The Determinants and Implications of Mutual Fund Cash Holdings: Theory and Evidence

Xuemin (Sterling) Yan*

In this article, I examine the determinants and implications of equity mutual fund cash holdings. In cross-sectional tests, I find evidence generally supportive of a static trade-off model developed in this article. In particular, small-cap funds and funds with more-volatile fund flows hold more cash. However, I do not find that fund managers with better stock-picking skills hold less cash. Aggregate cash holdings by equity mutual funds are persistent and positively related to lagged aggregate fund flows. Aggregate cash holdings do not forecast future market returns, suggesting that equity funds as a whole do not have market timing skills.

Cash is a critical component of equity mutual funds' portfolios. At the end of 2000, US equity funds held $228 billion, or 5.8% of their total assets under management, in cash. To put this amount in perspective, the equity fund industry as a whole had only $240 billion in total assets in 1990 (Investment Company Institute, 2002). And yet, despite their practical importance, fund cash holdings have received little direct attention in the academic literature.[1]

The purpose of this article is to examine the determinants and implications of equity mutual funds' cash holdings at both the fund level and the aggregate level. In particular, I address the following questions: How do transaction costs and investor flows affect fund cash holdings? Do managers with better stock-picking skills hold less cash? Do equity funds as a whole display market timing skills by holding more cash prior to down markets?

Equity mutual funds hold cash for several purposes. First, funds hold cash to meet shareholders' redemption needs. Second, funds use cash to pay management fees and other expenses, and to make dividend and capital gain distributions. Third, fund managers may hold cash when they expect future stock market returns to be low (market timing).

The primary cost of holding cash is the opportunity cost. Between 1926 and 2002, stocks outperformed cash by approximately 7.5% per year in the US.[2] Therefore, cash tends to be a drag on long-term fund performance. For example, Wermers (2000) estimates that for the period from 1975 to 1994, cash and bond holdings lower the performance of an average equity fund by 70 basis points per year.

[1]Chordia (1996) is an exception. Chordia develops a model of mutual fund fee structures. His model predicts that, among other things: 1) funds hold more cash when there is more uncertainty about redemptions, and 2) funds with load and redemption fees hold less cash than their no-load counterparts. Chordia tests these predictions using a sample of 397 funds in 1991 and finds supportive evidence for both.

[2]I use the CRSP value-weighted index returns as the stock return, and one-month T-bill returns as the return on cash. I obtain both data series from Kenneth French's website.

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**Xuemin (Sterling) Yan is an Assistant Professor of Finance at the University of Missouri – Columbia in Columbia, MO.*

Therefore, there is a trade-off between the costs and benefits of funds' cash holdings. Funds that maximize shareholder wealth should set the fund's cash holdings at a level such that the marginal benefit of cash holdings equals the marginal cost. To formalize this idea, I develop a static model of optimal cash holdings. For tractability, the model considers the trade-off between two factors, the expected trading cost of liquidating stocks to meet redemptions and the opportunity cost of cash.

The model produces four principal predictions. First, that funds with less-liquid stock holdings hold more cash because it is more costly for these funds to liquidate their stock holdings. The model predicts that small-cap funds hold more cash because small-cap stocks have higher transaction costs. Second, that funds with more-volatile fund flows hold more cash. Intuitively, funds with more-volatile fund flows have a greater probability of experiencing a cash shortage. Third, that funds expecting higher fund inflows hold less cash. Fourth, that managers with better stock-picking skills hold less cash. The intuition for this result is that the opportunity cost of holding cash is higher for more skilled managers.

Earlier studies on dynamic portfolio choice in the presence of transaction costs (e.g., Constantinides, 1986) suggest that funds' cash holdings should be persistent and positively related to recent fund flows. In a frictionless world, a fund rebalances its portfolio continuously to maintain an optimal level of cash. Therefore, past fund flows have no impact on a fund's current cash holding. However, in the presence of transaction costs, it is not optimal for a fund to rebalance its portfolio continuously. The optimal strategy for a fund is to adjust its cash holdings only when they are either too high or too low. As a result, fund cash holdings are persistent and positively related to recent fund flows.

I test the above predictions by using a comprehensive sample of US equity mutual funds for the period 1992 to 2001. I find that small-cap funds, funds with higher recent fund flows, and funds with more-volatile fund flows hold more cash. These cross-sectional results are consistent with models of optimal cash holdings. I do not find evidence of a systematic relation between fund cash holdings and risk-adjusted fund performance. This result does not support the static model's prediction that fund managers with better stock-picking skills tend to hold less cash.

To provide additional insight into the predictions of models of optimal cash holdings, I also examine aggregate cash holdings by equity mutual funds. Consistent with dynamic models of optimal fund cash holdings, I find that aggregate fund cash holdings are persistent and positively related to lagged aggregate fund flows. Aggregate fund cash holdings are also negatively related to lagged market returns. This finding is consistent with the idea that equity funds as a whole engage in positive-feedback trading at the market level. I find that aggregate cash holdings are not significantly related to future market returns, suggesting that equity funds as a whole do not have market timing skills.

