B of Table 1.1 report summary statistics for the characteristics of the funds and their holdings of Treasury securities, respectively. Out of

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agencies, or instrumentalities, with average maturities of five to ten years. GSM funds invest in securities backed by the Federal Government, its agencies, or instrumentalities, with average maturities of one to five years.

[7] According to Morningstar, general government bond funds pursue income by investing in a combination of mortgage-backed securities, Treasuries, and agency securities. In contrast, Treasury bond funds seek income by generally investing at least 80% of their assets in U.S. Treasury securities.

[8] While CRSP mutual fund database reports the detailed holdings information on Treasury bills, notes, and bonds, the holdings of Treasury bills are not available in Morningstar. Morningstar, however, reports quarterly cash holdings for each fund, which include any fixed-income securities that mature in less than 12 months. Therefore, we use the cash holdings as a proxy for the holdings of Treasury bills. We do not include TIPS and STRIPs in the holdings because the daily returns data required to compute their betas are not available. However, these securities only comprise less than 5% of total holdings. Therefore, we do not believe that the exclusion of these securities would impose systematic biases on our results.

[9] The holding observations might be unequally spaced as some funds might disclose their holdings at higher (than quarterly) frequencies especially in most recent years.

146 government bond funds, 60 are GGN funds, 44 are GIM funds, and 42 are GSM funds. By Morningstar prospectus objectives, 110 are general government bond funds and 36 are Treasury bond funds. The fund characteristics are first averaged over time and then across funds. On average, a government bond fund has TNA of $413 million, a Morningstar rating of 3, duration of 4 years, an annual turnover rate of 1.64, an annual expense ratio of 0.86%, and an annual return of 5.2%. In addition, a typical government bond fund holds 176 securities, of which only eight are Treasury securities but account for about 49% of the fund's total assets.[10] The funds' holdings of Treasury securities, on average, have a Sharpe ratio of 0.58, TNA of $204 million, and duration of 5.3 years. For an average fund, we have 41 observations with portfolio holdings information.[11]

When we further decompose the sample based on investment objectives, we observe several interesting patterns. First, while an average general government bond fund holds eight Treasuries which account for 42% of its total assets, Treasury bond funds, on average, invest 89% of their assets in 12 Treasuries. This suggests that Treasury funds are more concentrated on Treasury securities compared to general government funds. Similarly, we find that GSM funds are more concentrated than GIM and GGN funds. Second, consistent with their definitions, GGN funds have the longest durations,

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[10] Other portfolio compositions of an average government bond fund include 3% TIPS or STRIPS, 6% agency securities, 38% mortgage-backed securities, and 3% others.

[11] Portfolio holdings are sometimes available at higher (than quarterly) frequencies so that the holding observations might cluster in short time period for some funds. To have a better understanding of the data structure, we report the number of calendar years the funds span. We find that only two funds have life spans of 2-3 years. Out of the remaining 144 funds, 13 have life spans of 3-5 years with an average of 30 holding observations, 35 have life spans of 5-8 years with an average of 36 holding observations, and 96 have life spans of 8-10 years with an average of 45 holding observations. Overall, the results indicate that about 90% of funds in our sample have holding observations spread out over five years.

followed by GIM and GSM funds. Finally, GGN funds have higher expense ratios than GIM and GSM funds; Treasury bond funds have relatively lower expense ratios compared to general government bond funds.

We also obtain the daily returns of individual Treasury securities and one-month T-bill rates (our proxy for the risk-free rate) from CRSP.[12] In the empirical tests, we use the Lehman Brother long-term government bond index return from Datastream as a proxy for the long-term government bond return.

1.3 Methodology

1.3.1 Holdings-based Timing Measures

To examine the timing ability of government bond fund managers, we adopt the holdings-based timing measures developed by Jiang, et al. (2007). First, we compute the beta of individual Treasury security i on the portfolio holding date t, $b_{i,t}$, using daily returns during the past one year. Specifically, we use the following Fama and French (1993) one-factor model:[13]

[12] We merge the holdings data with the CRSP daily Treasury database by CUSIP. In the absence of CUSIP, we match two datasets by both coupon and maturity. Finally, we manually check the fund holdings with SEC mutual fund fillings from EDGAR and match the Treasuries with incomplete information. Over 95% of Treasury securities are matched in this process.

[13] Fama and French (1993) use two bond-market risk factors: interest rate risk and default risk. As we focus on government bond funds, in particular their holdings of Treasury securities, which are essentially free of default risk, we only include the interest rate risk factor in our model. We find that, on average, the interest rate risk factor explains over 70% of the variance of returns of individual Treasury securities.

$$r_{i\tau} = a_{i,t} + b_{i,t} Term_\tau + e_{i\tau}, \tau = t-k, \ldots, t-1 \quad , \tag{1.1}$$

where $r_{i\tau}$ is the excess return of Treasury security i at day τ, $Term_\tau$ is the term premium defined as the difference between the long-term government bond return and the risk-free rate at day τ, and k is the number of daily observations before the portfolio holding date t in the estimation. In this model, $Term$ proxies for the deviation of the long-term bond return from the expected return due to shifts in interest rates, and b_i measures the exposure of Treasury security i to the interest rate risk (Fama and French (1993)). To ensure a robust estimator, we require a Treasury security to have a minimum of 20 daily return observations; otherwise we set its beta to be the matching portfolio beta.[14]

Next, we compute the portfolio beta of Treasuries held by each government bond fund at the beginning of period $t+1$, $\hat{\beta}_t$, as follows:

$$\hat{\beta}_t = \sum_{i=1}^{N_t} w_{i,t} \hat{b}_{i,t} \quad , \tag{1.2}$$

where $w_{i,t}$ is the normalized portfolio weight of Treasury security i at the beginning of holding period $t+1$ such that $\sum_{i=1}^{N_t} w_{i,t} = 1$, $\hat{b}_{i,t}$ is the estimated beta of Treasury security i

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[14] We construct the duration-based matching portfolios similar to the maturity-based matching portolios in Fama (1984). Specifically, we sort Treasury securities into seven portfolios based on 12-month duration intervals: (1) from 1 to 12 months, (2) from 13 to 24 months, (3) from 25 to 36 months, (4) from 37 to 48 months, (5) from 49 to 60 months, (6) from 61 to 120 months, and (7) greater than 120 months from the quote date. The matching portfolio return is the equal-weighted average of the unadjusted holding period returns of individual Treasury securities held in the portfolio. For the cash portion in the Morningstar database, we set its beta to be the beta of the matching portfolio with the average duration of no more than one year.

from (1.1), and N_t is the number of Treasury securities held by each government bond fund at the portfolio holding date t.

We then construct the two holdings-based timing measures adopted by Jiang, et al. (2007). First, we estimate the holdings-based Treynor-Mazuy timing measure, γ, from the following regression:

$$\hat{\beta}_t = \alpha + \gamma Term_{t+1} + \eta_t \quad , \tag{1.3}$$

where $\hat{\beta}_t$ is the portfolio beta at the beginning of period $t+1$ from (1.2), and $Term_{t+1}$ is the term premium over the period $t+1$. We also construct a holdings-based Henriksson-Merton timing measure as follows for robustness check:

$$\hat{\beta}_t = \alpha + \gamma I_{Term_{t+1}>0} + \eta_t \quad , \tag{1.4}$$

where $I_{Term_{t+1}>0}$ is an indicator function with value of 1 if $Term_{t+1}$ is positive and 0 otherwise, and γ measures the timing ability of government bond fund managers. We compute the Newey-West heteroskedasticity- and autocorrelation- consistent *t*-statistics with a six-month lag for $\hat{\gamma}$ (Newey and West (1987)).[15] If government bond fund

[15] As noted before, the holding observations might be unequally spaced for some funds. We use a slightly modified Newey-West approach to correct for potential biases associated with unequally spaced time-series data. For example, for the Treynor-Mazuy timing measure, we multiply (1.3) by a dummy variable, d_t, as follows: $d_t \hat{\beta}_t = \alpha d_t + \gamma d_t Term_{t+1} + d_t \eta_t, t = 1, 2, 3, ..., \mathrm{T}$, where d_t is equal to 1 if fund holdings are available at the end of month *t* and 0 otherwise. We then follow the standard procedure to compute the Newey-West *t*-statistics for $\hat{\gamma}$.

managers possess positive timing ability, we expect the γ coefficients estimated from both (1.3) and (1.4) to be significantly positive.

As shown in Jiang, et al. (2007), the holdings-based timing measures have two main advantages over the traditional return-based measures. First, the holdings-based measures do not suffer from any biases induced by the interim trading or dynamic trading effect as they use only *ex-ante* information on portfolio holdings. They are also robust to the passive timing effect which could be an important concern for government bond funds given the convexity of bond prices to interest rate changes. Second, the holdings-based timing tests have better statistical power than their return-based counterparts because we can take advantage of return observations of individual Treasury securities at a daily frequency and over extended time periods.

1.3.2 Statistical Inference: Bootstrapping

Following Kosowski, Timmermann, Wermers, and White (2006) and Jiang, et al. (2007), we adopt a bootstrapping approach to statistical inference. The bootstrapping approach addresses two issues associated with the statistical inference based on the cross-sectional distributions of the holdings-based timing measures and their *t*-statistics: violation of the *i.i.d.* assumption across funds and the finite sample property of the test statistics. While these are important issues for equity funds, such issues are more of a concern in analyzing the cross-sectional statistics of timing measures for government bond funds. First, Treasury securities held by government bond funds are relatively homogenous and their returns are highly correlated. As a result, the fund betas are highly correlated and the timing statistics are not *i.i.d.* across funds. Moreover, as we only have a relatively small sample of government bond funds, the finite sample distributions for the cross-sectional statistics, particularly those extreme percentiles, may differ from their asymptotic counterparts.

In the bootstrapping procedure, we randomly resample the time-varying term premium under the null hypothesis that no fund has timing ability, while keeping the covariance structure across fund betas unchanged. Specifically, each time we randomly sample without replacement the term premium, $Term_{t+1}$, with the Treasury security portfolio betas, $\hat{\beta}_t$, unchanged for all funds and calculate the bootstrapped cross-sectional statistics of the holdings-based timing measures and their pivotal *t*-statistics. We repeat this procedure for a large number of times (*e.g.*, 2,000 times in this paper) to obtain the distributions of bootstrapped statistics and then calculate the bootstrapped *p*-value as follows:

$$p = \frac{1}{J}\sum_{j=1}^{J} I_{\Gamma_{bs}^{j} > \Gamma} \quad , \tag{1.5}$$

where Γ and Γ_{bs}^{j} are the cross-sectional statistics of the estimated and bootstrapped timing measures or their *t*-statistics, respectively, $I_{\Gamma_{bs}^{j} > \Gamma}$ is an indicator function with value of 1 if $\Gamma_{bs}^{j} > \Gamma$ and 0 otherwise, and J is the number of times the bootstrapping procedure is repeated. Under the null hypothesis of no timing ability, we expect the distributions of the bootstrapped statistics to approximate the empirical distributions of the timing statistics. If the estimated timing measures or their *t*-statistics are consistently higher than their bootstrapped values, *i.e.*, if the bootstrapped *p*-values are close to 0, we conclude that fund managers have positive timing ability. Similarly, if the estimated timing measures or their *t*-statistics are consistently lower than their bootstrapped values, *i.e.*, if the bootstrapped *p*-values are close to 1, we argue that fund managers have negative timing ability.

1.4 Empirical Analysis of Market Timing

In this section, we investigate the market timing performance of government bond fund managers using the holdings-based timing measures. We first conduct the baseline holdings-based Treynor-Mazuy timing tests and then several robustness tests to see whether the results are robust to alternative methods of estimating Treasury security betas, the length of data records, a different holding-based timing measure, and different time periods. We also conduct the return-based timing tests for our sample in order to compare our results with the existing literature. We then document the economic value of market timing. Finally, we identify certain fund characteristics which could help investors choose successful market timers.

1.4.1 Holdings-based Treynor-Mazuy Timing Tests

To examine the market timing ability of government bond fund managers, we first apply the holdings-based Treynor-Mazuy timing measures as described in Section 3.1 to a sample of government bond mutual funds with a minimum of 20 holding observations during the period 1997-2006. Statistical inference is based on a bootstrapping approach as described in Section 3.2 with 2,000 repetitions. We compute the bootstrapped *p*-values for the cross-sectional statistics of timing measures and their pivotal *t*-statistics as well. In particular, we base the statistical inference on the bootstrapped *p*-values for the pivotal *t*-statistics since the distributions of bootstrapped *t*-statistics are likely to have fewer problems associated with high variance or survival bias and thus have better property than the distributions of bootstrapped timing estimates.

Table 1.2 reports the cross-sectional statistics of the holdings-based Treynor-Mazuy timing measures and their Newey-West *t*-statistics, together with the bootstrapped *p*-values, for the forecasting horizons of one, three, and six months, respectively. As discussed earlier, we focus on the bootstrapped *p*-values for the pivotal *t*-statistics for more reliable statistical inference.[16] First, at the one-month forecasting horizon, the bootstrapped *p*-values for the *t*-statistics are below 5% for the mean, median, maximum, the 75, 95, and 99th percentiles.[17] For example, the bootstrapped *p*-values for the average

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[16] As shown in Table 2, the kurtosis of the Newey-West *t*-statistics is much smaller than that of the timing measures, $\hat{r}$, for all horizons, indicating that the pivotal *t*-statistics have more robust statistical inference than the non-pivotal timing measures. Therefore, we focus on the bootstrapped *p*-values for the pivotal *t*-statistics in the following discussions.

[17] The only exception is that at the 90th percentile, the *t*-statistic is positive, but not statistically significant according to the bootstrapped *p*-value.

t-statistics across 146 government bond funds is well below 1%, indicating that, on average, government bond fund managers exhibit significantly positive timing ability at the one-month horizon. Second, government bond fund managers generally do not exhibit positive timing ability at the horizons of three and six months. This suggests that it is difficult for government bond fund managers to time the market over longer horizons.

To further illustrate the results, Figure 1 plots the kernel density functions of the distributions of bootstrapped *t*-statistics for government bond funds at various points in the cross section, as well as the actual *t*-statistics of timing measures. For example, Panel A reports the actual *t*-statistic versus the distribution of the bootstrapped *t*-statistics of the top-ranked fund, namely Vanguard Intermediate Term U.S. Treasury Fund. We can see that the actual top-fund *t*-statistic of 5.74 (the dashed line in Panel A) lies well within the right-tail rejection region of the bootstrapped distribution, indicating evidence of significant and positive timing ability by the manager at Vanguard Intermediate Term U.S. Treasury Fund. Similarly, at the mean, median, the 75, 95, and 99^{th} percentiles, the bootstrapped distributions reject the null hypothesis of no significantly positive timing ability among government bond fund managers. In general, the results suggest that government bond fund managers, on average, exhibit significantly positive timing ability at the one-month horizon.

1.4.2 Holdings-based Treynor-Mazuy Timing Tests: Alternative Beta Estimates

In the baseline analysis, we estimate the Treasury security betas from the past one-year daily returns. To ensure that our results are not sensitive to the particular beta estimate used, we repeat our holdings-based Treynor-Mazuy timing tests using two alternative estimates of Treasury security betas. First, we estimate the Treasury security betas from (1) using daily returns over the past three months. The second beta measure is estimated using monthly returns over the past five years. For the second measure, we require an individual Treasury security to have at least 12 monthly return observations; otherwise we set its beta to be the matching portfolio beta. For both beta estimates, we further compute the value-weighted portfolio betas as in (1.2) and then estimate the holdings-based timing measures, $\hat{\gamma}$, from (1.3).

Table 1.3 reports the cross-sectional distributions of the Newey-West *t*-statistics for the holdings-based timing measures with alternative estimates of Treasury security betas. The results are generally consistent with those based on the daily Treasury security returns during the past one year. For example, at the one-month horizon, the mean, maximum, the 75, 90, 95, and 99th percentiles of *t*-statistics are significantly positive when the Treasury security betas are estimated from the past three-month daily returns; the mean, median, the 75, and 95th percentiles of *t*-statistics are significantly positive when the Treasury security betas are estimated from the past five-year monthly returns. These results suggest that evidence of positive timing ability by government bond fund managers is robust to different methods of estimating Treasury security betas.

1.4.3 Holdings-based Treynor-Mazuy Timing Tests: Adjusted for Benchmark Portfolio betas

To minimize potential passive timing effects and reduce cross-sectional heteroskedasiticity, we construct the adjusted beta for Treasury security *i*, $\hat{b}_i^a$, by subtracting its duration-matched portfolio beta, $\hat{b}_i^b$, from the security beta estimate, $\hat{b}_i$, i.e.,[18]

$$\hat{b}_i^a = \hat{b}_i - \hat{b}_i^b . \tag{1.6}$$

We then compute the portfolio beta similar to (1.2) using the adjusted Treasury security betas and repeat all the analysis. The results, reported in Table 1.4, remain qualitatively similar after controlling for the duration-based matching portfolio betas. For example, the mean (median) of *t*-statistics is 0.47 (0.51) with a bootstrapped *p*-value of 0.00 (0.00) at the one-month forecasting horizon, indicating that government bond fund managers on average exhibit significant and positive timing ability even after we adjust the security betas for their benchmark portfolio betas.

1.4.4 Holdings-based Treynor-Mazuy Timing Tests: Active Changes of Fund Betas

In the baseline analysis, we construct the holdings-based timing measures as the covariance between the time-varying fund betas at the beginning of a holding period and the holding period term premium. As noted in Jiang, et al. (2007), the time variation in

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[18] The construction of duration-matched benchmark portfolio is similar to Fama (1984).

fund beta levels might be solely driven by the non-proportional changes in security prices but not by the active trading activities of fund managers. This is not, however, as much a concern in the Treasury market as in the stock market given that Treasury security prices are much less volatile than stock prices. Regardless, we separate the effect of active trading from the effect of passive portfolio weight changes on market timing for a robustness check.

Specifically, we construct the fund beta changes induced by active trading of government bond fund managers from month *t-h* to month *t*, $\Delta\hat{\beta}_t$, as follows:

$$\Delta\hat{\beta}_t = \hat{\beta}_t - \hat{\beta}_t^{t-h} = \sum_{i=1}^{N_t} w_{it}\hat{b}_{it} - \sum_{i=1}^{N_{t-h}} w_{it}^{t-h}\hat{b}_{it} \tag{1.7}$$

where $\hat{\beta}_t$ is the fund portfolio beta at month *t*, $\hat{\beta}_t^{t-h}$ is the hypothetical fund portfolio beta at month *t* if a fund passively holds all the Treasury positions in its portfolio from *h* months ago, N_t and N_{t-h} are the number of Treasury securities held by the fund at month *t* and *t-h*, respectively, $\hat{b}_{it}$ is the beta estimate of Treasury security *i* at month *t*, w_{it} is the portfolio weight of Treasury security *i* at month *t*, and w_{it}^{t-h} is the hypothetical portfolio weight of Treasury security *i* at month *t* assuming a fund passively hold its portfolio from month *t-h*. In particular, w_{it}^{t-h} is defined as follows:

$$w_{it}^{t-h} = \frac{F_{it-h} * P_{it}}{\sum_{i=1}^{N_{t-h}} F_{it-h} * P_{it}} \tag{1.8}$$

where F_{it-h} is the face value of Treasury security i at month t-h, and P_{it} is the price of Treasury security i at month t. For a Treasury security with the maturity date between months t-h and t, we set its price to be one and its beta to be that of the matching portfolio with average duration of no more than one year at month t.

We measure the active timing activities of fund managers over the past three months, i.e., h=3, given that on average we have quarterly portfolio holdings.[19] Table 1.5 reports the cross-sectional distribution of Newey-West t-statistics for the holdings-based timing measures based on active change of portfolio betas as well as their bootstrapped p-values. The results are in general consistent with those based on the level of portfolio betas.[20] For example, at the one-month forecasting horizon, the mean (median) of t-statistics is significant and positive with a bootstrapped p-value of 0.08 (0.01). Overall, the results provide some further evidence of positive timing ability and government bond fund managers.

1.4.5 Sensitivity Analysis: Length of Data Records

In the baseline analysis, we require a fund to have a minimum of 20 holding observations to be included in our sample for reliable statistical inference. This

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[19] We only keep those where the changes of portfolio holdings over the three-month period can be observed. Due to the unequal frequency, the average number of portfolio holdings is smaller. Therefore, we require a fund to have a minimum of 10 observations of 3-moth portfolio changes to be included in the sample. The final sample includes 154 funds with an average number of 26 3-month portfolio changes.

[20] The power of the tests based on $\Delta\hat{\beta}_t$, however, is limited by the number of observations of portfolio betas' active changes.

requirement, however, may impose a survival bias on our results.[21] To check whether our results are sensitive to the length of data records, we vary the requirement to include government bond funds with a minimum of 10 and 30 holding observations, respectively. The sample thus includes 195 and 109 government bond funds, respectively.

Table 1.6 reports the bootstrap results for the sensitivity tests. The results indicate that the bootstrapped distributions strongly reject the null hypothesis of no significantly positive timing ability among government bond fund managers as we change the minimum requirement to 10 and 30 holding observations, respectively. For example, at the one-month horizon, the bootstrapped *p*-values for the Newey-West *t*-statistics are well below 5% at the mean, median, maximum, the 75, and 99th percentiles for both cases, indicating strong positive timing ability among government bond fund managers. The noticeable difference is that when we impose a minimum requirement of 30 holding observations, the mean and median of *t*-statistics are significantly positive at the forecasting horizons of three and six months. Overall, the results suggest that evidence of positive timing ability by government bond fund managers is not driven by the potential survival bias.

[21] Although the holding observations might be unequally spaced, in general, government bond funds with a smaller number of holding observations tend to be shorter-lived funds. For example, within the ten-year period from 1997 to 2006, funds with 10 to 20, 20 to 30, and more than 30 holding observations have average life spans of 4.2, 7, and 8.4 years, respectively. Therefore, when we exclude funds with less than 20 holding observations, we most likely exclude those with shorter life spans.

1.4.6 Holdings-based Treynor-Mazuy Timing Tests: Sub-period Analysis

To examine whether our results are robust across different time periods, we split our data into two sub-periods: one starting in 1997 and running through 2001, and the other starting in 2002 and running through 2006. For each time period, we only retain those funds with a minimum of 10 holding observations for robust statistical inference. The final sample includes 141 funds with an average of 16 holding observations in the first period, and 145 funds with an average of 27 holding observations in the second period.

Table 1.7 reports the cross-sectional distribution of Newey-West *t*-statistics and their bootstrapped *p*-values for the holdings-based Treynor-Mazuy timing tests during the two sub-periods. The results show that the evidence of positive timing ability is stronger in the second period. For example, the mean, median, and the upper percentiles of *t*-statistics are significantly higher than the bootstrapped ones during the 2002-2006 period; during the 1997-2001 period, the mean of *t*-statistics is significantly positive based on the bootstrapped *p*-value while the median of *t*-statistics is slightly negative but insignificant. However, we note that the holding reporting frequency is much lower in the first period than in the second period. Therefore, the statistical power of the test in the 1997-2001 period might be limited by the number of holding observations in this period.

We also examine whether those funds in the top and bottom decile in the first time period continue to do so in the second decile. The purpose is to get some rough idea of whether there is some evidence of persistence in the market timing ability among government bond funds. [22] We find that out of 15 funds in the top quintile in the first period, only two (Vanguard Short-term Treasury Fund and STI Classic US Short-term Treasury Security Fund) continue to stay in the top decile while three either move to the bottom decile or disappear in the second period. For those funds in the bottom quintile in the first period, six of them disappear in the second period. While the evidence is inconclusive, the results suggest some limited evidence of persistence in the timing ability of government bond funds over the 5-year period.

1.4.7 Holdings-based Henriksson-Merton Timing Tests

We also perform the holdings-based Henriksson-Merton timing tests in (1.4) for the forecasting horizons of one, three, and six months. The individual Treasury security betas are estimated using the past one-year daily returns. We also require government bond funds to have a minimum of 20 holding observations to be included in our sample.

The results, reported in Table 1.8, suggest that the holdings-based tests, based on the Henriksson-Merton timing measures, produce qualitatively similar patterns as the Treynor-Mazuy timing tests. For example, at the one-month horizon, the mean, maximum, the 75, 95, and 99th percentiles of *t*-statistics are significantly positive, indicating evidence of overall positive timing ability by government bond fund managers. At the three- and six-month horizons, the mean and median *t*-statistics are insignificant, indicating that, on average, government bond fund managers do not time the market,

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[22] Due to the limited frequency of portfolio holdings, it is not feasible to conduct a rigorous test of persistence in the timing ability of government bond funds in our sample.

although there is some evidence of significant timing at higher extreme percentiles for the six-month horizon. Overall, we document robust evidence of positive timing ability by government bond fund managers at the one-month horizon using the Henriksson-Merton timing measures.