This article is related to a growing literature that examines the determinants of corporate cash holdings (see, e.g., Kim, Mauer, and Sherman, 1998; Opler, Pinkowitz, Stulz, and Williamson, 1999 and Almeida, Campello, and Weisbach, 2004). Kim et al. (1998) and Opler et al. (1999) find that corporate cash holdings are higher among firms with riskier cash flows. Similarly, in this paper I find that equity mutual funds hold more cash when fund cash flows are more volatile. In addition, many papers in the corporate cash holding literature find that cash holdings increase in the cost of external financing. This result is similar to my result that fund cash holdings increase in transaction costs. Finally, Almeida, Campello, and Weisbach (2004) find that cash flow sensitivity of cash is positive, especially among financially constrained firms. In this article, I document a significant and positive relation between fund cash holdings and recent fund flows. These parallels suggest that industrial corporations and mutual funds are similar in many ways when it comes to managing liquidity.

The article proceeds as follows. I develop my static model of optimal cash holdings in Section I. I describe the mutual fund sample and present summary statistics in Section II. I examine the determinants of fund-level cash holdings in Section III and present the results for aggregate cash holdings in Section IV. Section V concludes the article.

I. A Static Model of Optimal Cash Holdings

In this section, I first develop a static model of optimal cash holdings and then present the predictions of this model. I also discuss the implications of dynamic models of optimal cash holdings.

A. The Model

I consider a two-period model. At $t=0$, the fund allocates its money between a risky asset (or portfolio) and a risk-free asset. Without loss of generality, I assume that the total net asset (*TNA*) of the fund is \$1 at $t=0$, and that the risk-free rate is zero. The expected return of the risky asset is $E(R)>0$, which is also the equity premium because the risk-free rate is zero. I denote the fund's cash allocation as c. In addition, I denote the fund manager's stock-picking ability as α.

At $t=1$, the return to the risky asset is realized, so is the net fund flow (denoted as x). The net fund flow can be positive or negative. When redemptions are greater (less) than new sales, the fund flow is negative (positive). For tractability, I assume that the net fund flow is drawn from a normal distribution.

$$x \sim N\left(\mu, \sigma^2\right) \tag{1}$$

When the fund does not have enough cash to meet redemptions (when $c<-x$), the fund must liquidate a portion of its risky asset to raise cash. I assume that there is a proportional cost (denoted as g) associated with liquidating the risky asset. This cost includes brokerage commissions, bid-ask spreads, and price impact.

The objective of the fund is to maximize the expected *TNA* at $t=1$, as the fund management fees are typically a fixed percentage of total assets under management. Since the fund starts with a *TNA* of \$1, maximizing expected *TNA* at $t=1$ is equivalent to:

$$\min_c \; L(c) = -\int_{-1}^{-c} (x+c)\cdot g \cdot f(x)dx + \left(E(R)+\alpha\right)\cdot c \tag{2}$$

That is, the fund minimizes the sum of the expected cost of liquidating the risky asset and the opportunity cost of cash holdings. The first term on the right-hand side of Equation (2) captures the expected cost of liquidating the risky asset to meet redemptions. The upper limit of the integral is $-c$, reflecting the fact that, when net redemption is greater than the level of cash holding c, the fund must sell the risky asset to meet redemption needs. The lower limit of the integral is -1 because the fund starts with a *TNA* of \$1. The second term on the right-hand side of Equation (2) captures the opportunity cost of cash holdings, and is increasing in the expected return of the risky asset $E(R)$, the manager's alpha, and the level of cash holding c. This model is admittedly simple, and does not capture many important features of mutual funds. My objective is to focus on fund cash holdings.

Using properties of truncated normal distributions, I can rewrite $L(c)$ as follows:

$$
\begin{aligned}
L(c) &= -\int_{-1}^{-c} x \cdot g \cdot f(x)dx - \int_{-1}^{-c} c \cdot g \cdot f(x)dx + \left(E(R)+\alpha\right)\cdot c \\
&= -g \cdot \left[\mu + \frac{Z\left(\frac{-1-\mu}{\sigma}\right) - Z\left(\frac{-c-\mu}{\sigma}\right)}{\Phi\left(\frac{-c-\mu}{\sigma}\right) - \Phi\left(\frac{-1-\mu}{\sigma}\right)}\sigma \right] \cdot \left[\Phi\left(\frac{-c-\mu}{\sigma}\right) - \Phi\left(\frac{-1-\mu}{\sigma}\right)\right] \\
&\quad - c \cdot g \cdot \left[\Phi\left(\frac{-c-\mu}{\sigma}\right) - \Phi\left(\frac{-1-\mu}{\sigma}\right)\right] + \left(E(R)+\alpha\right)\cdot c
\end{aligned} \tag{3}
$$

where Z(·) is the probability density function of the standard normal and Φ(·) is the cumulative distribution function of the standard normal.

To obtain closed-form solutions, I make two simplifying assumptions. First, I assume that the mean fund flow μ is zero. This assumption is reasonable when the evaluation period is relatively short. For example, Greene and Hodges (2002) report that the average daily percentage fund flow is -0.02% for a large sample of US mutual funds during the period 1998-2000. Second, I approximate the lower limit of the integral -1 with -∞. In practice, the probability of x being less than -1 is negligible for reasonable levels of flow volatility.[3]

Lemma 1: Assuming $\mu = 0$ and approximating the lower limit of the integral in Equation (2) with -∞, the optimal cash holding is:

$$
c^* = -\sigma \cdot \Phi^{-1}\left[\frac{\left(E(R)+\alpha\right)}{g}\right] \tag{4}
$$

Proof:

Under the assumptions stated in Lemma 1, I can simplify the objective function *L(c)* to:

$$
\begin{aligned}
L(c) &= -\int_{-\infty}^{-c} (x+c)\cdot g \cdot f(x)dx + \left(E(R)+\alpha\right)\cdot c \\
&= g \cdot \sigma \cdot \left[Z\left(\frac{-c}{\sigma}\right)\right] - g \cdot c \cdot \left[\Phi\left(\frac{-c}{\sigma}\right)\right] + \left(E(R)+\alpha\right)\cdot c
\end{aligned} \tag{5}
$$

The first order condition is:

$$
\frac{\partial L}{\partial c} = -g \cdot \left[\Phi\left(\frac{-c}{\sigma}\right)\right] + \left(E(R)+\alpha\right) = 0 \tag{6}
$$

Solving the first order condition gives c* stated in Equation (4).

The second order condition confirms that *L(c)* is minimized at c*.

[3]For example, with $\mu = 0$ and $\rho = 1\%$, the probability of $x < -1$ is $2.23\times e^{-308}$.

$$\frac{\partial^2 L}{\partial c^2} = \frac{g}{\sigma} \cdot Z\left(\frac{-c}{\sigma}\right) > 0 \tag{7}$$

Proposition: Under the assumptions stated in Lemma 1, the optimal cash holding is increasing in proportional transaction cost g and cash flow volatility σ, and decreasing in the manager's stock-picking skill α.

Proof:
Differentiating the first order condition, I obtain:

$$\frac{\partial^2 L}{\partial c \partial g} = -\Phi\left(\frac{-c}{\sigma}\right) < 0 \tag{8}$$

$$\frac{\partial^2 L}{\partial c \partial \sigma} = -g \cdot Z\left(\frac{-c}{\sigma}\right) \cdot \left(\frac{c}{\sigma^2}\right) < 0 \tag{9}$$

$$\frac{\partial^2 L}{\partial c \partial \alpha} = 1 > 0 \tag{10}$$

Combining Equations (8), (9), and (10) with Equation (7) and using the implicit function theorem, I obtain:

$$\frac{dc^*}{dg} > 0 \quad \frac{dc^*}{d\sigma} > 0 \quad \frac{dc^*}{d\alpha} < 0 \tag{11}$$

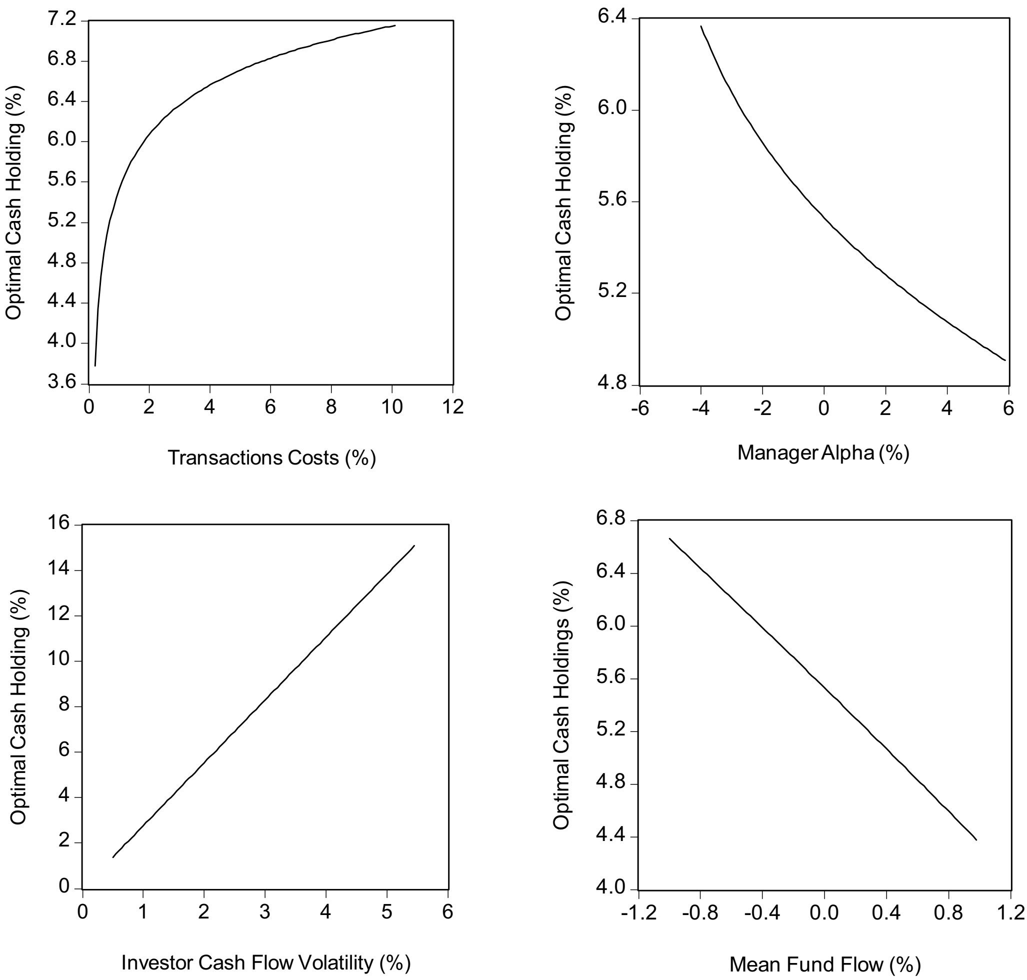
B. Numerical Results

Here, I study the comparative statics of the full model by using a numerical method. I examine a daily model with the following baseline parameter values: $\mu = 0$, $E(R) = 6\%$ per year, $\alpha = 0\%$, $g = 1\%$, and $\rho = 2\%$.