1.4.8. Return-based Timing Tests

Previous studies document that bond fund managers in general have no or negative market timing ability based on the return-based timing measures (Chen, et al. (2006) and Boney, et al. (2005)). To compare our results with the existing literature, we perform the return-based timing tests similar to Treynor and Mazuy (1966) for our sample of government bond funds as follows:

$$r_{it} = a_i + b_i Term_t + \gamma_i Term_t^{\,2} + e_{it} \qquad (1.9)$$

where r_{it} is the excess return of government bond fund i in month t, $Term_t$ is the term premium in month t, and γ_i is the return-based timing measure of individual government bond fund i.[23]

Following Jiang, et al. (2007), we base the statistical inference of the return-based timing tests on a parametric bootstrap approach. Specially, we retain the parameter

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[23] We note that the term premium (proxy for interest rate risk) might not completely explain the returns of government bond funds as these funds hold only 49% of their assets in Treasury securities. However, the average adjusted R2 is 76%, indicating that interest rate risk is the most important risk factor.

estimates $\hat{a}_i$ and $\hat{b}_i$, as well as the residuals $\hat{e}_{it}$ from the following OLS model for individual fund i :

$$r_{it} = a_i + b_i Term_t + e_{it} \tag{1.10}$$

We then resample the term premium $Term_t^*$ and construct the bootstrapped fund returns, r_{it}^*, as follows:

$$r_{it}^* = \hat{a}_i + \hat{b}_i Term_t^* + \hat{e}_{it} \tag{1.11}$$

With r_{it}^* and $Term_t^*$ we calculate the bootstrapped cross-sectional statistics of the return-based timing measures and their Newey-West *t*-statistics with a lag of 6. We repeat this procedure for 2,000 times to obtain the distributions of bootstrapped statistics and then calculate the bootstrapped *p*-value as in (1.5).

Panel A of Table 1.9 reports the cross-sectional distribution of the Newey-West *t*-statistics (t) and their bootstrapped *p*-values for the return-based timing measures. The results show that under the return-based timing measures, the government bond funds in our sample on average do not exhibit significant and positive timing abilities. For example, the mean (median) of *t*-statistics is 0.37 (0.37) with a bootstrapped *p*-value of 0.99 (0.98). These results are in general consistent with the previous evidence of no or negative timing ability among bond fund managers based on the return-based timing tests.

We also construct the hypothetical monthly returns of government bond funds based on their holdings of Treasury securities. In particular, we assume that the funds hold the same portfolios until the next portfolio report date. For those Treasury securities with the maturity date between the two portfolio report dates, we assume that the amount received on the maturity date will be reinvested at the market risk-free rate until the next portfolio report date.

We then repeat the above procedure to conduct the return-based timing tests using the hypothetical Treasury security portfolio returns. The results, reported in Panel B of Table 1.9, show that government bond funds exhibit significantly positive timing ability. This suggests that although the frequency is limited, the portfolio holdings provide valuable information to test for the timing ability among government bond funds.

1.4.9 Economic Value of Market Timing

Having documented the statistical significance of market timing performance of government bond fund managers, we subsequently examine the potential economic value of market timing. Following Henriksson and Merton (1981), Merton (1981), Glosten and Jagannathan (1994), and Jiang, et al. (2007), we quantify the economic value of market timing ability of government bond fund managers as a contingent claim on the bond market index return. Specifically, suppose government bond funds follow the following return generating process:

$$r_t = a + \beta_0 Term_t + \gamma Term_t^2 + e_t \quad , \tag{1.12}$$

where r_t is the excess bond fund return over the holding period *t*, $Term_t$ is the term premium, *i.e.*, the long-term government bond return (a proxy for the bond market index return) in excess of the risk-free rate, r_f, $\gamma = 0$ indicates no timing ability, and $\gamma > 0$ indicates positive timing ability. If government bond fund managers time a common risk factor in the bond market, *i.e.,* the interest rate risk, market timing would generate a payoff of $\gamma Term_t^2$ with the maturity equal to the forecasting horizon. Suppose the long-term government bond returns are log-normally distributed with a historical mean, μ_{bm}, and standard deviation, σ_{bm}, the value of market timing, *V*, is then the expected present value of $\gamma Term_t^2$ under the risk neutral measure (*Q*):

$$V = \frac{1}{1+r_f} E^Q[\gamma Term_t^2] = (1+r_f)\gamma(e^{\sigma_{bm}^2} - 1) \quad . \tag{1.13}$$

To compute the economic value of market timing, we assume an annual risk-free rate of 3.5% and monthly bond market return variance of 0.06%.[24] Based on the mean and median holdings-based Treynor-Mazuy timing measures of 0.21 and 0.19, respectively, at the one-month horizon in Table 1.2, the potential economic values of market timing from (13) for an average and median fund are 0.16% and 0.14% per year, respectively. These values are economically meaningful compared to the average excess return of government bond funds in our sample, which is about 1.7% per year (given the average annual return of 5.2% from Table 1.1 and an annual risk-free rate of 3.5%). This

[24] We use the average one-month Treasury bill rate during the 1997-2006 period as the risk-free rate and estimate the bond market return variance from the monthly returns of the Lehman-Brother long-term government bond index between 1997 and 2006.

indicates that, on average, market timing explains about 9.4% of the annual excess return of government bond funds. The ratio is comparable to what is documented in the equity fund literature. For example, Jiang, et al. (2007) find that for equity funds, roughly 9% of the average annual excess return, *i.e.*, 0.63% per year, can be attributed to market-timing activities. However, as noted in Jiang, et al. (2007), the above economic values of market timing might not be fully attainable as this framework is based on the assumptions of continuous trading and no transaction costs. Nonetheless, as the U.S. Treasury market is highly liquid, much of these potential economic values might still be achievable even after taking into account the transaction costs.[25]

1.4.10 Fund Characteristics and Market Timing

While we document positive timing ability for the average government bond fund, we also observe a wide variation of timing performance across funds. Therefore, an interesting question remains whether there is any commonality among successful market timers. In particular, we examine whether government bond funds with certain investment objectives are more likely to better time the market. We also identify the links between a few other fund characteristics and market timing to see whether these characteristics may help investors choose successful market timers.

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[25] Based on the data from GOVPX, Fleming (2003), for example, documents that the bid-ask spreads of U.S. Treasury Securities are only about 1 to 3 bps for the sample period of December 30, 1996 to March 31, 2000.

To examine whether investment objectives are associated with market timing, we perform the holdings-based timing tests for fund subgroups with different investment objectives, based on two classification methods. First, we divide the sample into three different subgroups by the CRSP S&P investment objectives, namely government general (GGN), government intermediate-maturity (GIM), and government short-maturity (GSM) bond funds. We also decompose the sample into general government and Treasury bond funds based on the Morningstar prospectus objectives.

Panel A of Table 1.10 reports the cross-sectional distributions of Newey-West *t*-statistics and their bootstrapped *p*-values at the one-month horizon for subgroups with different CRSP S&P investment objectives. The results suggest that GSM and GIM funds are generally more likely to time the market than GGN funds. For example, the mean, median, and the upper percentiles of *t*-statistics are significantly higher than the bootstrapped ones for GSM and GIM funds. GGN funds, however, on average, do not exhibit significantly positive timing ability with a bootstrapped *p*-value of 0.12 for the mean statistics, although there is some evidence of positive timing for the median fund and the fund at the 75% percentile. Ranked by the mean and median *t*-statistics, GSM funds are the most successful market timers, followed by GIM and GGN funds. A potential explanation for this finding is that government bond funds focusing on Treasury securities with relatively shorter durations are more flexible in adjusting fund betas, and therefore, more successful in timing the market. In addition, by their investment objectives GSM funds on average can choose from a pool of 128 Treasury securities, as compared to only 51 and 42 for GIM and GGN funds, respectively. Therefore, GSM funds have more flexibility in timing the market.

Panel B of Table 1.10 shows the bootstrap results at the one-month horizon for general government and Treasury bond funds, respectively. As discussed earlier, while general government funds pursue income by investing in a combination of mortgage-backed securities, Treasuries, and agency securities, Treasury funds seek income by generally investing at least 80% of their assets in U.S. Treasury securities. Moreover, Treasury funds tend to be more concentrated than general government funds. Therefore, we intuitively expect Treasury bond fund managers more likely to be successful market timers as they specialize in Treasury securities. Consistent with our intuition, Treasury fund managers exhibit superior positive timing ability compared to general government fund managers. For example, the bootstrapped *p*-values for the *t*-statistics at the mean, median, maximum, the 75, 90, 95, and 99th percentiles are all below 1% for Treasury funds, indicating strong evidence of significantly positive market timing ability by these fund managers. In addition, these timing activities generate significant economic value of 1.37% (1.49%) per year before transaction costs for an average (median) Treasury fund. On the other hand, the mean and median of *t*-statistics for general government bond funds are positive but barely significant with bootstrapped *p*-values of 0.13 and 0.11, respectively. This is not surprising given that, on average, Treasury securities only account for 42% of total assets held by general government funds. Therefore, general government fund managers are not as specialized in Treasury securities as Treasury fund managers.

We further examine whether the market-timing abilities are associated with a few other fund characteristics. For example, do successful market timers have higher risk-adjusted returns and thus attract more fund flow from the investors? Do active market timing bond funds tend to charge higher fees and have higher turnover rates? Are larger funds better market timers? Is duration associated with the market timing ability? Furthermore, do successful market timing government bond funds tend to specialize in Treasury securities?

To explore these issues, we consider eight fund characteristics. The first four are the characteristics of government bond funds, *i.e.*, Morningstar rating, fund flow, expense ratio, and turnover rate. Morningstar rating, commonly called the star rating, is a measure of a fund's risk-adjusted return, relative to the other funds in its category.[26] Funds are rated from one to five stars, with the best performers receiving five stars and the worst performers receiving a single star.[27] The next four characteristics are related to Treasury security holdings of government bond funds, namely the Sharpe ratio, total net assets (TNA), the value-weighted duration, and the percentage of assets held by Treasuries (%Holding).

We first examine the characteristics of market timers in Table 1.11. We rank 146 government bond funds into five quintile portfolios by their Newey-West *t*-statistics of

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[26] Risk-adjusted return is calculated by subtracting a risk penalty from each fund’s total return, after accounting for all loads, sales charges, and redemption fees. The risk penalty is determined by the amount of variation in the fund's monthly returns, with emphasis on downward variation. The greater the variation is the larger the penalty resulting.

[27] Funds are assigned one to five stars if they are ranked as bottom 10%, next 22.5%, middle 35%, next 22.5%, and top 10% within their categories, respectively.

the holdings-based Treynor-Mazuy timing measures from Table 1.2. The fund characteristics are first averaged over time for each fund and then averaged across funds within each quintile. From Table 1.9, we can see that the funds with the largest *t*-values (top quintile) have significantly higher Morningstar ratings and Sharpe ratios than the funds with the smallest *t*-values (bottom quintile). Given that the Morningstar rating and the Sharpe ratios are measures of funds' risk-adjusted returns, the result indicates that government bond fund managers generate higher returns by timing the market. In addition, funds in the higher quintiles have positive flow while those in the lower quintiles have negative flow, suggesting that more successful market timers attract more fund flow from the investors. Finally, most successful market timing funds have lower expense ratios, larger total net assets, and higher concentrations of holdings of Treasury securities than the funds with the most perverse timing ability.

We next examine whether these characteristics help identify successful market timers. To explore this issue, we take the time-series averages of fund characteristics and rank the funds into five quintiles by each characteristic.[28] We then examine the timing ability of government bond fund managers within each quintile. Panels A, B, C, and D of Table 1.12 report bootstrapped *p*-values for the *t*-statistics of the holdings-based Treynor-Mazuy timing measures at the one-month horizon within each quintile ranked by Morningstar rating, fund flow, expense ratio, and turnover rate, respectively. Interestingly, from Panel A, we find that the *t*-statistics are significantly positive at the

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[28] To remove potential trend in the fund characteristics, we also obtain the percentile rank of each characteristic across funds every year, which is averaged over time for each fund and then ranked into five quintiles across funds. The results, not reported here for brevity, remain qualitatively similar.

mean, median, and all the upper percentiles for the government bond funds with the highest Morningstar ratings. In contrast, the *t*-statistics are insignificant and even negative at the mean and median for funds with the lowest Morningstar ratings. As Morningstar rating is a measure of a fund's risk-adjusted return, the result suggests that funds with better performance are more likely to be successful market timers. Panel B shows that funds that attract more flow from the investors are more likely to successfully time the market. Based on the expense ratio, Panel C indicates that more successful market timing bond funds tend to charge lower fees from investors according to the mean and median of *t*-statistics. Panel D reports the results based on the turnover rate. However, the link between the turnover rate and market timing is not clear. For example, government bond funds with significantly positive market timing ability do not have the highest or lowest turnover rates. Instead, they tend to be the funds with turnover rates in the middle, indicating that successful market timers tend to trade more frequently, but they are not among those who trade the most frequently.

The bootstrap results at the one-month horizon for the quintile groups formed on the Sharpe ratio, TNA, duration, and %Holding are reported in Panels E, F, G, and H of Table 1.12, respectively. Panel E reports the results based on the Sharpe ratio, a measure of the risk-adjusted returns of portfolios of Treasury securities holdings. The results are similar to those based on the Morningstar rating. For example, funds with the highest Sharpe ratios exhibit significantly positive timing ability while funds with the lowest Sharpe ratios show no or negative timing ability. From Panel F, the mean, median, and the upper extreme percentiles of *t*-statistics are positive but not significant for the lowest

TNA quintile, but significantly positive for the highest TNA quintile. This indicates that more successful market timers tend to have relatively higher TNA. This might explain why more successful market timing funds tend to have relatively lower expense ratios. Panel G shows that the *t*-statistics are significantly higher than the corresponding bootstrapped values for the quintiles with the shortest (quintile 1) and intermediate (quintile 3) durations. For the quintile with the longest durations (quintile 5), the *t*-statistics are significantly below the corresponding bootstrapped values except for the mean. In general, successful market timers tend to be those focusing on short and intermediate-maturity Treasury securities. Panel H reports the results based on %Holding, a rough measure of how government bond fund managers specialize in Treasury securities. Intuitively, the higher the percentage of assets held by Treasury securities, the more likely government bond fund managers specialize in Treasury securities, and the more likely they are successful market timers. Consistent with our intuition, we document that government bond funds with higher concentrations of holdings of Treasury securities (quintiles 4 and 5) exhibit significantly positive timing ability according to bootstrapped *p*-values of the *t*-statistics.

Overall, we find that certain fund characteristics help identify successful market timing government bond funds. In particular, more successful market timers tend to have relatively higher Morningstar ratings, larger fund flow, lower expense ratios, higher Sharpe ratios, and higher concentrations of holdings of Treasury securities. These findings provide some useful guidelines for investors when they make investment decisions.

1.4.11 Market Timing and Public Information

Existing literature has identified a small set of macroeconomic variables which can predict long-term government bond returns (see e.g., Keim and Stambaugh (1986) and Ilmanen (1995)). Given that the horizon of bond return predictability is similar to the horizon at which government bond fund managers are found to time the market in this paper, it is natural to ask to whether managers rely on those macroeconomic variables in their market timing. In addition, do fund managers possess any private information about government bond market returns which is not captured by these variables?

To address the first question, we conduct the following regression for each fund *i*:

$$\hat{\beta}_{it} = a_i + b_i M_{t-1} + e_{it} \tag{1.14}$$

where $\hat{\beta}_{it}$ is the Treasury security portfolio beta at month *t* and M_{t-1} is the vector of one-month lagged macroeconomic variables. In this paper, we use four economic variables as in Ilmanen (1995), namely, term spread (*TERMSP*), real bond yield (*REALYLD*), inverse relative wealth (*INVRELW*), and bond beta (*BETA*). *TERMSP* is the difference between 10-year and 3-month Treasury yields. *REALYLD* is the difference between 10-year bond yield and the one-month lagged year-on-year inflation rate. The first two instruments proxy for the overall expected bond risk premium. *INVRELW* is the ratio of past to current real wealth which is defined as follows:

$$INVRELW_t = \frac{ewaW_{t-1}}{W_t} = \frac{\sum_{k=1}^{36} 0.1 * 0.9^{k-1} * W_{t-k}}{W_t} \tag{1.15}$$

where W_t is the real level of stock market (the value-weighted CRSP market index deflated by the consumer price index) at time *t*, $ewaW_{t-1}$ is the exponentially weighted average of real stock market levels up to *t*-1. *INVRELW* is a proxy for the time-varying risk aversion. Finally, we use the historical bond beta, which is the slope coefficient from a regression of excess long-term government bond returns on excess stock market returns, as a proxy for the time-varying risk.

We base the statistical inference on a parametric bootstrapping approach as in Jiang, et al. (2007). Panel A of Tale 13 reports the cross-sectional distributions of the Newey-West *t*-statistics and their bootstrapped *p*-values for the estimated coefficients on the macroeconomic variables. The results show that only the mean and median coefficient estimates on the historical bond beta are significantly positive, indicating that government bond fund managers are most concerned about time-varying risk of bond market when making their asset allocation decisions. This could be explained by the fact that macroeconomic information usually hit both stock market and bond market. Therefore, the bond beta in some way reflects the impact of macroeconomic information on the bond market.

To further examine whether government bond fund managers use private information in their market timing, we conduct the following tests for each fund *i*:

$$\hat{\beta}_{it} = a_i + b_i M_{t-1} + \gamma_i Term_{t+1} + e_{it}\,. \tag{1.16}$$

Similar to Jiang, et al. (2007), we base the statistical inference on a parametric bootstrapping method. If the holdings-based timing measure $\hat{\gamma}$ remains significant after controlling for the above pre-determined variables then fund managers might have information about long-term government bond returns beyond what is contained in the four instruments; otherwise fund managers do not possess private information. The result in Panel B of Table 1.13 suggests that private information plays little role in government bond fund managers' asset allocation decisions. In fact, the average timing measure even becomes slightly negative but insignificant after controlling for the four macroeconomic variables. This result is different from Jiang, et al. (2007) who document that equity fund managers use information about stock market returns not captured by those pre-determined macroeconomic variables. This is not surprising, however, given that both public and private information play an important role in the stock market while public information plays a major role in the Treasury market.

To summarize, we find that government bond fund managers adjust their portfolio betas in response to public information, especially the time-varying risk of bond market. In addition, private information appears to play little role in fund managers' asset allocation decisions.

1.5 Conclusion

In this paper, we examine the market timing ability of a sample of government bond fund managers, based on their holdings of Treasury securities during the period

1997 to 2006. By focusing on government bond funds, in particular their Treasury security holdings, we limit our sample to those funds for which it is easier to document the market timing ability if the managers do time the market, *i.e.*, if they do base their asset allocation decisions on their views of future market conditions.

Using the holdings-based timing measures developed by Jiang, et al. (2007), we find that, on average, government bond fund managers possess significantly positive market timing ability at the one-month horizon, based on a bootstrapping approach to statistical inference. The results are robust to alternative ways of estimating security betas, the length of data records, and a different holdings-based timing measure. We also document the economic value of market timing, which indicates that market timing is an important investment strategy by government bond fund managers.

We further identify certain fund characteristics which may help investors choose successful market timers. We find that, in general, fund managers specializing in Treasury securities exhibit significantly positive timing ability compared to general government fund managers who invest in a combination of Treasury securities, Mortgage-backed securities, and agency securities. In addition, government short-maturity fund managers are the most successful market timers, followed by government intermediate-maturity and government general fund managers. Finally, more successful market timers tend to have relatively higher Morningstar ratings and Sharpe ratios, larger fund flows, lower expense ratios, and higher concentrations of holdings of Treasury securities. Given that the Morningstar rating and the Sharpe ratio are measures of fund's risk-adjusted returns, the results provide supporting evidence that government bond fund managers enhance their performance by timing the market.

Finally, we find that government bond fund managers solely rely on public information, especially historical bond betas, when adjusting their portfolio betas. Private information appears to play little role in their market-timing decisions.

In conclusion, by using a more homogeneous sample, a better timing measure, and more robust statistical inference, this paper sheds light on the market timing ability of government bond fund managers. Its findings add to our understanding of the performance of bond mutual funds in general and thus have important implications for the performance evaluation of active bond fund managers and the investment decision-making of investors as well.

Table 1.1 Summary Statistics of Fund Characteristics

This table reports summary statistics for the characteristics of government bond funds and their holdings of Treasury securities, respectively, with a breakdown according to the investment objectives. Only funds with a minimum of 20 holding observations during the 1997 to 2006 period are included in the sample. Funds are divided into three subgroups by the CRSP S&P investment objectives: government general (GGN), government intermediate-maturity (GIM), and government short-maturity (GSM) bond funds. Funds are also divided into general government (General) and Treasury bond funds by the Morningstar prospectus objectives. The characteristics are first averaged over time for each fund and then averaged across funds. "NOBS – holdings" denotes the cross-sectional average number of observations with portfolio holdings information.

		By CRSP S&P Investment Objectives			By Morningstar Prospectus Objectives	
	All Funds	GGN	GIM	GSM	General	Treasury
Panel A: Government Bond Funds						
Number of funds	146	60	44	42	110	36
Total net assets ($ million)	412.82	516.69	288.79	394.38	401.23	471.72
Morningstar rating	3.05	2.73	3.14	3.41	3.05	3.07
Duration (years)	3.99	5.56	3.85	1.85	3.84	4.76
Turnover rate (per year)	1.64	1.85	1.63	1.35	1.67	1.47
Expense ratio (%/year)	0.86	0.99	0.84	0.67	0.89	0.70
Annual return (%)	5.22	5.64	5.46	4.36	5.17	5.47
Total number of holdings	176	318	90	63	202	43
Panel B: Treasury Security Holdings of Government Bond Funds						
Sharpe ratio	0.58	0.56	0.62	0.57	0.58	0.58
Total net assets ($ million)	203.55	243.74	125.85	208.05	168.05	420.34
Duration (years)	5.29	7.81	4.81	2.19	5.37	4.91
Investment in T-bills (%)	8.18	7.85	6.65	10.25	8.35	7.31
Investment in T-notes (%)	24.83	15.95	26.67	35.17	19.68	51.92
Investment in T-bonds (%)	16.30	23.38	10.25	7.34	13.85	29.88
Total investment in Treasury securities (%)	49.31	47.17	43.58	52.75	41.88	89.11
Average number of Treasury securities held	8	9	9	7	8	12
NOBS - holdings	41	40	43	39	42	38

Table 1.2 Holdings-based Treynor-Mazuy Timing Tests

This table reports the cross-sectional distribution of the holdings-based Treynor-Mazuy timing measures ($\hat{\gamma}$) and the Newey-West t-statistics (t) for government bond funds with a minimum of 20 holding observations during the 1997 to 2006 period. Treasury security betas are estimated using the past one-year daily returns. Panels A, B, and C report the results for the forecasting horizons of one, three, and six months, respectively. The bootstrapped p-values for the timing measures ($p(\hat{\gamma})$) and the Newey-West t-statistics (p) are shown in the parentheses underneath. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

	Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: One-Month Horizon															
$\hat{\gamma}$	-27.49	-4.60	-2.20	-1.57	-0.58	0.21	0.19	0.77	2.12	3.07	3.93	33.86	3.89	1.99	55.68
$p(\hat{\gamma})$	(0.35)	(0.07)	(0.02)	(0.05)	(0.03)	(0.13)	(0.01)	(0.47)	(0.11)	(0.15)	(0.85)	(0.12)	(0.65)	(0.19)	(0.68)
t	-3.16	-2.57	-1.67	-1.35	-0.56	0.25	0.22	1.05	1.64	2.35	4.05	5.74	1.28	0.57	2.14
p	(0.49)	(0.38)	(0.12)	(0.15)	(0.00)	(0.00)	(0.01)	(0.02)	(0.29)	(0.08)	(0.04)	(0.03)	(0.22)	(0.07)	(0.05)
Panel B:Three-Month Horizon															
$\hat{\gamma}$	-23.63	-3.90	-2.53	-1.58	-0.62	-0.22	-0.03	0.48	1.12	1.82	2.73	7.45	2.33	-6.87	71.20
$p(\hat{\gamma})$	(0.02)	(0.24)	(0.77)	(0.75)	(0.47)	(0.02)	(0.53)	(0.88)	(0.45)	(0.11)	(0.62)	(0.39)	(1.00)	(0.02)	(0.99)
t	-2.82	-2.64	-1.80	-1.49	-0.86	0.05	-0.04	0.92	1.68	2.10	3.25	3.62	1.26	0.36	-0.10
p	(0.26)	(0.39)	(0.12)	(0.21)	(0.30)	(0.14)	(0.48)	(0.23)	(0.32)	(0.41)	(0.31)	(0.49)	(0.55)	(0.20)	(0.61)
Panel C: Six-Month Horizon															
$\hat{\gamma}$	-4.27	-3.76	-2.44	-1.59	-0.50	0.48	0.13	0.74	1.28	1.71	7.86	62.43	5.40	10.66	122.71
$p(\hat{\gamma})$	(0.00)	(0.46)	(0.98)	(1.00)	(0.78)	(0.00)	(0.27)	(0.11)	(0.34)	(0.28)	(0.03)	(0.00)	(0.73)	(0.00)	(0.75)
t	-3.46	-3.17	-2.18	-1.74	-0.96	0.25	0.27	1.22	2.37	2.75	3.77	5.28	1.57	0.17	-0.08
p	(0.53)	(0.73)	(0.84)	(0.90)	(0.98)	(0.37)	(0.20)	(0.13)	(0.04)	(0.32)	(0.46)	(0.19)	(0.05)	(0.54)	(0.74)