Figure 1 plots the comparative statics of optimal cash holdings with respect to g, σ, α, and μ. The results indicate that the optimal cash holding increases in transaction costs. For example, the optimal cash holding increases from 4.9% to 6.6% when the proportional transaction costs increase from 0.5% to 4%. The optimal cash holding increases in fund flow volatility. The more volatile the fund flow is, the higher the probability that the fund will experience a cash shortage. Therefore, funds that experience more volatile fund flows hold more cash. Figure 1 also shows that the optimal cash holding decreases in manager's alpha. The intuition for this result is that the greater the alpha, the higher the opportunity cost of holding cash. I find that the optimal cash holding decreases in the expected fund flow. This result is also intuitive. All else equal, funds that expect cash inflows hold less cash than do funds that expect cash outflows.

Figure 1. Comparative Statics of Optimal Cash Holdings

This figure presents the comparative statics of optimal cash holdings based on the static model presented in Section I. The baseline parameter values are as follows: μ=0, $E(R)$ = 6% per year, α = 0%, g=1%, and σ=2%. μ is the mean fund flow, $E(R)$ is the expected return, α is the fund manager's stock-picking skill, g is the proportional transaction cost, and σ is the standard deviation of fund flows.



C. Additional Predictions

Although not explicitly modeled, several factors that influence transaction costs and fund flows also affect the optimal cash holding. I make the following additional predictions:

- Small-cap funds hold more cash because small-cap stocks have higher transaction costs.
- The optimal cash holding decreases in 12b-1 fees, because the literature has shown that advertising is effective in attracting investor cash flows (Jain and Wu, 2000 and Barber, Odean, and Zheng, 2004).

- The optimal cash holding increases in front-end loads because front-end loads discourage new cash inflows (Barber, Odean, and Zheng, 2004). The optimal cash holding decreases in deferred loads because deferred loads deter redemptions, thus reducing the probability of a cash shortage.

D. Implications from Dynamic Models

I expect the basic results of a dynamic model of optimal fund cash holdings in the presence of transaction costs to be qualitatively similar to that of Constantinides (1986). In the presence of transaction costs, it is not optimal for a fund to maintain its cash holding at a constant "optimal" level at all times, because this strategy would imply an infinite amount of trading and hence an infinite amount of transaction costs. The optimal strategy for a fund is to keep its cash holding within a certain range, and to trade only when the cash holding is either too high or too low. Specific optimal trading strategies depend on whether transaction costs are fixed or proportional. When transaction costs are proportional, the optimal trading strategy is to trade an infinitesimal amount at the boundary. When transaction costs are fixed, the optimal strategy is to trade a fixed amount at the boundary.[4]

The dynamic model above has two important implications for funds' cash holdings. First, funds' cash holdings are persistent in the short run and mean-reverting in the long run. Second, funds' cash holdings are positively related to recent fund flows. After experiencing cash inflows, funds tend to hold more cash; after experiencing cash outflows, funds tend to hold less cash.

II. Summary Statistics for Fund-Level Cash Holdings and Fund Characteristics

In this section, I first describe the data and sample and then present the summary statistics for fund-level cash holdings and various fund characteristics.

A. Data and Sample

The primary data source for fund-level cash holdings and fund characteristics is the CRSP Survivor-Bias Free Mutual Fund Database. I include only diversified domestic equity funds in my sample. I exclude international funds, sector funds, and balanced funds.

I use the ICDI fund objective code in the CRSP database to assign each sample fund one of three investment objectives: aggressive growth, long-term growth, or growth and income. I also identify index funds and small-cap funds. I identify index funds by searching for the word "index" in fund names. To ensure accuracy, I eyeball all selected index funds. I identify small-cap funds by using the Wiesenberger fund type code and Strategic Insight's fund objective code. Following Chen, Hong, Huang, and Kubik (2004), a fund is classified as a small-cap fund if it has ever had "SCG" as a Wiesenberger or Strategic Insight objective code.

The CRSP database reports fund asset compositions including cash balances annually, but the exact asset composition dates are not available prior to the 1990s. Furthermore, the CRSP database does not report monthly total net assets (TNA) prior to 1992. Therefore, I limit my analysis to the sample period 1992-2001.

[4]See Davis and Norman (1990), Liu and Loewenstein (2002), and references therein for more studies on optimal portfolio choice in the presence of transaction costs.

Many mutual funds have several share classes, and CRSP lists each class as a separate fund. These share classes represent claims on the same underlying assets, and have the same returns before expenses and loads. They usually differ only in their fee structures (e.g., load or no-load) and/or in their clienteles (e.g., institutional or retail). Because the cash holdings of these classes are always the same, in my analysis I combine the different classes into a single fund. I sum the TNA of each class to obtain the total TNA. For fund characteristics such as expense ratio, I use the TNA-weighted average. My final sample contains 16,354 fund-year observations representing 2,069 distinct funds.

B. Summary Statistics

Table I reports the summary statistics for fund characteristics. The average TNA is $1,207.35 million. The median TNA is substantially lower at $180.73 million, suggesting that the distribution of fund size is positively skewed. The sample funds have an average age of just over 11 years, an average expense ratio of 1.26%, and an average 12b-1 fee of 0.19%. The average front-end load is 1.34% and the average deferred load is 0.51%. The average turnover rate is 88.85% per year.

The average cash holding is 5.33%, and the median cash holding is 3.68%. There are large cross-sectional variations in funds' cash holdings. The middle 80% of the funds hold between 0.07% and 12.66% in cash, representing a spread of 12.59%. The average stock holding is 93.49%. Overall, equity funds hold approximately 99% of their assets in either stocks or cash.

Approximately one third of funds are aggressive growth funds, and 42.58% of funds are long-term growth funds. The remaining 24.92% are growth and income funds. Index funds comprise of 5.88% of all funds in my sample. Approximately 25% of funds are small-cap funds. I note that although aggressive growth, long-term growth, and growth and income funds are mutually exclusive, each index fund or small-cap fund belongs to one of these three investment objectives.

Panel C of Table I presents the correlations. Funds' cash holdings are positively correlated with expense ratio, turnover, 12b-1 fee, front-end load, and yield; and negatively correlated with fund size, deferred load, and fund family size.

III. Determinants of Fund-Level Cash Holdings

In this section, I examine the relation between fund-level cash holdings and various fund characteristics. I also examine whether funds' cash holdings are related to fund performance.

A. Fund Characteristics and Fund Cash Holdings

In this section, I study the relation between various fund characteristics and fund cash holdings by using two fixed-effects models, namely the fixed-time-effects model and the fixed-fund-effects model. Specifically, in the fixed-time-effects model, I include a dummy variable for each asset composition date. In the fixed-fund-effects models, I include a dummy variable for each fund.

1. Fixed-Time-Effects Models

I regress fund cash holdings on various fund characteristics including fund size, expense ratio, and lagged fund performance. I also include a dummy variable for each asset composition

Table I. Summary Statistics for Fund-Level Cash Holdings and Fund Characteristics, 1992 – 2001

The table presents the summary statistics for fund-level cash holdings and various fund characteristics. The sample period is 1992-2001. I obtain fund characteristics from the CRSP Survivor-bias Free Mutual Fund Database. I use the ICDI fund objective code to assign each fund one of three investment objectives: aggressive growth (AG), long-term growth (LG), and growth and income (GI). I identify index funds by searching for "index" in fund names. I identify small-cap funds by using the Wiesenberger fund type code and Strategic Insight's fund objective code. I classify a fund as a small-cap fund if it has ever had "SCG" as an objective code. LNTNA is the logarithm of the fund's total net assets.

Panel A. Characteristics of Funds

	Mean	Median	10th Percentile	90th Percentile
Total Net Assets (TNA) - $million	1207.35	180.73	13.94	2194.32
Age (AGE) – years	11.22	7.00	2.00	29.00
Expense Ratio (EXP) - %	1.26	1.23	0.69	1.92
12b-1 Fee (12B1) - %	0.19	0.03	0.00	0.61
Front Load (FLD) - %	1.34	0.00	0.00	4.59
Deferred Sales Charge (DLD) - %	0.51	0.00	0.00	2.00
Turnover (TURN) - %	88.85	67.10	16.00	182.00
Yield (YLD) - %	0.53	0.07	0.00	1.53
Number of Funds in the Fund Family (NUM)	37.63	10.00	1.00	108.00
Percent Cash Holding (CASH) - %	5.33	3.68	0.07	12.66
Percent Stock Holding (STOCK) -%	93.49	95.55	84.70	99.50

Panel B. Investment Objectives

	Percent of Funds
Aggressive Growth (AG)	32.50%
Long-term Growth (LG)	42.58%
Growth and Income (GI)	24.92%
Index Fund (INDEX)	5.88%
Small-cap Fund (SCG)	25.06%

Panel C. Correlations

	CASH	LNTNA	EXP	TURN	12B1	FLD	DLD	NUM	YLD
CASH	1.00								
LNTNA	-0.05	1.00							
EXP	0.13	-0.34	1.00						
TURN	0.05	-0.08	0.21	1.00					
12B1	0.04	0.06	0.60	0.06	1.00				
FLD	0.07	0.09	0.20	-0.01	0.32	1.00			
DLD	-0.02	-0.04	-0.03	-0.01	-0.10	-0.11	1.00		
NUM	-0.07	0.29	-0.11	0.03	0.09	0.08	0.04	1.00	
YLD	0.08	0.05	-0.27	-0.13	-0.18	-0.05	0.00	-0.03	1.00

date. The inclusion of these dummy variables ensures that the results are not driven by the *time series* variations in fund cash holdings. Since fund cash holdings are persistent over time, the regression residuals are likely to be serially correlated within a fund. To account for this serial autocorrelation, I use Rogers standard errors. As Petersen (2005) shows, Rogers standard errors are superior to alternative standard errors in the presence of within-fund correlation in residuals.[5]

Table II presents the results for fixed-time-effects models. On average, small-cap funds hold between 0.84% and 1.08% more cash than do other equity funds. This result is consistent with the prediction of my static model in Equation (11). Transaction costs are higher for small stocks, and consequently a shortage of cash is more costly for small-cap funds. Therefore, small-cap funds tend to hold more cash.