Table 1.3 Holdings-based Treynor-Mazuy Timing Tests: Alternative Beta Estimates

This table reports the cross-sectional distribution of the Newey-West *t*-statistics (*t*) for the holdings-based Treynor-Mazuy timing measures with alternative estimates of Treasury security betas for government bond funds with a minimum of 20 holding observations during the 1997 to 2006 period. Treasury security betas are estimated from the past three-month daily returns (3m) and the past five-year monthly returns (5y), respectively. Panels A, B, and C report the results for the forecasting horizons of one, three, and six months, respectively. The bootstrapped *p*-values for the Newey-West *t*-statistics (*p*) are shown in the parentheses underneath. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

		Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: One-Month Horizon																
3m	*t*	-4.22	-3.76	-2.59	-1.60	-0.78	0.62	0.57	1.79	3.23	4.24	7.31	7.93	2.06	0.48	0.98
	p	(0.39)	(0.51)	(0.96)	(0.76)	(0.94)	(0.08)	(0.37)	(0.03)	(0.00)	(0.00)	(0.01)	(0.10)	(0.00)	(0.13)	(0.50)
5y	*t*	-3.25	-2.21	-1.51	-1.17	-0.53	0.21	0.10	1.00	1.61	2.20	3.37	3.59	1.18	0.27	0.41
	p	(0.48)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)	(0.08)	(0.18)	(0.46)	(0.65)	(0.43)	(0.49)
Panel B: Three-Month Horizon																
3m	*t*	-2.83	-2.54	-1.91	-1.56	-0.86	-0.08	-0.22	0.80	1.43	1.85	2.67	3.26	1.19	0.17	-0.37
	p	(0.19)	(0.25)	(0.69)	(0.91)	(0.98)	(1.00)	(1.00)	(0.98)	(0.98)	(0.95)	(0.87)	(0.74)	(0.82)	(0.26)	(0.95)
5y	*t*	-3.01	-2.98	-2.21	-1.81	-1.04	-0.18	-0.13	0.61	1.30	1.79	2.68	4.92	1.26	0.35	1.02
	p	(0.30)	(0.65)	(0.77)	(0.88)	(0.70)	(0.34)	(0.07)	(0.29)	(0.60)	(0.48)	(0.51)	(0.11)	(0.19)	(0.29)	(0.27)
Panel C: Six-Month Horizon																
3m	*t*	-3.59	-3.30	-2.26	-1.93	-0.93	0.13	0.20	1.07	2.10	2.46	3.37	3.68	1.47	-0.13	-0.39
	p	(0.48)	(0.77)	(0.99)	(1.00)	(1.00)	(1.00)	(0.96)	(0.98)	(0.29)	(0.56)	(0.68)	(0.79)	(0.15)	(0.68)	(0.96)
5y	*t*	-4.00	-3.26	-2.67	-2.17	-1.24	-0.31	-0.23	0.75	1.52	2.03	2.78	2.91	1.44	-0.03	-0.50
	p	(0.67)	(0.63)	(1.00)	(1.00)	(1.00)	(1.00)	(0.98)	(0.80)	(0.93)	(0.88)	(0.91)	(0.97)	(0.16)	(0.78)	(0.99)

Table 1.4 Holdings-based Treynor-Mazuy Timing Tests: Adjusted for Benchmark Portfolio betas

This table reports the cross-sectional distribution of the Newey-West *t*-statistics (*t*) for the holdings-based Treynor-Mazuy timing measures with adjusted portfolio betas for government bond funds with a minimum of 20 holding observations during the 1997 to 2006 period. Treasury security betas are estimated from the past one-year daily returns and then are adjusted for their duration-based matching portfolio betas. Panels A, B, and C report the results for the forecasting horizons of one, three, and six months, respectively. The bootstrapped *p*-values for the Newey-West *t*-statistics (*p*) are shown in the parentheses underneath. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

	Minium	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: 1-Month Horizon															
t	-2.74	-2.12	-1.41	-1.00	-0.20	0.47	0.51	1.12	1.71	2.18	3.32	4.07	1.10	-0.09	0.61
p	(0.11)	(0.13)	(0.06)	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)	(0.16)	(0.23)	(0.16)	(0.53)	(0.85)	(0.70)	(0.50)
Panel B: 3-Month Horizon															
t	-3.28	-1.31	-1.03	-0.78	-0.23	0.50	0.55	1.14	1.65	2.11	3.13	3.25	1.00	-0.10	0.79
p	(0.69)	(0.00)	(0.04)	(0.04)	(0.11)	(0.04)	(0.09)	(0.22)	(0.71)	(0.61)	(0.30)	(0.59)	(0.95)	(0.63)	(0.33)
Panel C: 6-Month Horizon															
t	-3.90	-3.01	-1.23	-0.99	-0.36	0.39	0.38	1.15	2.03	2.23	2.99	3.07	1.19	-0.24	0.56
p	(0.74)	(0.77)	(0.06)	(0.48)	(0.52)	(0.67)	(0.61)	(0.58)	(0.26)	(0.83)	(0.82)	(0.96)	(0.66)	(0.77)	(0.57)

Table 1.5 Holdings-based Treynor-Mazuy Timing Tests: Active Changes of Portfolio Betas

This table reports the cross-sectional distribution of the Newey-West *t*-statistics (*t*) for the holdings-based Treynor-Mazuy timing measures with active changes of portfolio betas over the past three months for government bond funds with a minimum of 10 observations of active portfolio beta changes during the 1997 to 2006 period. Treasury security betas are estimated from the past one-year daily returns. Panels A, B, and C report the results for the forecasting horizons of one, three, and six months, respectively. The bootstrapped *p*-values for the Newey-West *t*-statistics (*p*) are shown in the parentheses underneath. “Stdev,” “Skew,” and “Kurto” denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

	Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
							Panel A: 1-Month Horizon								
t	-3.45	-2.79	-2.19	-1.80	-1.01	0.07	0.17	0.97	1.67	2.41	3.73	4.47	1.43	0.15	0.05
p	(0.06)	(0.13)	(0.63)	(0.88)	(0.83)	(0.08)	(0.01)	(0.08)	(0.21)	(0.04)	(0.15)	(0.64)	(0.23)	(0.41)	(0.96)
							Panel B: 3-Month Horizon								
t	-3.10	-3.02	-2.29	-1.84	-1.09	-0.16	-0.08	0.64	1.28	1.78	3.27	3.93	1.23	0.08	0.27
p	(0.13)	(0.34)	(0.66)	(0.82)	(0.88)	(0.83)	(0.47)	(0.94)	(0.96)	(0.88)	(0.45)	(0.51)	(0.89)	(0.45)	(0.67)
							Panel C: 6-Month Horizon								
t	-4.00	-3.33	-2.12	-1.64	-1.06	-0.10	-0.16	0.83	1.43	1.91	2.65	7.74	1.40	0.94	5.54
p	(0.45)	(0.49)	(0.27)	(0.27)	(0.68)	(0.48)	(0.46)	(0.38)	(0.85)	(0.85)	(0.92)	(0.08)	(0.47)	(0.08)	(0.10)

Table 1.6 Holdings-based Treynor-Mazuy Timing Tests: Length of Data Records

This table reports the cross-sectional distribution of the Newey-West *t*-statistics (*t*) for the holdings-based Treynor-Mazuy timing measures for government bond funds with a minimum of 10 (10*obs*) and 30 holding observations (30*obs*), respectively, during the 1997 to 2006 period. Treasury security betas are estimated using the past one-year daily returns. Panels A, B, and C report the results for the forecasting horizons of one, three, and six months, respectively. The bootstrapped *p*-values for the Newey-West *t*-statistics (*p*) are shown in the parentheses underneath. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

		Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: One-Month Horizon																
10*obs*	*t*	-3.76	-3.16	-1.81	-1.49	-0.60	0.24	0.22	1.08	1.72	2.45	5.74	7.85	1.44	1.00	4.58
	p	(0.37)	(0.43)	(0.15)	(0.33)	(0.01)	(0.00)	(0.01)	(0.01)	(0.20)	(0.06)	(0.00)	(0.01)	(0.07)	(0.01)	(0.05)
30*obs*	*t*	-3.16	-2.29	-1.58	-1.26	-0.56	0.24	0.22	0.94	1.62	2.05	4.05	5.74	1.25	0.76	3.22
	p	(0.65)	(0.28)	(0.06)	(0.05)	(0.01)	(0.00)	(0.01)	(0.04)	(0.12)	(0.13)	(0.00)	(0.00)	(0.10)	(0.01)	(0.01)
Panel B: Three-Month Horizon																
10*obs*	*t*	-3.38	-2.82	-1.93	-1.51	-0.85	0.03	-0.07	0.98	1.68	2.09	3.25	3.62	1.28	0.21	-0.15
	p	(0.20)	(0.16)	(0.17)	(0.16)	(0.21)	(0.20)	(0.63)	(0.10)	(0.34)	(0.52)	(0.58)	(0.69)	(0.80)	(0.27)	(0.92)
30*obs*	*t*	-2.82	-2.15	-1.80	-1.51	-0.85	0.03	0.01	0.80	1.56	2.02	3.08	3.21	1.19	0.20	-0.23
	p	(0.36)	(0.03)	(0.07)	(0.11)	(0.09)	(0.01)	(0.09)	(0.39)	(0.32)	(0.22)	(0.09)	(0.36)	(0.74)	(0.30)	(0.48)
Panel C: Six-Month Horizon																
10*obs*	*t*	-3.46	-3.17	-2.11	-1.74	-0.96	0.18	0.21	1.17	2.32	2.75	4.02	5.28	1.53	0.28	0.01
	p	(0.12)	(0.25)	(0.46)	(0.79)	(0.96)	(0.26)	(0.17)	(0.11)	(0.02)	(0.20)	(0.36)	(0.23)	(0.25)	(0.16)	(0.89)
30*obs*	*t*	-3.17	-2.49	-2.02	-1.72	-0.96	0.24	0.27	1.21	2.12	2.50	3.77	5.28	1.50	0.34	0.29
	p	(0.46)	(0.31)	(0.60)	(0.81)	(0.86)	(0.07)	(0.05)	(0.04)	(0.31)	(0.62)	(0.19)	(0.09)	(0.12)	(0.32)	(0.38)

Table 1.7 Holdings-based Henriksson-Merton Timing Tests

This table reports the cross-sectional distribution of the Newey-West *t*-statistics (*t*) for the holdings-based Henriksson-Merton timing measures for government bond funds with a minimum of 20 holding observations during the 1997 to 2006 period. The Treasury security betas are estimated using the past one-year daily returns. Panels A, B, and C report the results for the forecasting horizons of one, three, and six months, respectively. The bootstrapped *p*-values for the Newey-West *t*-statistics (*p*) are shown in the parentheses underneath. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

	Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: One-Month Horizon															
t	-3.76	-3.16	-1.81	-1.49	-0.60	0.24	0.22	1.08	1.72	2.45	5.74	7.85	1.44	1.00	4.58
p	(0.73)	(0.83)	(0.53)	(0.76)	(0.13)	(0.02)	(0.13)	(0.03)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Panel B: Three-Month Horizon															
t	-3.38	-2.82	-1.93	-1.51	-0.85	0.03	-0.07	0.98	1.68	2.09	3.25	3.62	1.28	0.21	-0.15
p	(0.54)	(0.53)	(0.64)	(0.62)	(0.70)	(0.74)	(0.93)	(0.24)	(0.30)	(0.41)	(0.38)	(0.51)	(0.30)	(0.23)	(0.76)
Panel C: Six-Month Horizon															
t	-3.46	-3.17	-2.11	-1.74	-0.96	0.18	0.21	1.17	2.32	2.75	4.02	5.28	1.53	0.28	0.01
p	(0.38)	(0.60)	(0.79)	(0.94)	(0.95)	(0.22)	(0.38)	(0.05)	(0.00)	(0.00)	(0.12)	(0.09)	(0.02)	(0.09)	(0.70)

Table 1.8 Holdings-based Treynor-Mazuy Timing Tests: Sub-period Analysis

This table reports the cross-sectional distribution of the Newey-West *t*-statistics (*t*) for the holdings-based Treynor-Mazuy timing measures for government bond funds with a minimum of 10 holding observations during the two sub-periods: 1997-2001 and 2002-2006, in Panel A and B, respectively. Treasury security betas are estimated using the past one-year daily returns. The forecasting horizon is one month. The bootstrapped *p*-values for the Newey-West *t*-statistics (*p*) are shown in the parentheses underneath. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

	Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
							Panel A: 1997-2001								
t	-4.56	-3.76	-1.64	-1.40	-0.96	0.24	-0.02	1.27	1.93	2.49	7.10	7.85	1.66	1.17	4.48
p	(0.41)	(0.44)	(0.00)	(0.05)	(0.73)	(0.06)	(0.77)	(0.03)	(0.25)	(0.33)	(0.01)	(0.06)	(0.21)	(0.02)	(0.10)
							Panel B: 2002-2006								
t	-2.91	-2.74	-1.69	-1.16	-0.47	0.41	0.34	1.18	1.81	2.91	5.98	6.50	1.47	0.91	3.11
p	(0.06)	(0.13)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.13)	(0.00)	(0.00)	(0.05)	(0.14)	(0.02)	(0.10)

Table 1.9 Return-Based Treynor-Mazuy Timing Tests

This table reports the cross-sectional distributions of the Newey-West *t*-statistics (*t*) and their bootstrapped *p*-values (*p*) for the return-based Treynor-Mazuy timing measures for a sample of government bond funds during the 1997 to 2006 period. Panels A and B show the results based on the government bond fund returns and the hypothetical Treasury security portfolio returns, respectively. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

	Minium	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: Fund Returns															
t	-3.70	-2.98	-1.59	-1.24	-0.36	0.37	0.37	1.32	1.87	2.22	3.02	3.28	1.25	-0.39	0.33
p	(0.94)	(0.95)	(0.88)	(0.97)	(0.96)	(0.99)	(0.98)	(0.79)	(0.98)	(0.99)	(1.00)	(1.00)	(0.93)	(1.00)	(0.34)
Panel B: Treasury Security Portfolio Returns															
t	-2.53	-1.84	-1.17	-0.59	0.52	1.50	1.56	2.49	3.41	3.84	4.47	6.21	1.51	-0.16	0.09
p	(0.15)	(0.04)	(0.08)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.49)	(0.17)	(0.27)	(0.75)	(0.84)

Table 1.10 Investment Objectives and Market Timing

This table reports the cross-sectional distribution of the Newey-West *t*-statistics (*t*) for the holdings-based Treynor-Mazuy timing measures for government bond funds with different investment objectives. Only funds with a minimum of 20 holding observations during the 1997 to 2006 period are included in the sample. In Panel A, funds are divided into three subgroups by the CRSP S&P investment objectives: government general (GGN), government intermediate-maturity (GIM), and government short-maturity (GSM) bond funds. In Panel B, funds are divided into general government (General) and Treasury bond funds by the Morningstar prospectus objectives. The Treasury security betas are estimated using the past one-year daily returns. The forecasting horizon is one month. The bootstrapped *p*-values for the Newey-West *t*-statistics (*p*) are shown in the parentheses underneath. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

		Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: By CRSP S&P Investment Objectives																
GGN	*t*	-2.29	-2.29	-1.65	-1.47	-0.62	0.04	0.14	0.93	1.36	1.73	2.35	2.35	1.05	-0.07	-0.49
	p	(0.15)	(0.15)	(0.12)	(0.36)	(0.05)	(0.12)	(0.04)	(0.08)	(0.57)	(0.67)	(0.78)	(0.78)	(0.90)	(0.68)	(0.88)
GIM	*t*	-3.16	-3.16	-1.67	-1.57	-0.35	0.36	0.31	1.07	1.71	2.87	5.74	5.74	1.46	0.91	3.68
	p	(0.87)	(0.87)	(0.42)	(0.75)	(0.01)	(0.03)	(0.10)	(0.23)	(0.45)	(0.02)	(0.01)	(0.01)	(0.06)	(0.04)	(0.01)
GSM	*t*	-2.57	-2.57	-1.35	-1.03	-0.35	0.45	0.48	1.25	2.05	2.60	4.05	4.05	1.37	0.29	0.70
	p	(0.58)	(0.58)	(0.09)	(0.07)	(0.03)	(0.01)	(0.01)	(0.03)	(0.04)	(0.08)	(0.11)	(0.11)	(0.15)	(0.33)	(0.26)
Panel B: By Morningstar Prospectus Objectives																
General	*t*	-3.16	-2.57	-1.67	-1.45	-0.58	0.10	0.17	0.89	1.45	1.72	2.87	3.11	1.12	-0.09	0.24
	p	(0.55)	(0.48)	(0.19)	(0.50)	(0.04)	(0.13)	(0.11)	(0.46)	(0.78)	(0.91)	(0.55)	(0.72)	(0.91)	(0.77)	(0.46)
Treasury	*t*	-2.32	-2.32	-0.96	-0.79	0.20	1.04	1.10	1.55	3.55	4.05	5.74	5.74	1.72	0.81	1.59
	p	(0.52)	(0.52)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.14)	(0.15)

Table 1.11 Characteristics of Market Timers

All government bond funds with a minimum of 20 holding observations during the 1997 to 2006 period are sorted into quintile portfolios based on the Newey-West *t*-statistics of their holdings-based Treynor-Mazuy timing measures from Table 1.2. The first three columns report the characteristics of government bond funds: Morningstar rating, fund flow expenses ratio, and turnover rate. The last four columns report the characteristics of their Treasury security holdings: Sharpe ratio, duration, total net assets, and % of assets held by Treasury securities (%Holding). The characteristics are first averaged over time for each fund and then averaged across funds within each quintile. The last two rows report the difference in fund characteristics between the best (highest *t*-statistics) and the worst (lowest *t*-statistics) timing fund quintiles and the *p*-values (in parentheses) for the t-tests for difference in means.

	Characteristics of the Fund				Characteristics of Treasury Security Portfolios			
Quintile fund groups ranked by *t*-value of timing measures	Morningstar Rating	Flow (%)	Expense Ratio (%/year)	Turnover (per year)	Sharpe Ratio	Duration (years)	TNA ($ million)	%Holding
Bottom	2.84	-0.42	0.98	1.43	0.54	5.31	93.69	38.66
2	2.97	-0.26	0.90	2.02	0.63	6.54	119.13	41.11
3	2.94	-0.06	0.89	1.41	0.53	5.45	181.78	40.90
4	3.28	0.00	0.73	1.48	0.56	4.53	53.86	46.91
Top	3.23	0.17	0.77	1.85	0.66	4.62	315.25	54.64
Difference (Top-Bottom)	0.39	0.59	-0.21	0.42	0.13	-0.68	221.56	15.98
pval	(0.02)	(0.07)	(0.01)	(0.34)	(0.06)	(0.38)	(0.03)	(0.01)

Table 1.12 Fund Characteristics and Market Timing

All government bond funds with a minimum of 20 holding observations during the 1997 to 2006 period are sorted into quintile portfolios based on various fund characteristics. The table reports the cross-sectional distribution of the Newey-West *t*-statistics for the holdings-based Treynor-Mazuy timing measures within each quintile. In Panels A-D, funds are ranked by the characteristics of government bond funds, *i.e.*, Morningstar rating, fund flow, expenses ratio, and turnover rate, respectively. In Panels E-H, funds are ranked by the characteristics of their Treasury security holdings, *i.e.*, Sharpe ratio, duration, total net assets, and % of assets held by Treasury securities (%Holding), respectively. Treasury security betas are estimated using the past one-year daily returns. The forecasting horizon is one month. The bootstrapped *p*-values for the Newey-West *t*-statistics (*p*) are shown in the parentheses underneath. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

		Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: Quintile Fund Groups ranked by Morningstar Ratings																
Bottom	*t*	-2.29	-2.29	-2.11	-1.45	-1.03	-0.18	-0.15	0.29	1.23	1.33	3.11	3.11	1.08	0.65	2.05
	p	(0.63)	(0.63)	(0.85)	(0.39)	(0.82)	(0.80)	(0.60)	(0.94)	(0.79)	(0.90)	(0.26)	(0.26)	(0.69)	(0.22)	(0.07)
2	*t*	-3.16	-3.16	-1.58	-1.49	-0.72	0.18	0.38	1.14	1.72	1.74	2.05	2.05	1.23	-0.63	0.28
	p	(0.81)	(0.81)	(0.14)	(0.25)	(0.12)	(0.03)	(0.01)	(0.04)	(0.36)	(0.64)	(0.74)	(0.74)	(0.50)	(0.96)	(0.32)
3	*t*	-2.32	-2.32	-1.74	-1.67	-0.50	0.26	0.21	1.10	1.44	2.60	4.05	4.05	1.29	0.59	1.76
	p	(0.33)	(0.33)	(0.25)	(0.44)	(0.04)	(0.01)	(0.04)	(0.02)	(0.54)	(0.08)	(0.07)	(0.07)	(0.36)	(0.17)	(0.15)
4	*t*	-2.57	-2.57	-1.57	-1.54	-0.67	0.15	0.29	0.84	1.76	1.84	2.35	2.35	1.12	-0.35	0.12
	p	(0.70)	(0.70)	(0.36)	(0.64)	(0.58)	(0.56)	(0.46)	(0.75)	(0.31)	(0.55)	(0.53)	(0.53)	(0.62)	(0.66)	(0.37)
Top	*t*	-1.81	-1.81	-1.56	-0.69	-0.24	0.85	0.83	1.58	2.87	3.55	5.74	5.74	1.53	1.11	2.71
	p	(0.35)	(0.35)	(0.51)	(0.01)	(0.10)	(0.00)	(0.00)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.04)	(0.05)	(0.04)
Panel B: Quintile Fund Groups ranked by Fund Flow																
Bottom	*t*	-3.16	-3.16	-1.81	-1.74	-0.49	0.05	0.09	0.60	1.38	1.72	2.35	2.35	1.16	-0.58	0.99
	p	(0.88)	(0.88)	(0.48)	(0.72)	(0.21)	(0.64)	(0.45)	(0.88)	(0.85)	(0.84)	(0.80)	(0.80)	(0.73)	(0.95)	(0.23)
2	*t*	-2.57	-2.57	-2.29	-2.11	-1.35	-0.45	-0.39	0.22	1.12	1.33	1.74	1.74	1.10	0.00	-0.61
	p	(0.61)	(0.61)	(0.80)	(0.90)	(0.98)	(0.99)	(0.87)	(0.98)	(0.88)	(0.89)	(0.89)	(0.89)	(0.75)	(0.58)	(0.79)
3	*t*	-2.32	-2.32	-1.56	-0.94	-0.37	0.65	0.34	1.23	2.99	3.55	5.74	5.74	1.62	1.15	2.43
	p	(0.45)	(0.45)	(0.17)	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)
4	*t*	-1.67	-1.67	-1.49	-1.21	-0.70	0.25	0.22	1.05	1.76	2.05	2.45	2.45	1.09	-0.01	-0.75
	p	(0.07)	(0.07)	(0.12)	(0.07)	(0.17)	(0.06)	(0.13)	(0.19)	(0.39)	(0.43)	(0.54)	(0.54)	(0.83)	(0.67)	(0.73)
Top	*t*	-1.03	-1.03	-0.72	-0.56	0.24	0.75	0.53	1.44	1.71	2.60	4.05	4.05	1.04	1.05	2.44
	p	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.01)	(0.38)	(0.09)	(0.03)	(0.03)	(0.72)	(0.03)	(0.07)

		Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel C: Quintile Fund Groups ranked by Expense Ratios																
Bottom	*t*	-1.81	-1.81	-1.56	-1.03	-0.25	0.57	0.60	1.12	2.45	2.87	5.74	5.74	1.48	1.44	4.24
	p	(0.29)	(0.29)	(0.48)	(0.19)	(0.12)	(0.03)	(0.04)	(0.24)	(0.09)	(0.12)	(0.00)	(0.00)	(0.05)	(0.02)	(0.01)
2	*t*	-2.57	-2.57	-1.54	-1.14	-0.35	0.44	0.50	1.45	1.76	2.60	3.55	3.55	1.28	0.07	0.65
	p	(0.59)	(0.59)	(0.18)	(0.07)	(0.05)	(0.01)	(0.03)	(0.01)	(0.42)	(0.14)	(0.14)	(0.14)	(0.45)	(0.47)	(0.22)
3	*t*	-2.32	-2.32	-1.74	-1.51	-0.32	0.30	0.20	1.11	1.55	2.05	4.05	4.05	1.25	0.48	2.01
	p	(0.37)	(0.37)	(0.24)	(0.32)	(0.00)	(0.00)	(0.02)	(0.02)	(0.24)	(0.22)	(0.03)	(0.03)	(0.35)	(0.26)	(0.08)
4	*t*	-3.16	-3.16	-2.11	-1.58	-0.67	0.04	0.22	0.99	1.38	1.44	2.35	2.35	1.24	-0.66	0.29
	p	(0.83)	(0.83)	(0.78)	(0.65)	(0.60)	(0.84)	(0.53)	(0.59)	(0.92)	(0.98)	(0.79)	(0.79)	(0.58)	(0.90)	(0.35)
Top	*t*	-2.29	-2.29	-1.45	-1.21	-0.96	-0.09	-0.15	0.44	1.64	1.72	3.11	3.11	1.12	0.76	1.21
	p	(0.57)	(0.57)	(0.11)	(0.07)	(0.53)	(0.23)	(0.30)	(0.56)	(0.10)	(0.28)	(0.08)	(0.08)	(0.32)	(0.09)	(0.10)
Panel D: Quintile Fund Groups ranked by Turnover																
Bottom	*t*	-1.56	-1.56	-1.54	-1.49	-0.32	0.50	0.40	0.94	2.35	2.60	5.74	5.74	1.44	1.70	5.48
	p	(0.04)	(0.04)	(0.17)	(0.35)	(0.03)	(0.04)	(0.26)	(0.78)	(0.12)	(0.21)	(0.01)	(0.01)	(0.23)	(0.00)	(0.00)
2	*t*	-2.32	-2.32	-1.81	-1.35	-0.69	0.40	0.54	1.10	1.64	3.55	4.05	4.05	1.39	0.52	1.17
	p	(0.37)	(0.37)	(0.42)	(0.23)	(0.42)	(0.01)	(0.01)	(0.04)	(0.32)	(0.00)	(0.05)	(0.05)	(0.14)	(0.12)	(0.26)
3	*t*	-3.16	-3.16	-1.74	-1.56	-0.60	0.28	0.35	1.23	2.25	2.87	3.11	3.11	1.42	-0.08	0.22
	p	(0.83)	(0.83)	(0.29)	(0.45)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.14)	(0.14)	(0.05)	(0.70)	(0.47)
4	*t*	-2.57	-2.57	-2.29	-1.14	-0.58	0.07	0.17	0.91	1.62	1.71	1.76	1.76	1.08	-0.55	0.40
	p	(0.75)	(0.75)	(0.90)	(0.11)	(0.19)	(0.48)	(0.27)	(0.37)	(0.60)	(0.78)	(0.95)	(0.95)	(0.83)	(0.96)	(0.31)
Top	*t*	-2.11	-2.11	-1.58	-1.57	-0.52	0.02	-0.15	0.76	1.64	1.72	1.84	1.84	1.06	0.00	-0.69
	p	(0.46)	(0.46)	(0.38)	(0.68)	(0.20)	(0.61)	(0.78)	(0.58)	(0.45)	(0.69)	(0.87)	(0.87)	(0.73)	(0.66)	(0.83)
Panel E: Quintile Fund Groups ranked by Sharpe Ratio of Treasury Security Portfolios																
Bottom	*t*	-3.16	-3.16	-2.57	-2.32	-0.60	-0.11	0.33	0.54	1.45	1.62	1.76	1.76	1.26	-0.80	0.08
	p	(0.83)	(0.83)	(0.89)	(0.94)	(0.05)	(0.42)	(0.01)	(0.74)	(0.59)	(0.68)	(0.86)	(0.86)	(0.40)	(0.98)	(0.27)
2	*t*	-2.29	-2.29	-2.11	-1.49	-0.90	0.00	0.18	0.56	1.64	1.72	2.60	2.60	1.14	0.00	-0.04
	p	(0.48)	(0.48)	(0.71)	(0.28)	(0.46)	(0.21)	(0.08)	(0.62)	(0.26)	(0.49)	(0.31)	(0.31)	(0.53)	(0.59)	(0.39)
3	*t*	-1.74	-1.74	-1.35	-1.06	-0.56	0.16	0.20	0.89	1.35	1.74	1.84	1.84	0.91	-0.06	-0.47
	p	(0.16)	(0.16)	(0.16)	(0.19)	(0.35)	(0.44)	(0.38)	(0.55)	(0.82)	(0.75)	(0.91)	(0.91)	(0.97)	(0.55)	(0.76)
4	*t*	-1.67	-1.67	-1.58	-1.57	-0.49	0.52	0.21	1.28	2.87	4.05	5.74	5.74	1.63	1.44	3.04
	p	(0.17)	(0.17)	(0.40)	(0.71)	(0.08)	(0.00)	(0.08)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.04)
Top	*t*	-1.54	-1.54	-1.05	-0.96	-0.32	0.71	0.97	1.25	2.45	3.11	3.55	3.55	1.28	0.30	-0.36
	p	(0.07)	(0.07)	(0.02)	(0.06)	(0.13)	(0.01)	(0.00)	(0.14)	(0.13)	(0.11)	(0.25)	(0.25)	(0.52)	(0.35)	(0.72)

		Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel F: Quintile Fund Groups ranked by TNA of Treasury Security Portfolios																
Bottom	*t*	-1.81	-1.81	-1.45	-1.14	-0.32	0.10	0.09	0.56	1.04	1.64	1.74	1.74	0.83	-0.26	0.19
	p	(0.08)	(0.08)	(0.08)	(0.04)	(0.01)	(0.23)	(0.26)	(0.81)	(0.97)	(0.80)	(0.94)	(0.94)	(1.00)	(0.78)	(0.40)
2	*t*	-1.74	-1.74	-1.49	-1.35	0.10	0.48	0.50	1.17	2.35	2.60	3.11	3.11	1.20	0.08	-0.10
	p	(0.18)	(0.18)	(0.24)	(0.34)	(0.00)	(0.03)	(0.06)	(0.12)	(0.09)	(0.19)	(0.34)	(0.34)	(0.60)	(0.54)	(0.52)
3	*t*	-3.16	-3.16	-2.57	-1.62	-1.03	0.04	0.11	0.99	1.67	1.76	3.55	3.55	1.43	-0.05	0.32
	p	(0.91)	(0.91)	(0.95)	(0.62)	(0.78)	(0.41)	(0.32)	(0.21)	(0.32)	(0.68)	(0.08)	(0.08)	(0.07)	(0.59)	(0.24)
4	*t*	-2.32	-2.32	-2.29	-2.11	-0.49	0.19	0.22	1.10	1.64	1.84	4.05	4.05	1.36	0.30	1.25
	p	(0.53)	(0.53)	(0.88)	(0.96)	(0.07)	(0.12)	(0.10)	(0.07)	(0.47)	(0.60)	(0.06)	(0.06)	(0.20)	(0.44)	(0.16)
Top	*t*	-1.56	-1.56	-0.96	-0.92	-0.58	0.48	0.24	1.23	2.45	2.87	5.74	5.74	1.49	1.70	4.32
	p	(0.10)	(0.10)	(0.01)	(0.04)	(0.25)	(0.00)	(0.09)	(0.01)	(0.01)	(0.03)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Panel G: Quintile Fund Groups ranked by Duration of Treasury Security Portfolios																
Bottom	*t*	-2.57	-2.57	-2.32	-1.54	-0.91	0.55	0.56	1.45	2.60	3.55	4.05	4.05	1.61	0.08	-0.12
	p	(0.59)	(0.59)	(0.79)	(0.35)	(0.49)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.01)	(0.49)	(0.55)
2	*t*	-1.67	-1.67	-1.58	-1.14	-0.15	0.31	0.40	0.91	1.13	1.28	2.87	2.87	0.92	0.01	1.72
	p	(0.14)	(0.14)	(0.37)	(0.19)	(0.04)	(0.36)	(0.32)	(0.73)	(0.99)	(1.00)	(0.48)	(0.48)	(0.99)	(0.57)	(0.06)
3	*t*	-1.74	-1.74	-1.04	-0.74	-0.32	0.58	0.43	1.14	2.06	3.11	5.74	5.74	1.42	1.75	5.08
	p	(0.10)	(0.10)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.09)	(0.13)	(0.05)	(0.00)	(0.00)	(0.18)	(0.01)	(0.01)
4	*t*	-3.16	-3.16	-2.29	-1.81	-1.03	-0.20	-0.04	0.54	1.23	1.44	1.58	1.58	1.18	-0.54	-0.06
	p	(0.82)	(0.82)	(0.86)	(0.80)	(0.85)	(0.82)	(0.41)	(0.70)	(0.80)	(0.84)	(0.94)	(0.94)	(0.45)	(0.87)	(0.58)
Top	*t*	-2.11	-2.11	-1.56	-1.45	-0.67	0.02	0.04	0.94	1.72	1.74	1.84	1.84	1.07	0.12	-0.72
	p	(0.31)	(0.31)	(0.25)	(0.41)	(0.37)	(0.54)	(0.48)	(0.32)	(0.36)	(0.65)	(0.86)	(0.86)	(0.80)	(0.40)	(0.84)
Panel H: Quintile Fund Groups ranked by %Holding of Treasury Security Portfolios																
Bottom	*t*	-3.16	-3.16	-2.11	-1.74	-1.26	-0.11	0.12	0.83	1.58	1.62	2.35	2.35	1.32	-0.29	-0.42
	p	(0.87)	(0.87)	(0.79)	(0.77)	(0.99)	(0.97)	(0.74)	(0.80)	(0.82)	(0.93)	(0.78)	(0.78)	(0.39)	(0.73)	(0.69)
2	*t*	-2.29	-2.29	-1.81	-1.14	-0.49	0.09	0.17	0.50	1.64	1.72	2.87	2.87	1.05	0.23	1.28
	p	(0.61)	(0.61)	(0.56)	(0.09)	(0.10)	(0.28)	(0.17)	(0.90)	(0.33)	(0.57)	(0.32)	(0.32)	(0.77)	(0.45)	(0.12)
3	*t*	-1.67	-1.67	-1.35	-1.15	-0.69	-0.04	0.10	0.46	1.20	1.25	1.45	1.45	0.83	-0.08	-0.76
	p	(0.09)	(0.09)	(0.10)	(0.14)	(0.28)	(0.65)	(0.37)	(0.96)	(0.86)	(0.97)	(0.98)	(0.98)	(1.00)	(0.64)	(0.88)
4	*t*	-2.57	-2.57	-2.32	-1.54	-0.30	0.35	0.50	1.13	1.74	2.60	3.11	3.11	1.33	-0.33	0.19
	p	(0.62)	(0.62)	(0.84)	(0.51)	(0.03)	(0.03)	(0.01)	(0.05)	(0.33)	(0.06)	(0.14)	(0.14)	(0.18)	(0.80)	(0.41)
Top	*t*	-1.05	-1.05	-0.96	-0.79	0.18	0.99	0.84	1.71	3.55	4.05	5.74	5.74	1.55	1.23	2.09
	p	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.03)	(0.06)	(0.09)

Table 1.13 Market Timing and Public Information

Panels A and B report the cross-sectional distributions of the Newey-West *t*-statistics (*t*) and their bootstrapped *p*-values (*p*) for the coefficient estimates in the following regressions:

$$\hat{\beta}_t = a + bM_{t-1} + e_t$$

and

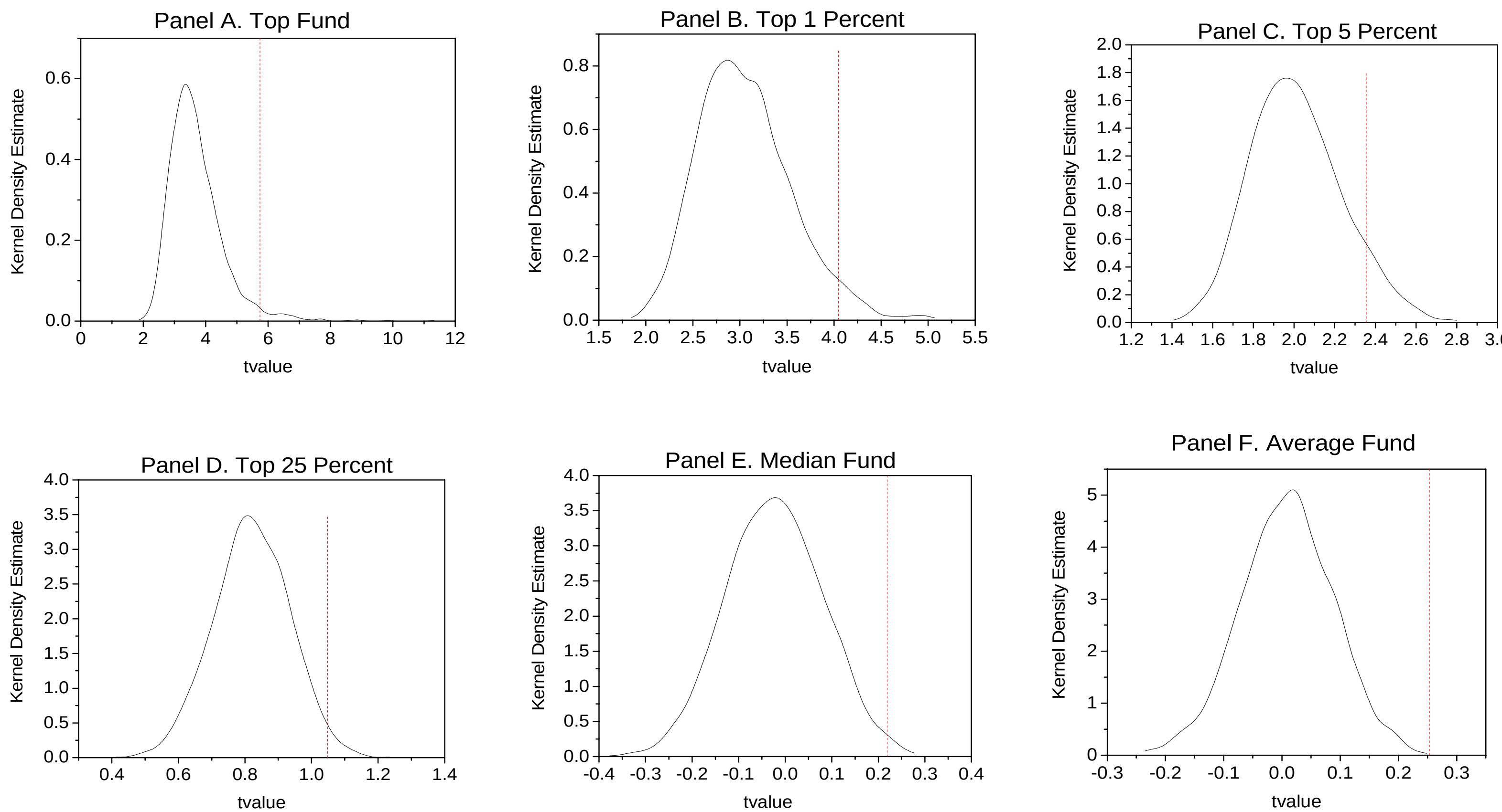
$$\hat{\beta}_t = a + bM_{t-1} + \gamma Term_{t+1} + e_t ,$$

respectively, where $\hat{\beta}_t$ is the portfolio beta at month *t*, M_{t-1} is a vector of four one-month lagged macroeconomic variables, namely, term spread (TERMSP), real bond yield (REALYLD), inverse relative wealth (INVRELW), and historical bond beta (BETA), $Term_{t+1}$ is the term premium over the month *t*+1, b=[b_{TERMSP} $b_{REALYLD}$ $b_{INVRELW}$ b_{BETA}]', and γ is the holdings-based timing measure. "Stdev," "Skew," and "Kurto" denote the cross-sectional standard deviation, skewness, and excess kurtosis, respectively.

		Minimum	1%	5%	10%	25%	Mean	Median	75%	90%	95%	99%	Maximum	Stdev	Skew	Kurto
Panel A: Fund Beta and Macroeconomic Variables																
b_{TERMSP}	*t*	-4.10	-3.92	-2.11	-1.42	-0.36	1.22	1.07	2.31	4.80	5.54	8.73	8.92	2.38	0.62	0.69
	p	(0.80)	(0.95)	(0.82)	(0.77)	(0.67)	(0.52)	(0.37)	(0.61)	(0.11)	(0.63)	(0.01)	(0.10)	(0.03)	(0.34)	(0.15)
$b_{REALYLD}$	*t*	-9.55	-9.00	-6.43	-5.10	-3.15	-2.18	-2.01	-0.76	0.17	1.13	2.71	2.95	2.20	-0.61	1.05
	p	(0.75)	(0.96)	(0.99)	(0.92)	(0.69)	(0.78)	(0.77)	(0.59)	(0.64)	(0.17)	(0.14)	(0.42)	(0.02)	(0.53)	(0.38)
$b_{INVRELW}$	*t*	-6.43	-4.99	-3.78	-2.67	-1.09	0.08	0.15	1.40	2.66	3.58	5.13	5.14	2.09	-0.13	0.43
	p	(0.83)	(0.66)	(0.88)	(0.57)	(0.26)	(0.27)	(0.30)	(0.13)	(0.04)	(0.15)	(0.58)	(0.91)	(0.10)	(0.90)	(0.88)
b_{BETA}	*t*	-2.23	-1.69	-1.29	-0.99	-0.32	0.51	0.53	1.30	1.85	2.17	3.17	3.50	1.10	0.07	-0.23
	p	(0.07)	(0.02)	(0.08)	(0.11)	(0.10)	(0.04)	(0.05)	(0.03)	(0.04)	(0.07)	(0.14)	(0.27)	(0.45)	(0.60)	(0.89)
Panel B: Market Timing Controlling for Public Information																
b_{TERMSP}	*t*	-4.10	-3.75	-2.12	-1.35	-0.22	1.27	1.12	2.32	4.66	5.48	8.57	9.08	2.31	0.63	0.80
	p	(0.77)	(0.89)	(0.81)	(0.60)	(0.41)	(0.38)	(0.29)	(0.56)	(0.20)	(0.62)	(0.01)	(0.09)	(0.14)	(0.31)	(0.12)
$b_{REALYLD}$	*t*	-9.40	-8.77	-6.31	-5.02	-3.13	-2.12	-1.93	-0.70	0.23	1.19	2.77	2.97	2.21	-0.60	0.91
	p	(0.72)	(0.93)	(0.97)	(0.88)	(0.67)	(0.71)	(0.70)	(0.52)	(0.57)	(0.14)	(0.14)	(0.42)	(0.02)	(0.49)	(0.49)
$b_{INVRELW}$	*t*	-6.36	-4.91	-3.55	-2.70	-1.08	0.11	0.18	1.40	2.64	3.64	5.21	5.35	2.10	-0.07	0.37
	p	(0.82)	(0.63)	(0.75)	(0.63)	(0.26)	(0.25)	(0.28)	(0.12)	(0.06)	(0.11)	(0.53)	(0.85)	(0.09)	(0.85)	(0.89)
b_{BETA}	*t*	-2.26	-1.71	-1.33	-1.04	-0.33	0.52	0.52	1.30	1.87	2.18	3.17	3.44	1.11	0.05	-0.25
	p	(0.07)	(0.02)	(0.09)	(0.14)	(0.10)	(0.04)	(0.05)	(0.03)	(0.04)	(0.07)	(0.14)	(0.30)	(0.45)	(0.62)	(0.91)
γ	*t*	-3.38	-2.12	-1.74	-1.54	-0.89	-0.24	-0.32	0.45	1.07	1.39	2.19	3.18	1.00	0.27	0.51
	p	(0.72)	(0.23)	(0.56)	(0.73)	(0.70)	(0.71)	(0.73)	(0.68)	(0.72)	(0.78)	(0.77)	(0.42)	(0.72)	(0.26)	(0.43)

Figure 1.1 Actual T-Statistics vs. the Distributions of Bootstrapped T-Statistics for the Holdings-based Timing Estimates of Individual Funds at Various Percentile Points in the Cross Section

This figure plots kernel density estimates of the bootstrapped distributions of *t*-statistics for the holdings-based Treynor-Mazuy timing estimates (solid lines) for government bond funds with a minimum of 20 holding observations during the 1997 to 2006 period. The forecasting horizon is one month. The *x*-axes show the *t*-statistics, and the *y*-axes show the kernel density estimates. The dashed vertical lines represent the actual *t*-statistics. Panels A-F show the results for the marginal fund at the maximum, top 1%, top 5%, top 25%, median, and mean of the distribution, respectively.



Chapter 2

Do Mutual Fund Managers Time Market Liquidity?

(Co-authored with Charles Cao and Timothy Simin)

2.1 Introduction

The literature on the timing ability of mutual fund managers has traditionally centered on the convex relationship between fund returns and the market wide risk factor. This research has produced little evidence that fund managers possess any ability to time market returns. For example, Treynor and Mazuy (1966) document that only 1 out of 57 funds exhibits significant positive market timing ability. More recent studies such as Chang and Lewellen (1984), Henriksson (1984), and Graham and Harvey (1996) and studies using a conditional framework such as Ferson and Schadt (1996) and Becker, Ferson, Myers, and Schill (1999) provide similar conclusions.[1] The paucity of evidence that fund managers appropriately change market exposure prior to market advances and declines is perhaps unsurprising given the difficulty in predicting market returns (Bossaerts and Hillion (1999), Ferson, Sarkissian, and Simin (2003), Goyal and Welch (2003)).

[1] Some notable exceptions are Bollen and Busse (2001) who document significant timing ability of funds using daily fund returns and Wermers (2000) and Jiang, Yao, and Yu (2007) who document the timing ability using holding-based performance analysis.

While market returns lack sufficient persistence to be reliably predictable, the autocorrelation in the conditional volatility of market returns is typically much higher. Busse (1999) investigates the funds' ability to time market volatility and documents that mutual fund managers tend to reduce exposure to market risk during periods of high volatility while increasing market exposure during periods of low volatility. Fund managers enhance risk-adjusted performance by timing volatility. Golec (2004) presents evidence that compensation incentives of portfolio managers partly determine the success of market volatility timing strategies. If managers must be motivated to time volatility, this will affect portfolio performance comparisons.

In this paper we study whether fund managers time market-wide liquidity risk. Given recent evidence linking liquidity risk and prices, (Acharya and Pedersen (2005), Pastor and Stambaugh (2003), and Sadka (2003)), we test if fund managers account for liquidity risk in their asset allocation decisions. Traditional performance measures such as Sharpe's ratio and Jensen's alpha adjust for risks unrelated to liquidity. If the liquidity factor captures information shocks or changes in the amount of activity of noise traders (Sadka (2003)), then understanding how fund managers deal with liquidity risk will be important for measuring performance.

To understand why fund managers would time market liquidity when making asset allocation decisions, consider a fund investing in two asset classes, stocks and bonds. The documented positive relation between market returns and liquidity risk, along with persistence in liquidity, implies that a high liquidity state of nature follows a high liquidity state and hence higher than average market returns. In high liquidity states a liquidity timing fund manager will allocate away from bonds and into stocks to increase market exposure. Similarly, if the equity market is illiquid, fund managers allocate away from stocks and into bonds to decrease their exposure to the equity market.

We examine liquidity timing from the perspective of fund managers who act in the best interests of fund shareholders. Our theoretical analysis predicts a positive response of fund systematic risk to market liquidity. Consistent with this prediction, we find that fund managers reduce market exposure in illiquid markets and increase exposure in liquid markets, indicating significant liquidity timing ability. We also find that relative to survivors, the negative performance of non-surviving funds is emphasized when the model includes market wide liquidity indicating that liquidity timing is an important component in evaluating the performance of active fund managers.

This paper is part of a growing literature on market timing that explores other possible timing variables. For instance, Ferson and Qian (2004) study fund manager's ability to time market returns conditional on a list of state variables including market liquidity. In contrast, we investigate the fund's ability to directly time market liquidity, offering new insights into the traditional timing issues of fund managers. We also motivate liquidity timing from the fund managers' perspective, assuming that managers attempt to maximize the fund shareholders' utility by timing market exposure. The model we derive explicitly describes the relationship between fund systematic risk and market liquidity.

This paper also adds to the market liquidity literature by demonstrating the importance of liquidity as a risk factor in institutional trading. Many studies concerning liquidity risk employ static portfolios. It is interesting to see whether liquidity is an important factor in actively managed and traded portfolios such as mutual funds. This paper fills this gap by showing that liquidity plays an important role in the trading decisions of active fund managers and in the time variation of mutual fund betas.

The remainder of the paper is organized as follows. Section 2.2 develops a model that establishes the relationship between fund systematic risk and market liquidity. Section 2.3 describes the mutual fund data and the liquidity measure. Section 2.4 presents the main empirical results. Section 2.5 reports robustness checks. Concluding remarks are presented in Section 2.6.

2.2 Theoretical Analysis

We motivate liquidity timing from the fund manager's perspective, assuming that the manager attempts to maximize the fund shareholders' utility by timing market exposure. Specifically, we start from Acharya and Pedersen (2005)'s liquidity-adjusted CAPM

$$E(R_t^p - c_t^p) = \beta^{net,p} E(R_t^m - c_t^m) \tag{2.1}$$

where R_t^P is the excess return of fund *p* at time *t*, c_t^P is the illiquidity cost of fund *p* at time *t*, R_t^m is the market excess return at time *t*, c_t^m is the market illiqudity cost at time *t*, and $\beta^{net,p}$ is the net beta which represents the sensitivity of fund *p* to liquidity-adjusted market portfolio.

The objective function is

$$\max_{\beta^{net,p}} E[U_{t+1}(R_t^p - c_t^p)]\,. \tag{2.2}$$

Differentiating (2.2) with respect to $\beta^{net,p}$ we have the first order condition

$$\frac{\partial}{\partial \beta^{net,p}} E[U_{t+1}(R_t^p - c_t^p)] = 0\,. \tag{2.3}$$

Applying Stein's (1973) lemma, we have

$$E[U_{t+1}'(R_t^p - c_t^p)]E(R_t^m - c_t^m) + E[U_{t+1}''(R_t^p - c_t^p)]\beta^{net,p}\,\mathrm{var}(R_t^m - c_t^m) = 0 \tag{2.4}$$

Solving Equation (2.4) for $\beta^{net,p}$ gives

$$\beta^{net,p} = \frac{1}{\alpha}\frac{E(R_t^m) - E(c_t^m)}{\mathrm{var}(R_t^m - c_t^m)} \tag{2.5}$$

where α is the Rubinstein (1973) measure of risk aversion, $-E[U_{t+1}''(R_t^p - c_t^p)]/E[U_{t+1}'(R_t^p - c_t^p)]$, which is assumed to be a parameter. Taking the partial derivative of $\beta^{net,p}$ with respect to market illiquidity cost $E(c_t^m)$ gives

$$\frac{\partial \beta^{net,p}}{\partial E(c_t^m)} = -\frac{1}{\alpha \operatorname{var}(R_t^m - c_t^m)} < 0 . \tag{2.6}$$

Equation (2.6) reveals a negative response of beta to market illiquidity cost. This result leads to our hypothesis:

H0: Mutual fund managers reduce market exposure (beta) when market liquidity is lower (*i.e.* when the market is more illiquid).