Index funds generally hold between 0.84% and 1.74% less cash than non-index funds. There are at least two explanations for this result. First, since the objective of an index fund is to track the performance of an index, to maintain a small tracking error it is important for index funds to hold as little cash as possible. Second, index funds can manage their cash flows more effectively by using index futures or index options.

Funds in larger fund families (as measured by the number of funds) hold less cash. This finding is consistent with the idea that funds may borrow from other funds in the same family to meet unexpected large redemptions. Effectively, funds in the same family share the redemption risk. As long as the redemption risk is not perfectly correlated across funds, this risk sharing implies lower cash holdings. However, the economic significance of this result is marginal. An increase in the number of funds by ten is associated with a decrease in cash holdings by just over 0.1%.

As predicted, fund cash holdings are positively related to front-end loads, and negatively related to deferred loads. The coefficients on the front-end loads are statistically significant at the 5% level. However, the coefficients on the deferred loads are not statistically significant.

Funds with higher expenses hold more cash. This result is statistically significant at the 1% level. On average, an increase in fund expense ratio by ten basis points would increase the cash balance by about 16 to 18 basis points. One possible explanation for this result is that, since fund expenses are paid with cash, funds with higher expenses need to hold more cash.

Controlling for total expenses, funds with higher 12b-1 fees (advertising or distributing expenditures) hold less cash. Jain and Wu (2000) and Barber, Odean, and Zheng (2004) show that funds with higher advertising expenditures attract greater investor cash flows, thereby facing a lower risk of cash shortage.

Fund cash holdings are significantly and positively related to past fund performance. The coefficient on lagged one-year investment-objective-adjusted fund returns is statistically significant at the 1% level in all regressions.[6] This result is driven by the combination of two effects: the positive effect of performance on investor cash flows and the positive effect of cash flows on cash holdings.

There are at least two reasons why I might expect a negative relation between fund size and a fund's cash holding. First, larger funds tend to hold more-liquid stocks. Mutual funds are constrained by the size of positions they can take.[7] These constraints force large funds

[5]Rogers standard errors can be used in the presence of either within-fund correlation in residuals or within-year correlation in residuals. In this article, I use Rogers standard errors to account for possible correlation within a fund. Although cash holdings for a given year might be correlated across funds, I include time dummies to account for this effect.

[6]The results are qualitatively identical when I use raw returns or risk-adjusted returns (alphas) to measure past fund performance.

[7]For instance, the 1940 Investment Company Act requires that, for 75% of their assets, funds may not acquire more than 10% of the voting securities of any one issuer and it may not invest more than 5% of total fund assets in any one issuer.

Table II. Determinants of Fund Cash Holdings – Fixed-Time-Effects Models

This table presents the results on the determinants of fund-level cash holdings using fixed-time-effects models. The sample period is 1992-2001. I include a dummy variable for each asset composition date. I obtain fund characteristics from the CRSP Survivor-bias Free Mutual Fund Database. It identifies index funds by searching for "index" in fund names. I identify small-cap funds by using the Wiesenberger fund type code and Strategic Insight's fund objective code. It classifies a fund as a small-cap fund if it has ever had "SCG" as an objective code. CASH is the fund cash holding as a percentage of the total net asset. TNA is the fund's total net assets. LNTNA is the logarithm of TNA. INDEX is a dummy variable for index funds. SCG is a dummy variable for small-cap funds. AG is a dummy variable for aggressive growth funds. LG is a dummy variable for long-term growth funds. NUM is the number funds in the fund family. EXP is the expense ratio. 12B1 is the 12b-1 fee. TURN is the turnover. FLD is the front-end load. DLD is the deferred load. YLD is the income yield. LRET is the lagged one-year investment objective-adjusted fund returns. I winsorize CASH, TURN, and YLD at the 1st and 99th percentiles. The dependent variable is CASH in all regressions. In each regression, the first row gives the OLS coefficient estimate. The second row gives the *p*-value based on Rogers standard errors which accounts for within-fund correlation in residuals. For brevity, I do not report the intercept and the coefficients on time dummy variables.

LNTNA	SCG	INDEX	AG	LG	NUM	EXP	12B1	TURN	FLD	DLD	YLD	LRET	R^2
-0.002	1.008	-1.738			-0.013							1.179	0.08
(0.96)	(0.01)	(0.01)			(0.06)							(0.01)	
-0.003			1.434	0.852	-0.016							1.066	0.08
(0.95)			(0.01)	(0.01)	(0.02)							(0.01)	
0.122	0.841	-0.882				1.508	-0.774	0.143				0.899	0.10
(0.02)	(0.01)	(0.01)				(0.01)	(0.13)	(0.19)				(0.01)	
-0.041	1.080	-1.647							0.131	-0.146		1.282	0.08
(0.39)	(0.01)	(0.01)							(0.01)	(0.73)		(0.01)	
0.132	1.001	-0.836			-0.012	1.698	-0.935	0.179	0.111	-0.141	0.505	0.990	0.10
(0.02)	(0.01)	(0.01)			(0.08)	(0.01)	(0.08)	(0.10)	(0.04)	(0.74)	(0.01)	(0.01)	
0.141			1.276	0.761	-0.013	1.814	-1.011	0.131	0.114	-0.170	0.545	0.915	0.10
(0.01)			(0.01)	(0.01)	(0.05)	(0.01)	(0.06)	(0.22)	(0.03)	(0.68)	(0.01)	(0.01)	

to hold large and liquid stocks. Because of the liquidity of their stock holdings, large funds need not hold as much cash. Second, larger funds tend to have a larger number of shareholders. Assuming that the redemption risk is not perfectly correlated across investors, an increase in the number of shareholders reduces the probability of a large aggregate redemption shock.