If we can reject this hypothesis, we infer that mutual fund managers are not utilizing the information content in liquidity.

2.3 Data

2.3.1 Mutual Funds

Our mutual fund data come from the 2005 CRSP Survivor Bias Free Mutual Fund Database. The sampling period spans January 1962 through December 2004. Like other fund performance studies (*e.g.* Ferson and Schadt (1996) and Busse (1999)), we only include domestic equity funds in our sample.

Following Pastor and Stambaugh (2002), we classify mutual funds based on the objective codes reported by Wiesenberger, ICDI, and Strategic Insight. We include funds with objectives of aggressive growth (AG), long term growth (LG), growth and income

(GI), and income (IN) in our sample.[2] Because they are unlikely to exhibit any form of timing, we remove index funds from our sample.[3] We also exclude multiple share classes of the same fund. Finally, we exclude the data where the fund-year is earlier than the reported year in which the fund was organized to reduce biases from data backfilling.

The sample for the aggressive growth funds begins in January of 1968. To facilitate comparisons we reduce the samples of the other funds to the matching period. The final sample includes 3,990 equity funds, among which are 2,441 live funds and 1,549 dead funds over the period of January, 1968 through December of 2004.

Summary statistics for monthly returns of the mutual fund portfolios with different investment objectives are presented in Panel A of Table 2.1. We construct an equally-weighted portfolio using all funds in a respective investment objective category and then compute returns.[4] Among the four categories, the largest is the long-term growth funds with an average number of 312 funds per month, and the smallest is the income funds with an average number of 118 funds per month. Sharpe ratios for the fund categories range between 0.16 for the aggressive growth funds up to 0.28 for the income funds. All the funds categories display slight negative skewness and are rather fat tailed. None of the fund categories exhibit autocorrelation above 16%.

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[2] AG funds are those whose Wiesenberger codes are SCG, AGG and MCG, whose ICDI codes are AG and AGG, or whose Strategic Insight codes are AGG and SCG. long-term growth funds include those with Wiesenberger codes of G, G-S, S-G, GRO, and LTG, ICDI code of long-term growth, or Strategic Insight code of GRO. GI funds are those with Wiesenberger codes of GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, and GRI, or ICDI code of GI, or Strategic Insight code of GRI. IN funds are those with Wiesenberger codes of I, I-S, IEQ, and ING, or ICDI code of IN, or Strategic Insight code of ING. Funds are assigned to each category in order from Wiesenberger, ICDI, and Strategic Insight. For example, if a mutual fund has Wiesenberger code of LTG, ICDI code of GI, and Strategic Insight code of AGG, it is classified as a long-term growth fund.

[3] We exclude funds with “index” in there names.

[4] We also construct value-weighted portfolios and the results are qualitatively similar.

In Panel B we report summary statistics for the surviving and non-surviving funds. There are almost twice as many surviving as non-surviving funds. As expected, the survivors exhibit higher returns and lower volatility than non-survivors. Surviving funds are slightly more negatively skewed, have less heavy tails, and are less autocorrelated then the non-surviving funds. In the fund-by-fund analysis we use a modified classification scheme to group funds where we fix the type of the fund to the objective that is most often reported, rather than allowing any particular fund's categorization to change through time. Summary statistics for the equally weighted portfolios of the reclassified funds are in Panel C and are similar to those in Panel A.

2.3.2 The Liquidity Measure

In general, liquidity indicates the ability to trade large quantities at low cost, quickly, and without changing the price. There are several measures of liquidity proposed in the literature. Pastor and Stambaugh (2003) develop a measure that focuses on the transitory price effects of trades, Acharya and Pedersen (2005) measure the total price impact, and Sadka (2003) focuses on permanent price effects. In this study we use the liquidity measure developed by Pastor and Stambaugh (2003) to examine whether mutual fund managers have the ability to time market liquidity. Specifically, we estimate the liquidity, $\gamma_{i,t}$, for stocks using the following OLS regression

$$r^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,t} sign(r^e_{i,d,t}) \times v_{i,d,t} + \varepsilon_{i,d+1,t}, \quad d = 1,...,D, \tag{2.7}$$

where $r_{i,d,t}$ is the return on stock *i* on day *d* in month *t*, $r^e_{i,d,t}$ is the excess return of stock *i* over the CRSP value-weighted market return on day *d* in month *t*, $v_{i,d,t}$ is the dollar volume for stock *i* on day *d* in month *t*. Let $\gamma_{i,t}$ denote the liquidity measure for stock *i* in month *t*. Intuitively, $\gamma_{i,t}$ measures how much it costs to trade say, 100 more shares of stock *i*. We construct a monthly market liquidity measure as the equally weighted average of the liquidity measures of individual stocks on the NYSE and AMEX as

$$\gamma_t = \frac{1}{N}\sum_{i=1}^{N}\gamma_{i,t} \tag{2.8}$$

The value of γ_t can be viewed as the cost of a \$1 million trade distributed equally across stocks. However, given that the market value of stock market has increased over time, a dollar trade size of \$1 million is less substantial in relative terms in the 1990's than in the 1960's. To reflect this size effect, we construct a scaled series L_{mt} as

$$L_{mt} = (m_{t-1} / m_1)\hat{\gamma}_t \tag{2.9}$$

where m_{t-1} is the total market value at the end of month *t*-1 and m_1 the total market value in August 1962. The more illiquid the stock, the greater the return reversal for the given "order flow", which is roughly measured as the signed volume. In general, the liquidity measure is expected to be negative and smaller in absolute value when liquidity is high.

Figure 2.1 plots the time series of liquidity measure. Summary statistics for the liquidity measure are in Panel D of Table 2.1. The mean (median) value of market liquidity is –2.9% (-1.8%), indicating about a 2-3% cross-sectional average liquidity cost of trading $1 million in 1962 "stock market" dollars. The first-order autocorrelation of market liquidity is 0.20, implying that liquidity is somewhat persistent over time.

2.4 Empirical Analysis

In this section, we test the hypothesis that mutual fund managers time market liquidity when making trading decisions. We then examine the performance of mutual funds conditional on market liquidity. Finally, we perform several robustness checks of the results. Before presenting our main results we validate our mutual fund data by estimating the Carhart (1997) four factor model with and without the Treynor and Mazuy (1966) market returns timing model for each fund group. These results are in Table 2.2 and are consistent with previous studies such as Carhart (1997).

In both panels adjusted R-square ranges from 70 to above 95 percent across fund categories. While alpha is insignificantly different from zero for any fund group, for the Carhart (1997) model in Panel A non-surviving funds under-perform surviving funds. In Panel B including the square of the market factor in the Carhart (1997) model produces results consistent with Treynor and Mazuy (1966), Chang and Lewellen (1984), and Graham and Harvey (1996). We find no evidence that fund managers possess market timing ability. The coefficients on the squared market returns are all insignificant except for long-term growth funds which have significantly negative coefficients at the 10% level. This perverse timing ability is consistent with Ferson and Schadt (1996).

2.4.1 Market Liquidity Timing

To examine the liquidity timing ability of fund managers we account for market liquidity timing using a first order Taylor series expansion to express market beta as a linear function of its time-series mean and abnormal market liquidity:

$$\beta_{mp} = \beta_{0p} + \gamma_{mp}(L_{mt} - \overline{L}_m) . \tag{2.10}$$

Equation (2.10) shows how the market risk of a mutual fund portfolio depends on market-wide liquidity. The coefficient γ_{mp} measures the impact on market risk as liquidity deviates from its mean.

While Acharya and Pedersen (2005)'s liquidity-adjusted CAPM is a single factor model, given their importance in explaining the cross-section of mutual funds, we include the Fama-French factors and Carhart's momentum factor as controls. Substituting Equation (2.10) into the Carhart four-factor model gives the liquidity timing model:

$$R_{pt} = \alpha_p + \beta_{0p}RM_t + \beta_{1p}SMB_t + \beta_{2p}HML_t + \beta_{3p}UMD_t + \gamma_{mp}(L_{mt} - \overline{L}_m)RM_t + \varepsilon_{pt} . \tag{2.11}$$

RM, SMB, and HML are Fama and French (1993)'s market proxy and factor mimicking portfolios for size and book-to-market equity, and UMD is Carhart (1997)'s momentum factor.

Table 2.3 reports the Newey-West test results of Equation (2.11) using the market liquidity measure of Pastor and Stambaugh (2003).[5] Consistent with our hypothesis, the liquidity coefficients for all equity funds are significantly positive for a one-sided test indicating evidence of liquidity timing by mutual fund managers.

For the subgroups of funds with different investment objectives all of the liquidity coefficients are significantly positive for aggressive growth funds and long-term growth funds, but insignificant for growth and income funds and income funds. This result is particularly strong for the aggressive growth fund portfolio, which suggests that aggressive growth funds are more aggressive in liquidity timing than other funds. The liquidity coefficients for surviving funds are also significantly positive, while the coefficient on liquidity is insignificant for the non-surviving funds. These results are consistent with fund managers demonstrating timing ability in market liquidity. Specifically, fund managers increase market exposure when market liquidity is higher than average while reducing market exposure when liquidity is lower than average. Furthermore, our results indicate that timing market liquidity also plays a role in the survival of a fund.

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[5] Interacting liquidity and the market returns produces some extremely large outliers. We winsorize the liquidity measure at the 1% level, which is equivalent to moving the two largest and two smallest values to the third largest and smallest values respectively to ensure that our results are not driven by data points that are significantly different from the bulk of the data.

2.4.2 Fund-by-fund Analysis of Market Liquidity Timing

In this subsection we investigate the liquidity timing ability of fund managers at the individual fund level for all the equity funds. The large sample in the CRSP database enables us to perform the fund-by-fund analysis not only for the entire domestic equity fund group but also within each fund group with different investment objectives. Because the investment objective codes for each fund often change over time, we follow Pastor and Stambaugh (2002) and assign a fund to the category into which it is classified most often. For example, if a fund with a history of 5 years is classified as a long-term growth fund for four years and as an aggressive growth fund for one year, it is assigned to the long-term growth fund group. Here we exclude funds that have existed for less than one year.

Table 2.4 reports the cross-sectional statistics of liquidity timing coefficients for individual funds. For all domestic equity funds, the cross-sectional mean (median) of the timing coefficients is 0.53 (0.32). The positive mean timing coefficient suggests that the average fund manager increases market exposure during periods of higher-than-normal liquidity and decreases market exposure during periods of lower-than-normal liquidity. This is consistent with the results for the equally weighted results in Table 2.3.

The average timing coefficient is positive for all the fund subgroups except income fund which has a mean (median) timing coefficient of -0.03 (-0.10). Among the different styles, the cross-sectional mean of the timing coefficients is greatest for the aggressive growth funds and smallest for the income funds. This suggests that the aggressive growth funds are more aggressively timing liquidity than other funds. In addition, the mean (median) of timing coefficients for surviving funds is higher than that for non-surviving funds.

Table 2.4 also reports the fraction of funds that show positive liquidity timing coefficients from regression (2.11) significant at 5% using one-tailed tests. For all equity funds, 19% demonstrate positive timing ability in market liquidity. Among the subgroups, 23% to 21% of aggressive growth and long-term growth funds exhibit significantly positive liquidity timing ability. The growth and income and income funds have fewer significant coefficients, 11% and 5% respectively. It is interesting that the surviving funds have only a marginally larger percentage of significant timing coefficients, 20%, versus the non-surviving fund category, 17% even though the average timing coefficient for surviving funds is larger then the timing coefficient for non-survivors.

Taken together these results indicate that market timing of liquidity varies with fund investment objective. Funds in aggressive growth and long-term growth style categories have more significant and larger average timing coefficients. Funds focused on growth and income and income have both fewer and smaller average timing coefficients. This is consistent with the intuition that funds with higher turnover are more likely to time liquidity. The aggressive funds in the aggressive growth group have the highest average turnover ratio, 1.24, followed by the long-term funds which have a turnover ratio of

0.74.[6] The less aggressive funds, growth and income and income funds are characterized by lower turnover ratios of 0.59 and 0.66.

2.4.3 Conditional Fund Performance and Market Liquidity Timing

To address the question of whether timing liquidity produces superior performance, we compare the unconditional alphas in Table 2.3 with conditional alphas in Table 2.5. Following Christopherson, Ferson, and Glassman (1998), we express time-varying alpha as a linear function of lagged abnormal market liquidity:

$$\alpha_p = \alpha_{0p} + \alpha_{1p}(L_{m,t-1} - \overline{L}_m)\,. \tag{2.12}$$

Substituting equation (2.12) into the liquidity timing model in equation (2.11) gives

$$\begin{aligned} R_{pt} &= \alpha_{0p} + \alpha_{1p}(L_{m,t-1} - \overline{L}_m) + \beta_{0p} RM_t + \beta_{1p} SMB_t \\ &\quad + \beta_{2p} HML_t + \beta_{3p} UMD_t + \gamma_{mp}(L_{mt} - \overline{L}_m) RM_t + \varepsilon_{pt}\,. \end{aligned} \tag{2.13}$$

The sign and significance of α_{1p} indicates whether performance is enhanced conditional on high or low liquidity.

The regression results of equation (2.13) are shown in Table 2.5. For all of the fund groups we find that conditioning alpha on lagged liquidity does little to change the

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[6] The turnover ratio of the fund (over the calendar year) is the minimum of aggregate purchases of securities or aggregate sales of securities, divided by the average total net assets of the fund.

inferences drawn from the unconditional alphas in Table 2.3. For both the conditional alphas in Table 2.5 and the unconditional alphas in Table 2.3 all the funds exhibit abnormal performance that is statistically indistinguishable from zero except for the aggressive growth and Non-Survivor fund groups. These two groups exhibit significant negative performance whether we condition on lagged liquidity or not.

These results imply that after controlling for the factors in the Carhart (1997) model and liquidity risk, none of the fund groups display positive abnormal performance. The funds with significant negative performance, aggressive growth and Non-Survivors are also the fund groups with the lowest Sharpe Ratios, 16% and 14%. By comparing the Carhart (1997) model alphas in Table 2.2 with those from the liquidity model in Table 2.3 and Table 2.5, we see that including market wide liquidity in the model emphasizes the negative performance of all the fund groupings, especially for the aggressive growth and non-surviving funds.

2.5 Robustness Checks

2.5.1 Sub-period Tests

The number of funds grows dramatically over the last twenty years. To check whether our results are sample specific we divide our sample period into two equally sized time periods: one from 1/1968 to 6/1986, and the other from 7/1986 to 12/2004 and replicate the tests for the two sub-periods.

The results presented in Table 2.6 indicate the liquidity timing is a more recent phenomenon. In the earlier sub-sample only the aggressive growth funds and surviving funds exhibit significant timing coefficients using a one-sided test. In the second sub-sample the liquidity coefficients are significant for aggressive growth and long-term growth funds. While both surviving and non-surviving funds have significant positive liquidity timing coefficients in the latter sample, the surviving funds have a larger and more significant timing coefficient. Consistent with our previous results, none of the fund categories display positive abnormal returns and the alphas for aggressive funds and the non-surviving funds are significantly negative.

2.5.2 Fund Classification

In the fund-by-fund analysis if a fund's objective changes over time, the fund is assigned to the category into which it is classified most often. We check whether our fund group results are robust to this reclassification. We repeat the regression (2.11) for all fund subgroups using this second classification scheme. The results using the reclassification are qualitatively identical to those found in Table 2.3. The liquidity coefficients γ_{mp} remain significantly positive at 5% level for aggressive growth and long-term growth funds using one-sided tests, none of the funds display positive alphas and only the aggressive growth funds display significant negative performance.

2.5.3 Returns Timing, Volatility Timing vs. Liquidity Timing

Given the positive correlation between market returns and liquidity and the negative correlation between market volatility and liquidity, it may be that funds are successfully timing market returns or market volatility, but the timing manifests itself in the liquidity coefficients.[7] To explore this possibility, we express fund beta as a function of market liquidity, market volatility and excess market return and substitute it into Equation (2.10). The specification is

$$\begin{aligned} R_{pt} = \alpha_p + \beta_{0p} RM_t + \beta_{1p} SMB_t + \beta_{2p} HML_t + \beta_{3p} UMD_t + \\ \gamma_{mp}(L_{mt} - \overline{L}_m) RM_t + \phi_{mp} RM_t^{\,2} + \delta_{mp}(V_{mt} - \overline{V}_m) RM_t + \varepsilon_{pt} \end{aligned} \quad (2.14)$$

where V_{mt} is the market volatility at month *t* estimated from a GARCH (1,1) model, and $\overline{V}_m$ is the time-series mean of market volatility.

The results appear in Table 2.7. The results suggest that adding the market return and market volatility terms to the fund return specification does not materially impact the significance of the liquidity timing coefficients. Comparing the adjusted *R*-squares of Table 2.3 with those in Table 2.7 indicate that the additional variables add little, if any explanatory power. These results indicate that the liquidity coefficients are not due to the positive correlation between market returns and liquidity and the negative correlation between market volatility and liquidity. Liquidity timing is therefore an important

[7] For example, Pastor and Stambaugh (2003), Acharya and Pedersen (2005), and Amihud (2002), among others, document a positive relation between market returns and market liquidity, while Pastor and Stambaugh (2003) document the negative correlation between conditional volatility and liquidity.

component of the strategies of active mutual fund managers in addition to volatility timing documented by Busse (1999).

2.6 Conclusion

In this paper, we investigate the liquidity timing ability of mutual funds by studying how fund managers change market exposure in response to changes in market liquidity. We show that funds increase market exposure in states of high market liquidity and decrease market exposure when the market is illiquid. This indicates that fund managers demonstrate the ability to time market liquidity. We also find that such strategies have performance implications for surviving and non-surviving funds. Specifically, relative to survivors, the negative performance of non-surviving funds is emphasized when the model includes market wide liquidity indicating that liquidity timing is an important component in evaluating the performance of active fund managers.

Our paper contributes to the literature in several aspects. First, we examine the timing issue from a new perspective by focusing on market liquidity rather than market returns. This enables us to investigate the risk management behaviors and risk-adjusted performance of fund managers, which would have significant implications for manager compensation. In addition, this paper adds to the conditional mutual fund performance literature by examining how managers respond to publicly available information. Our paper also contributes to the liquidity literature in that it examines the importance of liquidity as a risk factor in the context of institutional trading.

Table 2.1 Summary Statistics of Monthly Returns of Equally Weighted Mutual Fund Portfolios and the Liquidity Measures

Summary statistics for monthly returns of equally weighted mutual fund portfolios by investment objectives (Panels A and C) and current status (Panel B) in the CRSP database based on both classification schemes described in the text. Q25 and Q75 are the 25th and 75th percentiles. The data are for the period 1/1968 through 12/2004 (444 observations). In Panel D, P.S. Liq. is the Pastor-Stambaugh liquidity measure.

	Mean	Median	Std. Dev.	Min	Max	Skewness	Kurtosis	ρ(1)	Q25	Q75
Panel A: Fund Returns										
AG	0.009	0.012	0.056	-0.255	0.153	-0.497	4.359	0.157	-0.029	0.047
LG	0.008	0.012	0.047	-0.235	0.15	-0.588	4.756	0.117	-0.02	0.041
GI	0.009	0.01	0.039	-0.163	0.207	-0.148	5.505	0.074	-0.014	0.034
IN	0.007	0.008	0.025	-0.118	0.092	-0.556	5.585	0.088	-0.004	0.019
Panel B: Current Status										
Survivor	0.009	0.011	0.039	-0.165	0.132	-0.503	4.169	0.105	-0.015	0.036
Non Survivor	0.006	0.009	0.042	-0.168	0.164	-0.447	4.416	0.148	-0.019	0.035
All	0.008	0.01	0.04	-0.166	0.133	-0.473	4.223	0.127	-0.017	0.035
Panel C: Fund Reclassification:										
AG	0.009	0.012	0.057	-0.256	0.155	-0.494	4.336	0.161	-0.028	0.048
LG	0.008	0.012	0.047	-0.232	0.15	-0.583	4.71	0.117	-0.02	0.041
GI	0.008	0.01	0.039	-0.159	0.217	-0.096	5.765	0.075	-0.014	0.034
IN	0.007	0.008	0.025	-0.118	0.093	-0.558	5.581	0.085	-0.004	0.019
Panel D: Liquidity Measure										
P.S. Liq	-0.029	-0.018	0.061	-0.437	0.207	-1.578	10.915	0.201	-0.054	0.005

Table 2.2 Preliminary Tests

Panel A reports the coefficients from the Fama-French three-factor model

$$R_{pt} = \alpha_p + \beta_{1p} RM_t + \beta_{2p} SMB_t + \beta_{3p} HML_t + \beta_{4p} UMD_t + \varepsilon_{pt}$$

and Panel B reports the coefficients from the market returns timing model

$$R_{pt} = \alpha_p + \beta_{1p} RM_t + \beta_{2p} SMB_t + \beta_{3p} HML_t + \beta_{4p} UMD_t + \delta_p RM_t^2 + \varepsilon_{pt}$$

for the equally weighted fund portfolios by objective codes and current status for the time period as specified in Table 2.1. RMRF, SMB, and HML are Fama and French's (1993) market proxy and factor mimicking portfolios for size and book-to-market equity. UMD is Carhart (1997)'s momentum factor. The Newey-West *t*-statistics are in parentheses.

Fund Group	*Panel A: Fama-French Three-factor Model*						*Panel B: Market Returns Timing Model*						
	α_p	β_{mp}	β_{SMB}	β_{HML}	β_{UMD}	Adj. R^2	α_p	β_{0mp}	β_{SMB}	β_{HML}	β_{UMD}	δ_p	Adj. R^2
AG	-0.002*	0.993*	0.493*	-0.091*	0.001*	0.952	-0.002*	0.995*	0.496*	-0.090*	0.001*	0.153	0.952
	(-2.86)	(50.26)	(17.57)	(-2.73)	(3.86)		(-2.97)	(47.53)	(16.00)	(-2.56)	(4.07)	(0.68)	
LG	-0.000	0.926*	0.138*	-0.074*	0.000	0.962	0.000	0.924*	0.134*	-0.076*	0.000	-0.205	0.962
	(-0.69)	(63.00)	(5.98)	(-3.29)	(0.20)		(0.32)	(63.07)	(5.65)	(-3.41)	(0.04)	(-1.71)	
GI	-0.000	0.841*	-0.020	0.117*	-0.000*	0.941	-0.000	0.842*	-0.020	0.117*	-0.000*	0.025	0.941
	(-0.12)	(44.17)	(-1.03)	(5.62)	(-3.48)		(-0.23)	(40.98)	(-0.91)	(5.31)	(-3.49)	(0.12)	
IN	0.000	0.477*	-0.038	0.163*	-0.001*	0.708	0.000	0.477*	-0.038	0.162*	-0.001*	-0.020	0.707
	(0.11)	(14.42)	(-1.36)	(5.28)	(-4.33)		(0.13)	(16.38)	(-1.43)	(5.53)	(-4.78)	(-0.03)	
Survivors	0.000	0.769*	0.162*	-0.017	-0.000	0.933	-0.000	0.771*	0.166*	-0.015	-0.000	0.202	0.934
	(0.56)	(28.68)	(7.58)	(-0.69)	(-0.95)		(-0.15)	(34.72)	(8.02)	(-0.63)	(-0.94)	(0.45)	
Non-survivor	-0.002*	0.774*	0.206*	-0.027	-0.001*	0.881	-0.002*	0.777*	0.211*	-0.024	-0.001*	0.238	0.881
	(-2.75)	(22.56)	(7.19)	(-0.83)	(-2.12)		(-2.86)	(26.29)	(7.31)	(-0.76)	(-2.28)	(0.42)	
All Funds	-0.000	0.772*	0.187*	-0.016	-0.000	0.916	-0.001	0.775*	0.192*	-0.014	-0.000	0.247	0.916
	(-1.50)	(25.76)	(7.80)	(-0.60)	(-1.45)		(-1.61)	(30.76)	(8.09)	(-0.52)	(-1.52)	(0.50)	

* Significant at 0.05 level, two-tailed tests.

Table 2.3 Market Liquidity Timing

The table reports the coefficients on the three-factor liquidity timing model

$$R_{pt} = \alpha_p + \beta_{1p} RM_t + \beta_{2p} SMB_t + \beta_{3p} HML_t + \beta_{4p} UMD_t + \gamma_{mp}(L_{mt} - \overline{L}_m) RM_t + \varepsilon_{pt}$$

for the equally weighted fund portfolios by objective codes and current status for the time period as specified in Table 2.1. RMRF, SMB, and HML are Fama and French's (1993) market proxy and factor mimicking portfolios for size and book-to-market equity. UMD is Carhart (1997)'s momentum factor. L_{mt} is the Pastor and Stambaugh's (2003) market liquidity measure at month *t*, and $\overline{L}_m$ is the time-series mean of market liquidity. The Newey-West *t*-statistics are in parentheses.