The results in Table II indicate that the relation between fund size (measured by the logarithm of TNA) and cash holdings is not stable. Three of the six coefficients on *LNTNA* are negative and the other three are positive. One possible explanation for this finding is that fund size is correlated with other fund characteristics. For instance, Table I shows that the correlation between *LNTNA* and expense ratio is significant and negative at -0.34. Consistent with this observation, I find that the coefficients of *LNTNA* are positive whenever I include expense ratio in the regression.

The R-squares for the regressions in Table II are between 8% and 10%, suggesting that much of the variation in cash holdings is left unexplained. One possible explanation for the modest R-square is that according to a dynamic model of optimal cash holdings in the presence of transaction costs, it may be optimal for funds to hold a potentially wide range of cash.

2. Fixed-Fund-Effects Models

To check whether my results are robust to the presence of fund-specific effects, I repeat my analysis by using fixed-fund-effects models. There are two important caveats about this approach. First, the number of sample funds is large (2,069 funds). The inclusion of 2,068 dummy variables could give the model insufficient degrees of freedom for adequately powerful tests. Moreover, the model may suffer from multicollinearity, which increases the standard errors and thus drains the model of statistical power to test parameters. Second, given that many of the fund characteristics are persistent, the effects of such variables on funds' cash holdings will be difficult or impossible to detect. For example, variables such as "Index Funds" and "Small-cap Funds" cannot be identified in this model because there is virtually no variation in these variables for any given fund. In addition to fund dummies, I again use Rogers standard errors to account for cluster at the fund level.

Table III reports the results. Despite the limitations of the fixed-fund-effects models, I find that the results are similar to those for the fixed-time-effects models. For example, funds in larger fund families hold less cash. Funds with higher expense ratios hold more cash. Funds with higher 12b-1 fees hold less cash. Past fund performance is positively related to cash. These results are consistent with those reported in the previous section.

I find a strong and negative relation between fund cash holdings and fund size. Doubling the fund asset base is associated with a decrease in cash balance by approximately 56 basis points. As I noted earlier, the relation between fund cash holdings and fund size is unstable when I use the fixed-time-effects model. Taken together, these findings suggest that the negative relation between fund size and cash holdings is more evident in the time series of each fund than it is across funds.

Funds hold approximately 0.5% less cash at year-end. There are two possible explanations for this result. First, funds generally make dividend and capital gain distributions in December. Second, funds may engage in window dressing by using cash to purchase past winning stocks at year-end. Consistent with the first explanation, I find that funds with higher yields hold more cash.

The R-squares are much higher for fixed-fund-effects models than for fixed-time-effects models. However, the higher R-square is largely attributable to the 2,068 dummy variables. Overall, the results for fixed-effects models are consistent with the predictions of models of optimal cash holdings.

Table III. Determinants of Fund Cash Holdings – Fixed-Fund-Effects Models

This table presents the results for the determinants of fund-level cash holdings using fixed-fund-effects models. The sample period is 1992-2001. I include a dummy variable for each fund. I obtain fund characteristics from the CRSP Survivor-bias Free Mutual Fund Database. It identifies index funds by searching for "index" in fund names. I identify small-cap funds by using the Wiesenberger fund type code and Strategic Insight's fund objective code. It classifies a fund as a small-cap fund if it has ever had "SCG" as an objective code. CASH is the fund cash holding as a percentage of the total net asset. TNA is the fund's total net assets. LNTNA is the logarithm of TNA. NUM is the number funds in the fund family. EXP is the expense ratio. 12B1 is the 12b-1 fee. TURN is the turnover. FLD is the front-end load. DLD is the deferred load. YREND is a dummy variable for year-end. YLD is the income yield. LRET is the lagged one-year investment objective-adjusted fund returns. I winsorize CASH, TURN, and YLD at the 1st and 99th percentiles. The dependent variable is CASH in all regressions. In each regression, the first row gives the OLS coefficient estimate. The second row gives the *p*-value based on Rogers standard errors which accounts for within-fund correlation in residuals. For brevity, I do not report the intercept and the coefficients on fund dummy variables.