Fund Group	α_p	β_{0mp}	β_{SMB}	β_{HML}	β_{UMD}	γ_{mp}	Adj. R^2
AG	-0.002*	1.041*	0.523*	0.028	0.054**	0.695*	0.954
	(-3.03)	(41.58)	(12.71)	(0.66)	(1.74)	(2.36)	
LG	-0.001	0.990*	0.069*	-0.016	0.001	0.316**	0.961
	(-1.71)	(82.24)	(3.27)	(-0.80)	(0.08)	(1.89)	
GI	-0.001	0.912*	-0.065*	0.152*	-0.044*	0.012	0.942
	(-1.37)	(71.18)	(-4.07)	(5.57)	(-3.06)	(0.08)	
IN	-0.000	0.798*	-0.058*	0.295*	-0.051*	-0.154	0.719
	(-0.78)	(48.62)	(-3.22)	(9.10)	(-2.61)	(-0.77)	
Survivors	-0.000	0.978*	0.174*	0.054*	0.011	0.348*	0.938
	(-0.34)	(69.52)	(7.87)	(2.02)	(0.57)	(2.01)	
Non-survivors	-0.003*	0.972*	0.153*	0.028	-0.01	0.122	0.885
	(-3.94)	(38.64)	(4.73)	(0.85)	(-0.51)	(0.70)	
All Funds	-0.001	0.971*	0.168*	0.047**	0.004	0.284**	0.921
	(-1.45)	(64.19)	(7.40)	(1.95)	(0.24)	(1.73)	

* Significant at 0.05 level, two-tailed tests.

** Significant at 0.05 level, one-tailed tests.

Table 2.4 Cross-sectional Summary Statistics of Liquidity Timing Coefficients

Cross-sectional summary statistics of market liquidity timing coefficients γ_{mp} from the model:

$$R_{pt} = \alpha_p + \beta_{0mp} RMRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \gamma_{mp} (L_{mt} - \overline{L}_m) RMRF_t + \varepsilon_{pt}$$

for individual funds within the fund groups by objective codes or current status. RMRF, SMB, and HML are Fama and French's (1993) market proxy and factor mimicking portfolios for size and book-to-market equity. UMD is Carhart (1997)'s momentum factor. L_{mt} is the Pastor and Stambaugh's (2003) market liquidity measure at month *t*, and $\overline{L}_m$ is the time-series mean of market liquidity. In the last two columns we report the percentage of funds with positive liquidity timing coefficients γ_{mp} significant at 5% level in one-tailed tests, and funds with positive liquidity timing coefficients, respectively.

Fund Group	# of Funds	Mean	Median	Std of Mean	t-value	% of funds with t>=1.64	% of funds with t>=0
AG	1045	0.82	0.67	0.11	7.26	22.70%	69.80%
LG	1662	0.61	0.34	0.06	9.42	21.10%	63.10%
GI	676	0.03	0.06	0.08	0.33	10.80%	53.30%
IN	190	-0.03	-0.1	0.16	-0.16	5.30%	43.70%
Survivors	2221	0.6	0.36	0.05	12.71	20.20%	64.20%
Non-survivors	1352	0.4	0.26	0.1	4.01	16.50%	58.90%
Funds	3573	0.53	0.32	0.05	10.98	18.80%	62.20%

Table 2.5 Conditional Performance and Market Liquidity Timing

The table reports the coefficients on the model

$$R_{pt} = \alpha_{0p} + \alpha_{1p}(L_{m,t-1} - \bar{L}_m) + \beta_{0mp}RMRF_t + \beta_{SMB}SMB_t$$
$$+\beta_{HML}HML_t + \beta_{UMD}UMD_t + \gamma_{mp}(L_{mt} - \bar{L}_m)RMRF_t + \varepsilon_{pt}$$

for the equally weighted portfolios of surviving and non-surviving mutual funds for the time period as specified in Table 2.1. RMRF, SMB, and HML are Fama and French's (1993) market proxy and factor mimicking portfolios for size and book-to-market equity. UMD is Carhart (1997)'s momentum factor. L_{mt} is the Pastor and Stambaugh's (2003) market liquidity measure at month *t*, and $\bar{L}_m$ is the time-series mean of market liquidity. The Newey-West *t*-statistics are in parentheses.

Fund Group	α_{0p}	α_{1p}	β_{0mp}	β_{SMB}	β_{HML}	β_{UMD}	γ_{mp}	Adj. R^2
AG	-0.002* (-3.75)	0.005 (0.39)	1.016* (50.07)	0.497* (13.33)	-0.084* (-2.19)	0.093* (3.56)	0.959* (2.90)	0.954
LG	-0.000 (-0.97)	-0.007 (-0.91)	0.964* (64.88)	0.155* (4.12)	-0.062* (-2.08)	0.038 (1.78)	0.443** (1.90)	0.942
GI	-0.001* (-1.96)	-0.014 (-1.54)	0.873* (71.34)	-0.002 (-0.08)	0.104* (4.99)	-0.02 (-1.24)	0.151 (1.20)	0.720
IN	-0.000 (-0.90)	-0.012 (-1.52)	0.672* (35.81)	0.009 (0.34)	0.248* (10.76)	-0.057* (-2.96)	-0.002 (-0.01)	0.961
Survivors	0.000 (0.00)	-0.007 (-1.02)	0.923* (74.16)	0.187* (8.04)	-0.009 (-0.40)	0.032* (2.00)	0.469* (2.45)	0.938
Non-survivors	-0.002* (-5.34)	0.000 (0.00)	0.919* (49.87)	0.224* (6.28)	-0.015 (-0.54)	0.017 (0.86)	0.400** (1.76)	0.885
All Funds	-0.001* (-2.36)	-0.005 (-0.72)	0.920* (64.70)	0.206* (7.50)	-0.009 (-0.38)	0.028 (1.59)	0.433* (2.12)	0.920

* Significant at 0.05 level, two-tailed tests.

** Significant at 0.05 level, one-tailed tests.

Table 2.6 Sub-period Tests of Market Liquidity Timing

The table reports the coefficients on the four-factor liquidity timing model

$$R_{pt} = \alpha_p + \beta_{1p}RM_t + \beta_{2p}SMB_t + \beta_{3p}HML_t + \beta_{4p}UMD_t + \gamma_{mp}(L_{mt} - \overline{L}_m)RM_t + \varepsilon_{pt}$$

for the equally weighted fund portfolios by objective codes and current status for the sub-time periods of 1/1968-6/1986 and 7/1986-12/2004, respectively. RMRF, SMB, and HML are Fama and French's (1993) market proxy and factor mimicking portfolios for size and book-to-market equity. UMD is Carhart (1997)'s momentum factor. L_{mt} is the Pastor and Stambaugh's (2003) market liquidity measure at month *t*, and $\overline{L}_m$ is the time-series mean of market liquidity. The Newey-West *t*-statistics are in parentheses.

Fund Group	α_p	β_{0mp}	β_{SMB}	β_{HML}	β_{UMD}	γ_{mp}	Adj. R^2
Time Period: 1968-1986							
AG	-0.002*	0.986*	0.536*	-0.182*	0.138*	0.597**	0.950
	(-3.47)	(39.72)	(15.90)	(-4.77)	(3.84)	(1.89)	
LG	-0.000	0.928*	0.275*	-0.141*	0.093*	0.324	0.920
	(-0.10)	(63.46)	(7.51)	(-4.56)	(3.09)	(1.58)	
GI	-0.001	0.838*	0.096*	0.049*	0.021	0.287	0.736
	(-1.35)	(81.06)	(5.41)	(2.78)	(1.17)	(1.37)	
IN	-0.001	0.599*	0.112*	0.230*	-0.03	0.061	0.957
	(-1.20)	(33.57)	(4.34)	(7.33)	(-1.05)	(0.28)	
Survivors	-0.000	0.887*	0.229*	-0.051*	0.063*	0.279**	0.953
	(-0.29)	(73.77)	(9.65)	(-2.15)	(2.63)	(1.71)	
Non-survivors	-0.002**	0.874*	0.334*	-0.075*	0.069*	0.253	0.875
	(-3.70)	(53.86)	(11.81)	(-2.41)	(2.55)	(0.97)	
All Funds	-0.001	0.882*	0.277*	-0.062*	0.065*	0.247	0.921
	(-1.57)	(65.17)	(10.90)	(-2.32)	(2.56)	(1.43)	
Time Period: 1986-2004							
AG	-0.002*	1.015*	0.491*	-0.081	0.089*	0.433*	0.964
	(-2.89)	(49.63)	(12.20)	(-1.91)	(3.38)	(3.21)	
LG	-0.000	0.962*	0.152*	-0.06	0.035	0.150*	0.976
	(-0.34)	(65.36)	(3.91)	(-1.89)	(1.61)	(2.03)	
GI	-0.000	0.871*	-0.005	0.107*	-0.022	0.069	0.779
	(-1.39)	(71.38)	(-0.18)	(4.74)	(-1.34)	(1.22)	
IN	-0.000	0.674*	0.009	0.247*	-0.060*	0.075	0.973
	(-1.03)	(36.21)	(0.33)	(10.86)	(-3.06)	(0.74)	
Survivors	0.000	0.922*	0.184*	-0.007	0.029	0.220*	0.934
	(0.57)	(73.93)	(7.53)	(-0.27)	(1.76)	(3.25)	
Non-survivors	-0.002*	0.917*	0.221*	-0.017	0.013	0.143*	0.909
	(-3.67)	(50.59)	(6.03)	(-0.57)	(0.66)	(2.04)	
All Funds	-0.001	0.919*	0.203*	-0.008	0.024	0.231*	0.926
	(-1.75)	(65.14)	(7.10)	(-0.32)	(1.36)	(2.87)	

* Significant at 0.05 level, two-tailed tests.

** Significant at 0.05 level, one-tailed tests.

Table 2.7 Returns Timing, Volatility Timing vs. Liquidity Timing

The table reports the coefficients on the model

$$R_{pt} = \alpha_p + \beta_{1p} RM_t + \beta_{2p} SMB_t + \beta_{3p} HML_t + \beta_{4p} UMD_t + \gamma_{mp}(L_{mt} - \bar{L}_m) RMRF_t + \phi_{mp} RM_t^2 + \delta_{mp}(V_{mt} - \bar{V}_m) RM_t + \varepsilon_{pt}$$

for the equally weighted fund portfolios by objective codes and current status for the time period as specified in Table 2.1. RMRF, SMB, and HML are Fama and French's (1993) market proxy and factor mimicking portfolios for size and book-to-market equity. UMD is Carhart (1997)'s momentum factor. L_{mt} is the Pastor and Stambaugh's (2003) market liquidity measure at month *t*, and $\bar{L}_m$ is the time-series mean of market liquidity. V_{mt} is the market volatility at month *t* estimated from GARCH (1,1) model, and $\bar{V}_m$ is the time-series mean of market volatility. The Newey-West *t*-statistics are in parentheses.

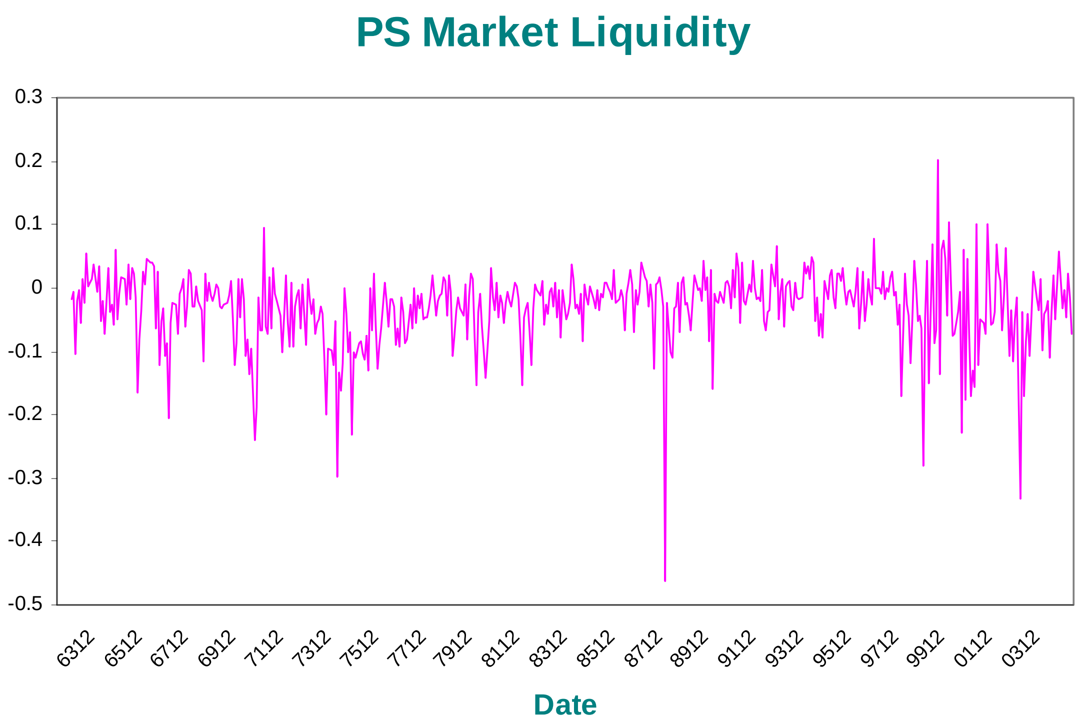
Fund Group	α_p	β_{0mp}	β_{SMB}	β_{HML}	β_{UMD}	γ_{mp}	ϕ_{mp}	δ_{mp}	Adj. R^2
AG	-0.002*	1.018*	0.492*	-0.086*	0.086*	0.760*	0.000	-5.391*	0.956
	(-3.34)	(52.22)	(12.60)	(-2.10)	(3.29)	(2.84)	(0.00)	(-2.46)	
LG	-0.000	0.963*	0.152*	-0.061*	0.033	0.278**	-0.141	-4.002*	0.944
	(-0.47)	(66.18)	(3.95)	(-1.99)	(1.54)	(1.63)	(-1.01)	(-2.64)	
GI	-0.000	0.872*	-0.005	0.106*	-0.023	0.151	0.011	-4.513*	0.724
	(-1.51)	(73.18)	(-0.17)	(4.78)	(-1.39)	(1.06)	(0.05)	(-2.66)	
IN	-0.000	0.672*	0.008	0.250*	-0.058*	-0.01	-0.413	-2.253	0.963
	(-0.88)	(36.23)	(0.31)	(10.53)	(-2.95)	(-0.05)	(-1.04)	(-0.93)	
Survivors	0.000	0.923*	0.184*	-0.008	0.028	0.356*	-0.103	-2.389	0.939
	(0.42)	(77.08)	(7.68)	(-0.36)	(1.69)	(2.25)	(-0.35)	(-1.23)	
Non-Survivors	-0.002*	0.916*	0.221*	-0.016	0.014	0.167	0.014	-3.928	0.885
	(-4.73)	(50.50)	(6.03)	(-0.53)	(0.69)	(0.92)	(0.04)	(-1.52)	
All Funds	-0.001	0.920*	0.203*	-0.009	0.024	0.283	-0.021	-3.327	0.921
	(-1.87)	(66.46)	(7.17)	(-0.35)	(1.33)	(1.70)	(-0.06)	(-1.53)	

* Significant at 0.05 level, two-tailed tests.

** Significant at 0.05 level, one-tailed tests.

Figure 2.1 Time Series of Market Liquidity Measure

The figure shows the time series of monthly market liquidity measure developed by Pastor and Stambaugh (2003). The sample covers the period from January 1962 to December 2004.



Chapter 3

An Empirical Analysis of the Dynamic Relationship between Mutual Fund Flow and Market Return Volatility

(Co-authored with Charles Cao and Eric Chang)

3.1. Introduction

We have witnessed an unprecedented growth in mutual funds since the 1980s. Shares in mutual funds now represent a major part of household wealth, and the funds themselves have become important intermediaries for savings and investments. Over the past 10 years, several studies have examined aggregate mutual fund flow into U.S. (or, international) equity funds. We now know that (1) flow into equity funds is positively correlated with concurrent and subsequent market returns, while market returns are negatively related to subsequent flow in the monthly data (Warther (1995)); (2) daily flow is positively associated with concurrent and previous day’s market return, but daily returns are not associated with lagged flow (Edelen and Warner (2001)); and (3) the documented relation between market returns and flow for U.S. equity funds is uncovered in other developed markets and emerging markets (Froot, O'Connell, and Seasholes (2001)). These findings suggest that flow and flow-induced trade have an effect on market returns, and this effect is not idiosyncratic. Also there is evidence of positive feedback trading by mutual fund investors in daily data, but not in monthly data. These studies concentrate, exclusively, on the relation between flow and market returns.

The purpose of this paper is to offer new insights on aggregate mutual fund flow. We focus on the relation between aggregate flow and market volatility and answer three questions that are not addressed by the previous literature. First, we examine the dynamic relation between flow and market volatility and investigate whether market volatility is associated with concurrent and past aggregate flow. Second, we study whether mutual fund investors time market volatility by moving money into (or out of) equity funds in response to a decrease (or an increase) in market volatility. Finally, we examine the relation between intraday market volatility and daily flow and assess the differential impact of inflow versus outflow on intraday market volatility.

We use a data set of daily mutual fund flow provided by Trim Tabs Investment Research. Using the data from 1998 to 2003, we estimate the dynamic relation between market volatility and flow by using a Vector Autoregression (VAR) approach. Our primary finding is that daily market volatility is negatively related to concurrent and lagged flow. We also find a negative contemporaneous relationship between innovations in flow and market volatility. A structural VAR impulse response analysis suggests that shock in flow has a negative impact on market volatility. This effect is particularly significant over the next ten days, and gradually disappears. In other words, an inflow shock induces lower market volatility, while an outflow induces higher volatility. Further, daily flow is negatively related to lag-1 volatility, providing evidence that mutual fund investors time market volatility. Finally, our test results suggest that the relation between intraday volatility and inflow becomes weaker, while the relation between intraday volatility and outflow becomes stronger, from morning to afternoon.

This paper is the first that presents direct evidence on the relation between flow and market volatility, and contributes to the literature on mutual funds in several aspects. First, the daily flow data allows us to study the dynamic relation between aggregate flow and market volatility at a daily interval. Second, existing literature focuses on the relation between flow and market returns, and suggests that such a relation may arise from information revelation by mutual fund flow, price pressure, or investor sentiment. However, it is unclear how flow is related to volatility at the aggregate level. Presumably, common components to flow should have an impact on market volatility if flow (and flow-induced trading) is highly correlated. However, the impact of flow on market volatility can be strictly idiosyncratic in nature if flow is driven by the pursuit of different investment strategies/styles. We fill this gap by providing evidence of the dynamic relationship between flow and volatility. Third, this paper highlights the asymmetric relation between flow and market volatility: inflow is associated with lower volatility, and outflow is associated with higher volatility on the next day. Last, this study extends research on the issue of volatility timing by using a larger sample of more than 800 domestic equity funds for the most recent period. Busse (1999) provides evidence of volatility timing at an individual fund level for a sample of 230 funds and for the period of 1985-1995. Since the percentage of U.S. households owning mutual funds has increased from about 30% in 1995 to 50% in 2003, it is important to re-examine volatility timing for this more recent period.

The remainder of the chapter is organized as follows. In Section 3.2 we discuss related literature. Section 3.3 presents the mutual fund flow data and alternative measures of market volatility. Our main empirical results are presented in Section 3.4 with the results of robustness checks in Section 3.5. Concluding remarks are provided in Section 3.6.

3.2. Related Literature and Background

There is a large body of literature on mutual fund flow. Earlier studies have focused on the micro-level relation between individual fund performance and the flow of money into or out of a mutual fund. For example, Sirri and Tufano (1998) analyze annual fund flow and document a striking performance-flow relationship. They conclude that "Mutual fund consumers chase returns, flocking to funds with the highest recent returns, though failing to flee from poor performers." Other studies, including Ippolito (1992), also conclude that mutual fund investors move cash into funds that had the best performance in the preceding year. Coval and Stafford (2006) study asset fire sales and institutional price pressure by examining stock transactions of mutual funds. They find supporting evidence that widespread selling by financially distressed mutual funds leads to transaction prices that occur below fundamental value. They also find that price effects are long-lived and last two quarters.

Recent papers by Warther (1995) and Edelen and Warner (2001) extend earlier studies by studying the relation between flow and returns at the macro level (e.g., the relation between aggregate fund flow and market returns). According to Warther (1995), there is a fundamental difference between the micro-level and macro-level analyses. Since investors often take money out of one fund and then invest in another fund, much of the cash into one fund is at the expense of another fund. The micro-level analysis helps understand how funds compete against each other to increase their respective market share. At the macro-level, in contrast, flows among funds are offsetting, so only the aggregate flow into (or out of) all funds is relevant. The current paper studies the relation between aggregate flow and market-wide volatility.

There are at least two channels through which the fund flow and stock return volatility are related. First, we observe lumpy cash infusion (or withdraw) into (or out of) funds at the individual fund level over a short period of time (e.g., at daily frequency). Such exogenous cash flow might be related to past performance. Take positive feedback strategies as an example. Fund managers who follow such strategies rely on past performance to predict future returns. They buy securities in up markets and sell in down markets, pushing security prices away from their fundamental values. Other fund managers may follow negative feedback (contrarian) strategies, and their trades drive security prices toward their fundamental values. Since positive (negative) feedback strategies increase (decrease) short-term volatility, the extent to which flow-induced trades depend on past return is important. As fund managers pursue a variety of investment strategies, their aggregate actions may be offsetting. The overall impact of these effects on market volatility is an open empirical question, which is the focus of our study.

Second, studies of Black (1986) and Lee, Andrew, and Thaler (1991) conclude that noise traders cause wide swings away from fundamentals, and that investor sentiment and noise traders are an important factor in the overall market movement. It is a common belief that mutual fund investors are the least informed investors. Thus, it is reasonable to use mutual fund flow as a proxy for uninformed investor sentiment.

Reports in the popular press claim that fund flow is a good indicator of retail investor sentiment, and this sentiment is often irrational. To the extent that investor sentiment is important in the market place and aggregate flow is a good proxy of the sentiment, flow into (or out of) mutual funds will be related to market-wide returns and volatility.

The current paper is also related to Busse (1999) who sheds light on the question of whether mutual funds time market volatility. Using a proprietary dataset and a sample of 230 domestic equity funds during 1985 and 1995, Busse shows that mutual funds do time market volatility and funds change market exposure when volatility changes. According to a survey conducted by Investment Company Institute and U.S. Census Bureau, there has been a dramatic increase in the ownership of mutual funds by U.S. households in the past decade, up from about 30% in 1995 to 50% in 2003. Given the fact that the increase in ownership of mutual funds over time is significant, and that daily fund return data is not available to academia, we extend Busse's work by studying the question of volatility timing from the perspective of the flow-volatility relationship. Our test is based on flow data for more than 800 domestic equity funds and is for a recent period of 1998 to 2003.

3.3. Data

3.3.1. Mutual Fund Flow

Our daily mutual fund flow data come from Trim Tabs Investment Research of Santa Rosa, California. The sample spans the period from February 1998 to December

2003. Starting from February 1998, the vendor collects daily data on net asset values (NAVs), total net assets (TNAs), and flow for a sample of over 1,600 mutual funds.

Trim Tabs' data collection procedures are briefly summarized as the follows: Each day, mutual fund investors send orders for purchase or redemption to the fund customer service center (or the transfer agent). Whenever a fund receives an order from an investor, the order, by law, should be executed at the next calculated net asset value. Each day, the NAV is determined by the day's closing prices of securities held by the fund and shares outstanding on the previous trading day. Before 5:30 p.m. EST, the NAV is reported to the National Association of Security Dealers and the transfer agent. After the NAV is calculated, the transfer agent processes all orders overnight and uses this NAV to compute the change in the fund's payables, receivables, cash and shares outstanding. The transfer agent then reports these numbers back to fund managers and these numbers are entered into the fund's balance sheet the next morning. Trim Tabs receives data of the previous day's total net assets and net asset values from each fund every morning (We refer readers to Edelen and Warner (2001) who provide a detailed description of Trim Tabs data). Relying on these data on date t and t-1, Trim Tabs calculates the net flow on date t for a single fund as

$$Flow_t = TNA_t - NAV_t \frac{TNA_{t-1}}{NAV_{t-1}}. \tag{3.1}$$

Since the focus of this paper is on the relationship between aggregate fund flow and market return volatility, we include only domestic equity mutual funds in our sample. We match our sample with funds in the Center for Research in Security Prices (CRSP) survivor-bias free U.S. mutual fund database and include the funds with the following

Investment Company Data Institute (ICDI) investment objectives: aggressive growth (AG), growth and income (GI), income (IN), long-term growth (LG), sector funds (SF), total return (TR), and utility funds (UT). The final sample contains 859 domestic equity mutual funds. Funds with other investment objectives (e.g., bond funds and international funds, etc.) are excluded.

Trim Tabs advises that mutual funds do not make adjustment in distributions (e.g., dividends and capital gains) in a uniform manner. For this reason, we obtain the distribution data from the CRSP mutual fund database and adjust the NAVs accordingly. Recent studies using Trim Tabs data report solitary typographical errors in NAVs and TAVs (see Edelen and Warner (2001), Chalmers, Edelen, and Kadlec (2001) and Greene and Hodges (2002)).

We use the two filters suggested by Chalmers, et al. (2001) to identify potential data error in NAV and TNA series. The first is a five-standard-deviation filter intended to eliminate outliers that occur as a result of recording errors. If the daily change in NAV (or in TNA) for a single fund is more than five standard deviations, we hand-check NAV (or TNA) against alternative sources, because a five standard-deviation change is an extremely rare event. The second filter captures observations when a three-standard-deviation move is followed by a reversal to within 1.5 standard deviations (or by a further 1.5 standard deviations move in the same direction) the next day. This filter intends to catch false reversals or continuations. Chalmers, et al. (2001) recommend using both filters to spot potential errors. We keep those observations if they can be corrected or verified and discard the remaining spurious observations. In total, we eliminate 0.34% of our sample observations. After filtering, we use equation (1) to calculate the net flow for each fund.

Finally, the dollar value of the Trim Tabs asset base varied dramatically from 280 to 810 billion during our six-year sample period. Therefore, we aggregate the fund flow and normalize the aggregate flow by expressing it as a percentage of the previous day's total asset base for our sample of 859 funds.

Summary statistics of normalized flow data are presented in Table 3.1. Panel A reports the characteristics of aggregate net flow for our sample funds. The mean of aggregate flow over the sample period is -0.20 basis points (-0.002%) per day, or -0.5% in annualized term. The median of the daily flow is -0.64 basis points and the standard deviation is 10.69 basis points. While the total asset base increased during our sample period, the mean and median daily fund flows are slightly negative because funds experienced a significant outflow after the burst of the internet bubble in early 2000.

Despite the average negative aggregate flow, we notice that among the 1,484 observations of aggregate net flow data, 685 are positive, while 799 are negative. That is, during about 54% of trading days, aggregate cash flows out of, rather than into, equity mutual funds. We present summary statistics of aggregate net inflow and outflow, respectively, in Panel A. We observe that the average of net inflow (0.084% per day) is greater than that of net outflow (0.076% per day). Panel B shows that there are significant and negative partial autocorrelations (PAC) for aggregate flow at lags 1 and 2, and there are significant and positive PAC at lags 4 and 5. The time series of daily aggregate fund flow is plotted in Figure 3.1.

3.3.2. Measurement of Daily Volatility

We use three measures of daily market volatility in this study. The first is the high-frequency volatility estimator proposed by Andersen, Bollerslev, Diebold, and Ebens (2001). They develop the daily volatility estimator by summing intraday squared five-minute returns. They argue that this estimator is free of measurement errors and model-free.[36] The second volatility estimator is the extreme value estimator (σ_{HL}) developed by Parkinson (1980), while the third one is similar to the high-frequency volatility estimator, but we pre-filter the intraday return by using a GARCH model. To save space, we present our main results by using the high-frequency volatility estimator and extreme value estimator.[37]

The first and third volatility measures are calculated by using the intraday levels of the S&P 500 index, while we calculate the second volatility measure by using the daily high/low levels of the S&P 500 index. We obtain the intraday and daily levels of the S&P 500 index from Tick Data, Inc. The tick-by-tick Futures and Index Database provided by Tick Data is comprised of over 85 symbols. The S&P 500 index and other data are collected via multiple real-time data feeds. Tick Data takes several steps to ensure the accuracy of its ongoing data collection process, beginning at the source. To ensure continuity, Tick Data collects data from two geographical locations. All data are

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[36] Andersen, et al. (2001) justify using a sampling frequency of five minutes, stating that this interval is long enough to avoid most measurement errors and short enough to avoid microstructure biases.

[37] To ensure that our inferences are not sensitive to the particular estimator used, we repeat all the analyses by using the extreme value estimator and the third volatility estimator, reporting our results in Section 5.

passed through the Data Manager, a suite of scrubbing and verification programs developed for the purpose of producing clean and robust data.

Following Andersen, et al. (2001), we construct the five-minute return series of the S&P 500 index from the logarithmic difference between the prices recorded at or immediately before the corresponding five-minute interval. Since the five-minute return is serially correlated, we estimate an AR (5) model for the five-minute return series each day to remove the serial correlation. We then construct the high-frequency volatility estimator as

$$\sigma_{High,t} = \sqrt{\sum_{i=1}^{N} (r_{t+i\Delta})^2} \tag{3.2}$$

where $\sigma_{High,t}$ denotes daily market volatility based on high-frequency data on day t, Δ is the observation interval length (i.e., five minutes), N is the number of five-minute intervals in one trading day (N=78), and $r_{t+i\Delta}$ is the intraday de-meaned and filtered S&P 500 index return in interval Δ on day t.

Summary statistics of alternative volatility estimators are provided in Table 3.2. Panel A shows that the daily average of high-frequency volatility (σ_{High}) and high-low volatility (σ_{HL}) are 14.7% and 15.9%, respectively. These two volatility estimators are highly correlated, with a correlation of 0.78 (see Panel C). Both volatility estimators are negatively correlated with daily fund flow (The correlations are -0.19 and -0.16). Finally, both volatility estimators exhibit substantial positive autocorrelations. Thus, we control for the autocorrelations in our later tests. The time series of two volatility estimators are plotted in Figure 3.2.

3.4. Empirical Results

In the previous section, we provide correlation evidence for the co-movement between market volatility and mutual fund flow. Although these unconditional results suggest a relationship between volatility and flow, they do not clearly depict the structure of the relationship and do not control for other factors that are likely to influence volatility and flow. In this section, we use a VAR approach to examine the dynamic relationship between market volatility and flow.

3.4.1. VAR Analysis

In its general form, a *p*-th order Gaussian VAR model can be represented as

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t \,, \tag{3.3}$$

where $Y_t = (Y_{1,t},...,Y_{K,t})'$ is a vector time series of variables, μ is a *k*-vector of intercepts, $\phi_i (i = 1,..., p)$ are $k \times k$ parameter matrices with all eigenvalues of ϕ having moduli less than one so that the time series is stationary, and e_t is the error vector, which is assumed to be i.i.d. *k*-variate normally distributed with expectation the zero vector, and variance matrix Σ. Before conducting the VAR analysis, it is important to note that each time series should be a stationary process. To test the stationarity of the variables of our interest, we perform both Dickey-Fuller and Phillips-Perron unit root tests (with and without drift). The results, although not reported, suggest that the unit root hypotheses are strongly rejected in favor of the stationary hypotheses for all the variables of our interest. We obtain maximum likelihood estimates of ϕ and Σ using iterated least squares method. The selection of VAR lag length is based on a top-down approach.[38]

We first examine a bivariate model that consists of high-frequency volatility ($\ln(\sigma_{High})$) and flow, *i.e.*, $Y_t = (\ln(\sigma_{High,t}), flow_t)$, which provides a preliminary overview of the dynamic relationship between market volatility and flow. Given the well-documented negative correlation between market returns and volatility (see French, Schwert, and Stambaugh (1987) and Nelson (1991)), it is possible that the volatility-flow relationship is a spurious result of the positive flow-return relationship documented by Edelen and Warner (2001). To address this issue, we examine a three-factor VAR model including S&P 500 returns (*mkret*) (*i.e.*, $Y_t = (\ln(\sigma_{High,t}), flow_t, mkret_t)$) to determine whether meaningful changes occur after we control for market returns.

In our bivariate VAR specification, the coefficients of our main interest are the off-diagonal coefficients $\phi_1(1,2)$, $\phi_2(1,2)$, $\phi_3(1,2)$, etc.. Specifically, the coefficient $\phi_1(1,2)$ characterizes the relationship between market volatility and fund flow with one-day lag. If $\phi_1(1,2)$ is negative and significant, then there exists an asymmetric relationship between volatility and inflow versus volatility and outflow: more inflow is associated with lower volatility while more outflow is associated with higher volatility on the next day. Other off-diagonal coefficients, such as $\phi_1(2,1)$, $\phi_2(2,1)$, $\phi_3(2,1)$, characterize the impact of lagged volatility on flow.

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[38] Given an initial choice of the lag length *p*, the top-down approach entails conducting joint Wald tests of the null hypotheses that the lag length can be reduced to *q for q* = *p*-1, *p*-2, and so forth., up to the point where the null hypothesis is rejected.

Table 3.3 reports coefficient estimates of the bivariate and three-factor VAR models. The top-down methodology indicates that we should use lag 13 and 11, respectively, for each model.[39] Looking first at the bivariate model, we find that market volatility is negatively related to flow at lags 1, 2, and 3, suggesting that flow has a negative impact on subsequent market volatility. Since flow can take a positive value (inflow) or a negative value (outflow), our results indicate that, holding everything else constant, inflow is associated with lower volatility while outflow is associated with higher volatility on the next day.

Other results, including the positive autocorrelations in market volatility and negative autocorrelations in fund flow, are consistent with findings of Bollerslev, Chou, and Kroner (1992) and Edelen and Warner (2001). Table 3.3 also shows that flow is negatively related to the previous day's volatility, which suggests that mutual fund investors might time market volatility (A test of volatility timing using impulse response analysis is presented in the next section).

The estimation results from the three-factor VAR model provide additional evidence for the volatility-flow relation. First, the volatility-flow relationship obtained from the bivariate model still holds after we control for market returns. Thus, the uncovered flow-volatility relationship is not driven by the correlation between flow and returns. Second, concurrent flow is positively related to the previous day's market returns and negatively related to returns with a two-day lag, while concurrent return is not related to lagged flow. This flow-return relationship is consistent with Edelen and

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[39] For brevity, only the coefficients for the first three lags are reported in Table 3.

Warner (2001). This exercise not only validates our self-constructed flow data, but it also extends Edelen and Warner's tests to a more recent period and to a dynamic setting. Finally, we document that volatility is negatively related to lagged returns, but return is not related to lagged volatilities. This suggests that the documented negative volatility-return relationship might result from higher (lower) returns leading to lower (higher) volatility.

Based on the VAR results, we test the Granger causality between volatility and flow. As the focus of this paper is on the dynamic relation between mutual fund flow and market volatility, we test (1) whether flow Granger-causes market volatility and (2) weather volatility Granger-causes flow. If flow does not Granger-cause volatility, the coefficients of volatility on the lagged flow should be jointly zeros. Similarly, if market volatility does not Granger-cause flow, the coefficients of flow on the lagged volatility should be jointly zeros.

Table 3.3 presents the Wald test results and corresponding p-values. The results reject the null hypothesis that flow does not Granger-cause market volatility at the 5% significance level for both VAR specifications. For example, for the bivariate VAR model, the Wald test statistic is 30.6 and the corresponding p-value is 0.00. For the three-factor VAR model, the p-value of the Wald test is 0.03. Further, the Wald test rejects the null hypothesis that the coefficients of flow on the lagged volatility are jointly zeros—all p-values of the Wald test are less than 5% significant level. These results reaffirm our earlier finding that flow has a significant impact on volatility and vice verse. The Granger-causality test implies that the level of flow and volatility Granger-cause each other, suggesting that we should study the inter-temporal relationship between innovations in flow and volatility in both directions.

3.4.2. Structural VAR Impulse Response Analysis

In the previous section, the VAR results and the Granger-causality tests focus on the level of market volatility and flow. Since there are substantial autocorrelations in both flow and volatility, a natural question to ask is whether unexpected flow has an impact on subsequent unexpected volatility. We now investigate the dynamic relationship between innovations in market volatility and flow.

Table 3.4 reports the contemporaneous correlations between innovations of the three-factor VAR model. As shown in the table, volatility shocks are negatively correlated with flow shocks at the 5% significance level with a correlation of -0.10. Next, we assess the impact of flow shocks on volatility shocks using the structural VAR approach proposed by Bernanke (1986) and Sims (1986). Specifically, we examine the three-factor structural VAR model, which consists of high-frequency volatility ($\ln(\sigma_{High})$), *flow*, and market returns (*mkret*). Assuming that volatility shocks are determined by flow and return shocks, and that flow shocks are determined only by return shocks, we find volatility shocks respond negatively to concurrent flow shocks with a coefficient estimate of –0.284 and a T-statistic of –4.44.[40]

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[40]We reach similar conclusions under other assumptions that innovations in market volatility are determined by innovations in flow, and (1) innovations in returns are determined by innovations in volatility and flow; (2) innovations in flow are determined by innovations in returns, which are determined

To examine the dynamic relationship between innovations in volatility and innovations in flow, we study the impulse response functions, which provide the estimated dynamic response of a variable to a unit standard deviation shock in other variables. Figure 3.3 plots the impulse response function of $\ln(\sigma_{High})$ to a unit shock in *flow* over a 60-day period. Two standard-error bands are also provided to assess the significance of the impact of flow shocks on volatility. The figure indicates that flow shocks have a pronounced negative impact on market volatility, especially over the subsequent 10 days. For example, a positive unit standard deviation shock in *flow* generates an initial day decline of 0.06 standard deviation of volatility and its impact is less than 0.02 standard deviation of volatility after 20 days.

Therefore, much as we did for the VAR coefficient estimates we reported previously, we document an asymmetry between the impact of inflow shocks and outflow shocks on market volatility--A unit shock in inflow (outflow) predicts a decline (increase) in concurrent and next-day volatility. Further, the impact of flow shocks on volatility is large during the first few days and then gradually dissipates over two months.

3.4.3. Evidence of Volatility Timing

Busse (1999) investigates the question of whether mutual funds time market volatility using daily fund returns from 1985 to 1995, and finds that (1) there is a significant relation between volatility timing and a traditional measure of investment

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by innovations in volatility; or (3) innovations in volatility are determined by innovations in returns, which are determined by innovations in flow.

performance at individual fund level; (2) funds decrease market exposure when the market volatility is high; and (3) the systematic risk of surviving funds is sensitive to market volatility. In this subsection, we extend the test for volatility timing for a recent period (1998—2003) from the perspective of flow-volatility relationship for a recent period.

The estimation results reported in Table 3.3 suggest that flow is negatively related to the previous day's volatility. If the previous day's market volatility is high (low), the next day's flow tends to be low (high). Now we examine the ability of timing volatility by using the three-factor VAR model consisting of $\ln(\sigma_{High})$, flow, and *mkret*, and by analyzing impulse responses. We assume that flow shocks are determined by volatility and return shocks, and that volatility shocks are determined by return shocks.[41]

Our result indicates a significantly negative contemporaneous response of flow to shocks in volatility (the coefficient estimate is –0.04 with a t-stat of –4.32). The impulse response function of flow to a unit standard deviation shock in market volatility is plotted in Figure 3.4. The plot suggests that a unit shock in market volatility has a significant, but temporary, impact on flow. In particular, a positive shock in market volatility results in less inflow one day after the shock, and the impact dissipates to zero very soon thereafter. Therefore, the impact of volatility shock on flow is short-lived, compared to the impact of flow shock on volatility. Overall, the structural VAR impulse response analyses provide supporting evidence that mutual fund investors time volatility.

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[41] We also consider other assumptions and find that our results remain unchanged.

3.4.4. Test for Relationship between Intraday Volatility and Daily Flow

According to Edelen and Warner (2001), mutual fund managers may receive flow information provided by their transfer agent prior to the close of a trading day, and the information has some predictability. Some fund managers have informal arrangements with their transfer agent, who is expected to telephone fund managers about unusually large individual transactions by mid-afternoon. Further, institutional investors in a fund often give a one-day advance notice for large wire transfers. This common practice helps fund managers to predict flow and subsequent returns. Edelen and Warner (2001) find a stronger relation between market return and flow in the afternoon than in the morning.

Our previous results indicate that there is a negative concurrent relationship between daily market volatility and daily flow--inflow is associated with lower volatility, while outflow is associated with higher volatility. If fund managers have access to flow information prior to the end of a trading day, and if they make trades based on that flow information (fund-share transactions), we expect intraday volatility to decrease over the trading day, as fund managers receive additional information about fund inflow. On the other hand, we expect intraday volatility to increase as fund managers learn about outflow during a typical day. Now we examine the relation between intraday volatility and daily flow.

Table 3.6 presents estimates from the following regression equations:

$$\ln(\sigma^{T}_{High,t}) = \alpha_0 + \alpha_1\, flow_t + \sum_{i=1}^{5} \beta_i \ln(\sigma_{High,t-i}) + \varepsilon_t\,, \tag{3.4}$$

$$\ln(\sigma^{T}_{High,t}) = \alpha_0 + \alpha_1\, inflow_t + \alpha_2 outflow_t + \sum_{i=1}^{5} \beta_i \ln(\sigma_{High,t-i}) + \varepsilon_t\,, \tag{3.5}$$

where $inflow_t = \begin{cases} flow_t, & if \ \ flow_t >= 0 \\ 0, & if \ \ flow_t < 0 \end{cases}$ and $\text{out}flow_t = \begin{cases} 0, & \text{if } \ flow_t >= 0 \\ flow, & \text{if } \ flow_t < 0 \end{cases}$.

The superscript T denotes an intraday period (Open-11:00, 11:00-15:00, or 15:00-close). The two regression models are estimated for each intraday period separately. The dependent variable is the high-frequency volatility, computed by using intraday returns on the S&P 500 index during a given intraday period. The lagged daily volatilities from previous days are used as control variables.

Table 3.6 reveals that the relation between intraday volatility and daily flow is negative for each of the three intraday periods. For the time periods of open-11:00, 11:00-15:00 and 15:00-close, the coefficient estimates are -0.47, -0.52 and -0.39, respectively (with T-statistics being -6.62, -7.59 and -3.54). While there is a difference between early morning and late afternoon results, the difference appears to be small. One drawback of the regression specification in equation (4) is that it does not allow us to assess the differential impact of inflow versus outflow on volatility.

We decompose flow into inflow and outflow, and we include both variables in equation (5). The separation of inflow from outflow reveals several interesting results. For example, the two coefficients of inflow are close to each other for the time periods of open-11:00 and 11:00-15:00 (-0.38 versus -0.41) and both are significant at 5% level with T-statistics being -3.07 and -3.48. However, the coefficient estimate (-0.10) becomes close to zero and insignificant during the period of 15:00-close (T-statistic= -0.55). As a result, the relation between intraday volatility and inflow is significant and stable prior to

15:00, but non-exist in the last trading hour. A possible explanation for this result is that fund managers may decide, during the last trading hour, to wait until the next day to purchase more stocks, even though they learn more about inflow during the last hour than during earlier periods.

The coefficient estimate of outflow during each period shows a different pattern: it increases in the magnitude monotonically from morning to afternoon. For instance, the estimated coefficients are -0.57, -0.64 and -0.71 for the three time periods. The relation between intraday volatility and outflow becomes progressively stronger from morning to afternoon. The negative coefficient, together with outflow (which takes a negative value), implies that intraday volatility increases from morning to afternoon, assuming everything else is equal. One explanation for this finding is that as fund managers know more about outflow toward the end of a trading day, they may furiously sell securities before the market closes, in order to meet redemption requirements.

3.5. Robustness Check

To ensure that our results are not sensitive to the particular volatility estimator used, we re-examine the volatility-flow relationship by using two alternative volatility estimators. The first one is the high-low volatility (σ_{HL}). Table 3.7 reports the VAR coefficient estimates and shows that the results using σ_{HL} are similar to the previously presented results. For example, σ_{HL} is negatively related to previous flow at lags 1 and 2, with *T*-statistics being -3.25 and -2.86, respectively.

We then re-examine the structural VAR model consisting of $\ln(\sigma_{HL})$, *flow*, and *mkret*. Under the hypothesis that flow causes volatility, we assume that volatility shocks are determined by both flow and return shocks, while flow shocks are only determined by return shocks. Similar to the results relying on high-frequency volatility estimator, σ_{High}, we find that flow shocks response significantly to shocks in σ_{HL} with a coefficient estimate of -0.396 (*T-statistic* = –3.80). Figure 3.5 plots the impulse response function of σ_{HL} to *flow*. The figure provides evidence that is qualitatively similar to that in Figure 3.3, when the volatility is the high-frequency volatility estimator, σ_{High}.

The second alternative volatility estimator is obtained by using a GARCH model. Extant literature documents that market returns exhibit conditional heteroskedasticity (French, et al. (1987) and Nelson (1991). To take this property into account, we adopt a two-step procedure. In the first step, we estimate a GARCH(1,1) model with an AR(5) specification for the intraday return on the S&P 500 index. The estimation is done for each day in our sample. In the second step, we use the residual from the mean equation of the GARCH model and equation (2) to obtain a new volatility estimator each day. We then re-estimate the three-factor VAR model and re-do the impulse response analysis. Once again, the results are similar to those reported in Table 3.3 and Figures 3.3 and 3.4. For example, the relation between market volatility and lag-1 flow is negative and significant (the coefficient estimate is -0.21 and the T-statistic is -3.36).

The next robustness test addresses the concern of whether our results are driven by (1) a few large volatility spikes and (2) the events of September 11, 2001, which has a large impact on market volatility. Indeed, our sample period is characterized by five large volatility spikes related to the Russian financial crisis, the burst of the internet bubble, the 9/11 events, etc. We remove five observations corresponding to the five largest volatility outliers from the sample and find that our main results remain unchanged. To ensure that our results are robust and not being driven by the 9/11 events, we split our data into two sub-periods: one starting in February of 1998 and running through August of 2001, and the other starting in October of 2001 and running through the end of 2003. We find that the result of testing volatility-flow relationship is stronger during the first than during the second sub-period (a shorter period). The VAR coefficient that characterizes the relation between volatility and the lag-1 flow is -0.18 and significant at 5% level during the pre-9/11 period, however, this coefficient is -0.12 and only significant at the 10% level during the post-9/11 period. Overall, while a shorter sample could lead to less powerful tests, our analysis based on the two sub-samples yields findings similar to those presented in previous sections, suggesting that our results are not a byproduct of including the 9/11 events in our sample.

3.6. Conclusion

This paper empirically examines the dynamic relation between aggregate mutual fund flow and market-wide volatility. There are many arguments for and against the linkage between flow and market volatility, however, most of them are heuristic and judgmental. This paper is the first that provides direct evidence of the relation between flow and market volatility.

Our sample comprises 859 domestic equity funds and spans the time period from 1998 to 2003. Using a VAR approach, we show that market volatility is negatively related to concurrent and lagged flow, and that shock in flow has a negative impact on market volatility. One implication of this result is that a positive shock in flow (inflow shock) predicts a decline in volatility, while a negative shock in flow (outflow shock) predicts an increase in volatility on the next day. We also find evidence of volatility timing for a recent period of 1998-2003. Last, we uncover a differential impact of daily inflow versus outflow on intraday volatility. The relation between intraday volatility and daily flow is stable from morning until 15:00, but this relation disappears during the last trading hour. Further, the relation between volatility and outflow becomes stronger, progressively, from morning to afternoon. These results suggest that the response of fund managers to inflow is different from that to outflow as a trading day progresses.

Table 3.1 Summary Statistics of Daily Aggregate Mutual Fund Flow

Daily aggregate mutual fund flow from February 1998 to December 2003 for a sample of 859 domestic equity funds. Panel A reports summary statistics of aggregate net fund flow, inflow, and outflow, respectively. Aggregate flow is scaled by the total TNAs of our sample funds on the previous day. Panel B presents the partial autocorrelations of aggregate net equity fund flow.

Panel A. Aggregate Mutual Fund Flow

	Obs.	Mean (b.p.)	Median (b.p.)	Std. (b.p.)	Min (b.p.)	Max (b.p.)
Daily Net Flow	1484	-0.20	-0.64	10.69	-58.93	60.64
Daily Net Inflow	685	8.40	6.19	7.62	0.00	60.64
Daily Net Outflow	799	-7.57	-5.80	6.70	-58.93	0.00

Panel B. Partial Autocorrelations of Aggregate Mutual Fund Flow

	lag 1	2	3	4	5
Daily Net Flow	-0.12*	-0.10*	0.02	0.06*	0.08*

* Significant at 5% level, two-tailed test.

Table 3.2 Summary Statistics of Alternative Volatility Estimators

Summary statistics of high-frequency volatility (σ_{High}) and high-low volatility (σ_{HL}) from February 1998 to December 2003. σ_{High} is calculated using intraday S&P 500 index returns and σ_{HL} is based on the extreme value method of Parkinson (1980). Panels A and B present summary statistics and partial autocorrelations of both volatility estimators. Panel C reports the correlations of two volatility estimators and *flow*, where *flow* is the aggregate flow for a sample of 859 domestic equity funds.

Panel A. Summary Statistics

	Mean (%)	Median (%)	Std. (%)	Min (%)	Max (%)
σ_{High}	14.7	13.4	6.2	3.5	52.2
σ_{HL}	15.9	14.2	8.3	2.7	80.9

Panel B. Partial Autocorrelations

	Lag 1	2	3	4	Lag 5
σ_{High}	0.70*	0.26*	0.10*	0.16*	0.07
σ_{HL}	0.41*	0.32*	0.19*	0.11*	0.10*

Panel C. Correlations

	σ_{High}	σ_{HL}	*flow*
σ_{High}	1.00		
σ_{HL}	0.78*	1.00	
Flow	-0.19*	-0.16*	1.00

* Significant at 5% level, two-tailed test.

Table 3.3 Coefficient Estimates of the Bivariate and Three-factor VAR Models

The table reports the coefficient estimates of the VAR model

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t$$

where $Y_t = (Y_{1,t},...,Y_{K,t})'$ is a vector time series of variables, μ is a *k*-vector of intercepts, $\phi_i (i = 1,..., p)$ are $k \times k$ parameter matrices, and e_t is the error vector. The bivariate model consists of $\ln(\sigma_{High})$ and *flow*, where σ_{High} is the high-frequency volatility estimator, and *flow* is the aggregate flow for a sample of 859 domestic equity funds. The three-factor model includes $\ln(\sigma_{High})$, flow and market returns (*mkret*) where *flow* and *mkret* are in percentage. The VAR lag length, *p*, is chosen using a top-down method. For brevity, only the coefficient estimates of the first three lags are reported. *t*-statistics are reported in parentheses. The null hypothesis of the Wald test is that the coefficients of lagged variables are jointly 0. *p*-values for the Wald test are reported in braces. The sample period is from February 1998 to December 2003.

	Bivariate Model (p=13)		Three-factor Model (p=11)		
	$\ln(\sigma_{High,t})$	$flow_t$	$\ln(\sigma_{High,t})$	$flow_t$	$mkret_t$
Intercept	-0.21* (-4.37)	0.01 (0.53)	-0.20* (-4.41)	-0.01 (-0.52)	0.56* (2.25)
$\ln(\sigma_{High,t-1})$	0.38* (14.26)	-0.09* (-8.28)	0.30* (10.88)	-0.04* (-3.94)	0.09 (0.60)
$\ln(\sigma_{High,t-2})$	0.14* (4.95)	0.06* (4.85)	0.16* (5.50)	0.03* (2.98)	0.30* (1.97)
$\ln(\sigma_{High,t-3})$	0.04 (1.20)	0.02 (1.74)	0.05 (1.87)	0.01 (1.19)	-0.19 (-1.23)
Wald test P-value	{0.00}	{0.00}	{0.00}	{0.00}	{0.41}
$flow_{t-1}$	-0.22* (-3.43)	-0.22* (-8.37)	-0.18* (-2.53)	-0.15* (-5.61)	0.16 (0.40)
$flow_{t-2}$	-0.26* (-3.90)	-0.17* (-6.02)	-0.23* (-3.19)	-0.14* (-5.43)	0.16 (0.40)
$flow_{t-3}$	-0.17* (-2.43)	-0.04 (-1.33)	-0.12 (-1.61)	-0.01 (-0.42)	0.19 (0.49)
Wald test P-value	{0.00}	{0.00}	{0.03}	{0.00}	{0.72}
$mkret_{t-1}$			-0.05* (-9.90)	0.04* (22.80)	0.04 (1.47)
$mkret_{t-2}$			-0.01* (-2.07)	-0.01* (-5.64)	-0.02 (-0.52)
$mkret_{t-3}$			-0.01 (-1.80)	0.00 (1.01)	0.02 (0.55)
Wald test P-value			{0.00}	{0.00}	{0.54}
R^2	58.9%	13.8%	62.0%	37.9%	2.2%

* Significant at 5% level, two-tailed test.

Table 3.4 Contemporaneous Correlations between VAR Innovations

The table reports the contemporaneous correlations between innovations from the VAR (11) model consisting of $\ln(\sigma_{High})$, *flow*, and market returns (*mkret*), where σ_{High} is the high-frequency volatility estimator and *flow* is the aggregate flow for a sample of 859 domestic equity funds. The VAR lag length was chosen using a top-down approach. The sample period is from February 1998 to December 2003.

	$\ln(\sigma_{High,t})$	$flow_t$	$mkret_t$
$\ln(\sigma_{High,t})$	1.00		
$flow_t$	-0.10*	1.00	
$mkret_t$	-0.26*	0.04	1.00

* Significant at 5% level, two-tailed test.

Table 3.5 Coefficient Estimates of the VAR Model including Market Turnover

The table reports the coefficient estimates of the VAR model

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t$$

where $Y_t = (Y_{1,t},...,Y_{K,t})'$ is a vector time series of variables, μ is a *k*-vector of intercepts, $\phi_i (i = 1,..., p)$ are $k \times k$ parameter matrices, and e_t is the error vector. The model consists of high-frequency volatility ($\ln(\sigma_{High})$), *flow*, market return (*mkret*), and market turnover rate (TR). *flow* and *mkret* are denominated in percentages. The VAR lag length, *p*, is set at 10 using a top-down method. For brevity, only the coefficient estimates of the first three lags are reported. The sample period is from February 1998 to December 2003.

	$\ln(\sigma_{High,t})$		$flow_t$		$mkret_t$		TR_t	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Intercept	-0.21*	-4.01	-0.01	-0.69	0.22	0.78	0.57	1.28
$\ln(\sigma_{High,t-1})$	0.28*	10.33	-0.03*	-3.34	0.11	0.74	0.18	0.76
$\ln(\sigma_{High,t-2})$	0.16*	5.50	0.03*	3.27	0.28	1.82	-0.48	-1.95
$\ln(\sigma_{High,t-3})$	0.05	1.84	0.01	1.28	-0.19	-1.18	-0.28	-1.10
$flow_{t-1}$	-0.19*	-2.68	-0.14*	-5.21	0.15	0.39	-0.55	-0.89
$flow_{t-2}$	-0.24*	-3.24	-0.13*	-5.07	0.15	0.38	-1.36*	-2.18
$flow_{t-3}$	-0.12	-1.65	0.00	-0.01	0.18	0.45	-0.87	-1.37
$mkret_{t-1}$	-0.05*	-10.11	0.04*	22.7	0.04	1.46	0.05	1.18
$mkret_{t-2}$	-0.01*	-2.16	-0.01*	-5.41	-0.02	-0.6	-0.06	-1.24
$mkret_{t-3}$	-0.01	-1.82	0.00	1.21	0.01	0.39	0.00	0.04
TR_{t-1}	0.01*	2.14	-0.00*	-2.09	-0.02	-1.34	0.21*	7.78
TR_{t-2}	-0.00	-0.72	0.00	-0.32	0.01	0.79	0.33*	12.35
TR_{t-3}	0.00	-0.15	-0.00	-0.45	0.01	0.26	-0.00	-0.08
R^2	62.2%		37.5%		3.0%		46.8%	

* Significant at 5% level, two-tailed test.

Table 3.6 Test for the Relationship between Intraday Volatility and Daily Flow

The regression results are based on the following equations:

$$Ln(\sigma^T_{High,t}) = \alpha_0 + \alpha_1 flow_t + \sum_{i=1}^{5} \beta_i Ln(\sigma_{High,t-i}) + \varepsilon_t, \quad (1)$$

$$Ln(\sigma^T_{High,t}) = \alpha_0 + \alpha_1 \text{ inflow}_t + \alpha_2 outflow_t + \sum_{i=1}^{5} \beta_i Ln(\sigma_{High,t-i}) + \varepsilon_t, \quad (2)$$

where $inflow_t = \begin{cases} flow_t, & if \ flow_t >= 0 \\ 0, & if \ flow_t < 0 \end{cases}$ and $\text{out}flow_t = \begin{cases} 0, & \text{if } flow_t >= 0 \\ flow, & \text{if } flow_t < 0 \end{cases}$.

The superscript T denotes an intraday period (Open—11:00, 11:00—15:00, or 15:00-close). The two regression models are estimated for each intraday period. The dependent variable is the high-frequency volatility computed by using intraday returns on the S&P 500 index during an intraday period. The lagged daily volatility from previous days are used as control variables. T-statistics are in parentheses.

Intraday Period	Open_t – $11{:}00_t$		$11{:}00_t$ – $15{:}00_t$		$15{:}00_t$ - Close_t	
	(1)	(2)	(1)	(2)	(1)	(2)
Intercept	-0.19*	-0.21*	-0.45*	-0.47*	-0.20*	-0.26*
	(-4.09)	(-4.14)	(-9.96)	(-9.69)	(-2.82)	(-3.30)
$flow_t$	-0.47*		-0.52*		-0.39*	
	(-6.62)		(-7.59)		(-3.54)	
$inflow_t$		-0.38*		-0.41*		-0.10
		(-3.07)		(-3.48)		(-0.55)
$outflow_t$		-0.57*		-0.64*		-0.71*
		(-4.30)		(-4.97)		(-3.43)
$\ln(\sigma_{High,t-1})$	0.44*	0.44*	0.39*	0.39*	0.40*	0.40*
	(14.77)	(14.70)	(13.47)	(13.40)	(8.60)	(8.50)
$\ln(\sigma_{High,t-2})$	0.24*	0.23*	0.22*	0.22*	0.21*	0.20*
	(7.28)	(7.22)	(7.03)	(6.96)	(4.10)	(4.00)
$\ln(\sigma_{High,t-3})$	0.02	0.02	0.04	0.04	0.07	0.07
	(0.54)	(0.53)	(1.31)	(1.30)	(1.44)	(1.42)
R^2	51.3%	51.4%	53.9%	54.0%	32.0%	32.1%

* Significant at 5% level, two-tailed test.

Table 3.7 Coefficient Estimates of the three-factor VAR model Using High-Low Volatility

The table reports the coefficient estimates of the VAR model

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t$$

where $Y_t = (Y_{1,t},...,Y_{K,t})'$ is a vector time series of variables, μ is a *k*-vector of intercepts, $\phi_i (i = 1,..., p)$ are $k \times k$ parameter matrices, and e_t is the error vector. The model consists of $\ln(\sigma_{Hl})$, *flow*, and market return (*mkret*), where σ_{Hl} is the high-low volatility estimator and *flow* is the aggregate flow for a sample of 859 domestic equity funds. *flow* and *mkret* are denominated in percentages. The VAR lag length, *p*, is set at 11 using a top-down method. For brevity, only the coefficient estimates of the first three lags are reported. The sample period is from February 1998 to December 2003.

	$\ln(\sigma_{HL,t})$		$flow_t$		$mkret_t$	
	Estimate	*t*-stat	Estimate	*t*-stat	Estimate	*t*-stat
Intercept	-0.32*	-4.74	0.00	0.16	0.52*	2.14
$\ln(\sigma_{HL,t-1})$	-0.01	-0.50	-0.00	-0.32	-0.02	-0.21
$\ln(\sigma_{HL,t-2})$	0.16*	5.98	0.01*	1.97	-0.00	-0.03
$\ln(\sigma_{HL,t-3})$	0.10*	3.61	0.00	0.77	0.04	0.43
$flow_{t-1}$	-0.39*	-3.25	-0.10*	-3.97	0.12	0.43
$flow_{t-2}$	-0.35*	-2.86	-0.13*	-4.78	0.17	0.39
$flow_{t-3}$	-0.11	-0.95	0.01	0.19	0.04	0.08
$mkret_{t-1}$	-0.08*	-11.28	0.05*	28.57	-0.02	-0.67
$mkret_{t-2}$	-0.05*	-5.17	-0.01*	-6.20	-0.04	-1.19
$mkret_{t-3}$	-0.03*	-2.78	0.00	0.95	-0.05	-1.36
R^2	42.8%		43.8%		2.1%	

* Significant at 5% level, two-tailed test.

Figure 3.1 Time Series of Daily Aggregate U.S. Equity Mutual Fund Flow

The figure plots the time series of daily aggregate domestic equity mutual fund flow from February 1998 to December 2003. Flow is scaled by the total TNAs on the previous day.

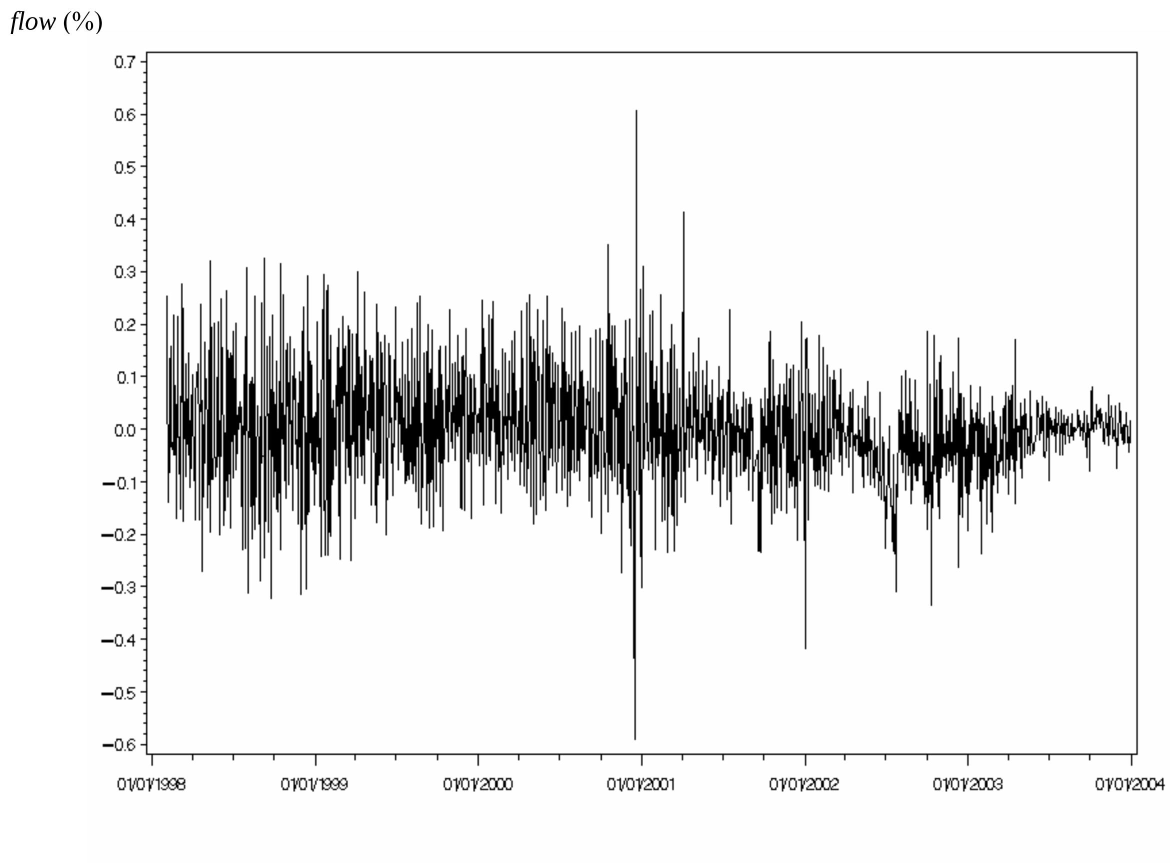
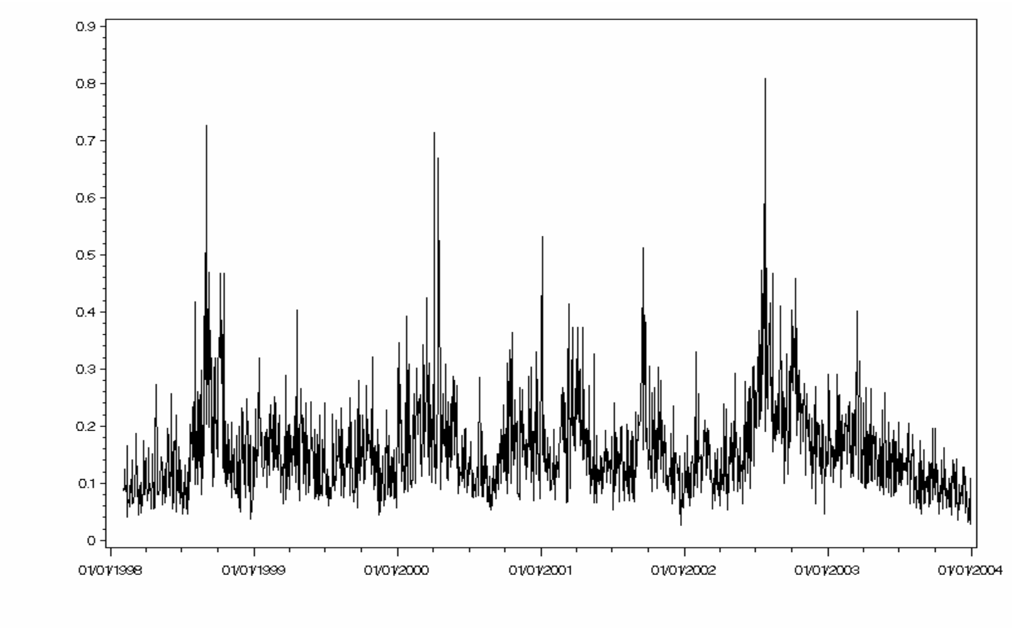


Figure 3.2 Time Series of Alternative Market Volatility Estimators

The figures plot time series of two market volatility estimators from February 1998 to December 2003: high-frequency volatility (σ_{High}) in Panel A and high-low volatility (σ_{HL}) in Panel B.

Panel A. High-Frequency Volatility

σ_{High}



Panel B. High-Low Volatility

σ_{HL}

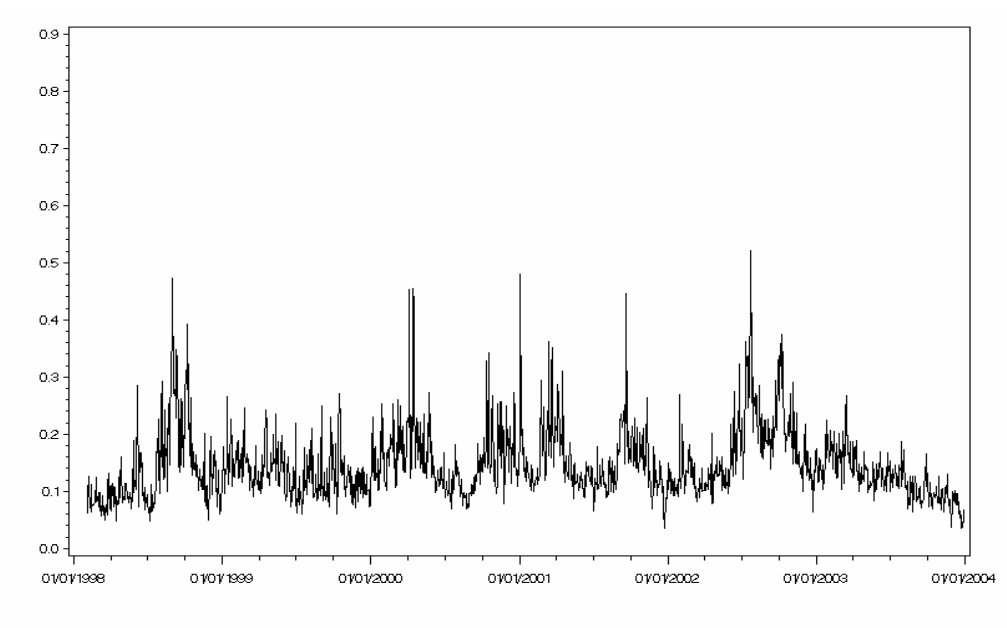


Figure 3.3 Impulse Responses of High-frequency Volatility to Flow

The figure plots the impulse responses of high-frequency volatility ($\ln(\sigma_{High})$) to a unit standard deviation shock in flow in a structural VAR(11) model that consists of $\ln(\sigma_{High})$, *flow*, and market returns (*mkret*), assuming that volatility shocks are determined by flow and return shocks and that flow shocks are determined by return shocks. The VAR lag length is chosen using a top-down approach. The dotted lines represent the plus and minus two standard error bands. The sample period is from February 1998 to December 2003.

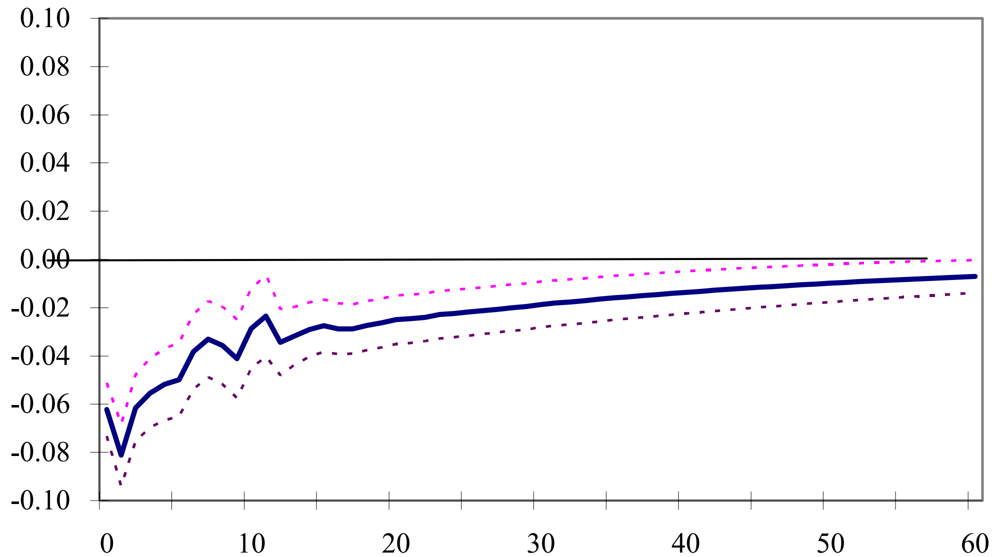


Figure 3.4 Impulse Responses of Flow to High-frequency Volatility

The figure plots the impulse responses of flow to a unit standard deviation shock high-frequency volatility ($\ln(\sigma_{High})$) in a structural VAR (11) model that consists of $\ln(\sigma_{High})$, *flow*, and market returns (*mkret*), assuming that flow shocks are determined by volatility and return shocks and that volatility shocks are determined by return shocks. The VAR lag length is chosen using a top-down approach. The dotted lines represent the plus and minus two standard error bands. The sample period is from February 1998 to December 2003.

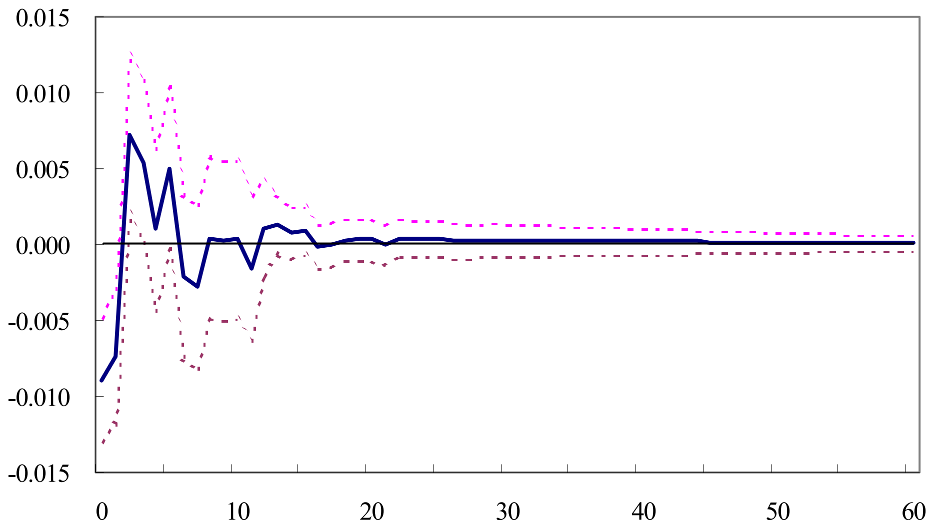
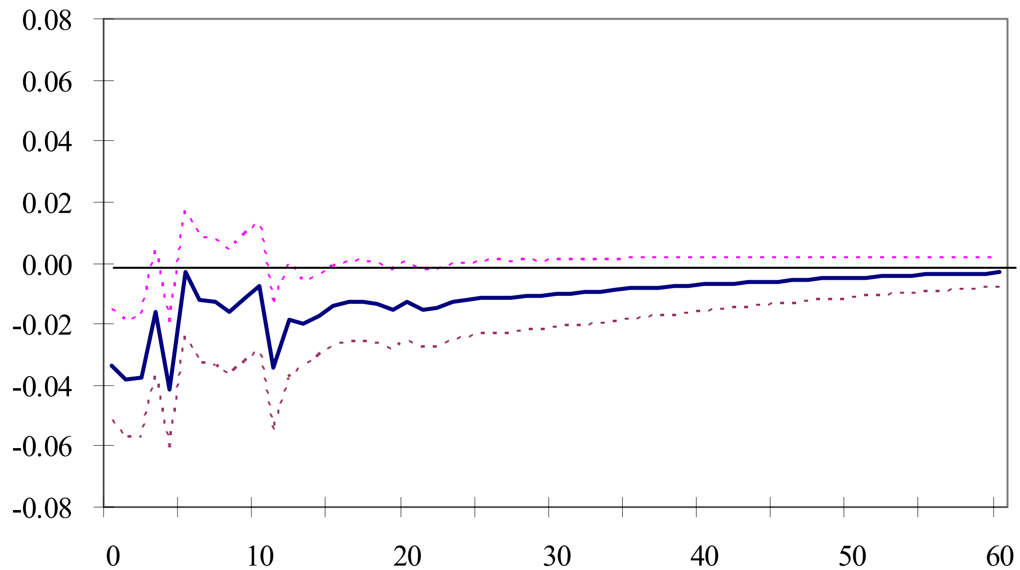


Figure 3.5 Impulse Responses of High-Low Volatility to Flow

The figure plots the impulse responses of high-low volatility ($\ln(\sigma_{HL})$) to a unit standard deviation shock in flow in a structural VAR (12) model that consists of $\ln(\sigma_{HL})$, *flow*, and market returns (*mkret*), assuming that volatility shocks are determined by flow and return shocks and that flow shocks are determined by return shocks. The VAR lag length is chosen using a top-down approach. The dotted lines represent the plus and minus two standard error bands. The sample period is from February 1998 to December 2003.



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