LNTNA	NUM	EXP	12B1	TURN	FLD	DLD	YLD	YREND	LRET	R^2
-0.716	-0.066							-0.498	0.815	0.47
(0.01)	(0.01)							(0.01)	(0.01)	
-0.763		1.141	-1.744	-0.119				-0.593	0.909	0.47
(0.01)		(0.01)	(0.05)	(0.42)				(0.01)	(0.01)	
-0.824					0.120	-0.589		-0.557	0.927	0.47
(0.01)					(0.23)	(0.25)		(0.01)	(0.01)	
-0.558	-0.064	1.198	-1.013	-0.116	0.105	-0.590	0.571	-0.546	0.805	0.48
(0.01)	(0.01)	(0.01)	(0.24)	(0.42)	(0.29)	(0.28)	(0.01)	(0.01)	(0.01)	

B. Fund Flow, Flow Volatility, and Cash Holdings

Models of optimal cash holdings predict that funds' cash holdings are positively related to both recent fund flows and fund flow volatility. I test these predictions by including two additional explanatory variables in the cross-sectional regressions of fund cash holdings. These two variables are the past year's fund flow and the past year's fund flow volatility. Following previous studies (e.g., Zheng, 1999), I compute fund flow for each month as follows:

$$Fund\ Flow_t = \frac{TNA_{t+1} - TNA_t\left(1+R_t\right) - MGTNA_t}{TNA_t} \tag{12}$$

where R_t is the fund return in month *t* and $MGTNA_t$ is the assets acquired from merger during month *t*. I compute yearly fund flow using a similar equation. I compute flow volatility by using the standard deviation of the past 12 months' fund flows.

Table IV presents the regression results. Panel A uses fixed-time-effects models. Panel B uses fixed-fund-effects models. As in the previous section, I find that small-cap funds, funds with higher expenses, higher yields, higher front-end loads, and better past performance hold more cash. Index funds and funds with higher 12b-1 fees hold less cash.

More importantly, a fund's cash holdings are positively related to its past year's fund flow and flow volatility. These results are statistically significant and hold in both Panels A and B. The positive relation between fund cash holdings and past fund flows is consistent with the predictions of dynamic models of optimal cash holdings, in which funds adjust their cash holdings only infrequently. The positive relation between fund cash holdings and fund flow volatilities is consistent with the prediction of my static model of optimal cash holdings (see *Proposition* in Section I.A.). The intuition is that the higher the fund flow volatility, the greater the probability that a fund might experience a shortage of cash. Therefore, funds with more-volatile fund flows tend to hold more cash. Overall, these results are consistent with models of optimal cash holdings.

C. Cash Holdings and Fund Performance

As predicted by my static model of optimal cash holdings, managers with better stock-picking skills tend to hold less cash because the opportunity cost of holding cash is higher for these managers. Based on this argument, I expect low-cash funds to outperform high-cash funds on a risk-adjusted basis. I test this prediction using two approaches.

1. Portfolio Approach

Each year I form five cash quintiles based on funds' cash holdings at the end of the previous year. I rebalance these portfolios once a year and compute monthly TNA-weighted returns for each quintile. I evaluate the performance of these portfolios by using several standard one- and multi-factor models. Specifically, I use the CAPM model, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and a conditional four-factor model. Following earlier studies, I use alpha, the intercept term in the regression of fund returns on risk factors, as the performance measure. Below is the Carhart (1997) four-factor model:

$$r_{p,t} - r_{f,t} = \alpha + b \cdot MKT_t + s \cdot SMB_t + h \cdot HML_t + u \cdot UMD_t + e_t \tag{13}$$

Table IV. Fund Flow, Flow Volatility, and Fund Cash Holdings – Fixed-Time-Effects Models and Fixed-Fund-Effects Models

This table presents the results for the relation between fund cash holdings and fund flows using both fixed-time-effects models (Panel A) and fixed-fund-effects models (Panel B). The sample period is 1992-2001. Panel A includes a dummy variable for each asset composition date. In Panel B, I include a dummy variable for each fund. I obtain fund characteristics from the CRSP Survivor-bias Free Mutual Fund Database. It identifies index funds by searching for “index” in fund names. It identifies small-cap funds by using the Wiesenberger fund type code and Strategic Insight’s fund objective code. It classifies a fund as a small-cap fund if it has ever had “SCG” as an objective code. CASH is the fund cash holding as a percentage of the total net asset. TNA is the fund’s total net assets. LNTNA is the logarithm of TNA. INDEX is a dummy variable for index funds. SCG is a dummy variable for small-cap funds. EXP is the expense ratio. 12B1 is the 12b-1 fee. TURN is the turnover. FLD is the front-end load. DLD is the deferred load. YREND is a dummy variable for year-end. YLD is the income yield. CF is past-year’s fund flow. CFSTD is past-year’s fund flow volatility. LRET is the lagged one-year investment objective-adjusted fund returns. It winsorizes CASH, TURN, YLD, CF, and CFSTD at the 1st and 99th percentiles. The dependent variable is CASH in all regressions. In each regression, the first row gives the OLS coefficient estimate. The second row gives the *p*-value based on Rogers standard errors which accounts for within-fund correlation in residuals. For brevity, I do not report the intercept and the coefficients on time and fund dummy variables.

Panel A. Fixed Time Effects

LNTNA	SCG	INDEX	NUM	EXP	12B1	TURN	FLD	DLD	YLD	CF	CFSTD	LRET	R^2
0.140	1.026	-0.881	-0.012	1.674	-1.027	0.166	0.120	-0.170	0.502	0.224		0.571	0.11
(0.01)	(0.01)	(0.01)	(0.07)	(0.01)	(0.05)	(0.13)	(0.03)	(0.68)	(0.01)	(0.01)		(0.04)	
0.140	1.005	-0.852	-0.012	1.698	-0.943	0.167	0.114	-0.146	0.503		0.654	0.869	0.10
(0.01)	(0.01)	(0.02)	(0.08)	(0.01)	(0.07)	(0.12)	(0.03)	(0.73)	(0.01)		(0.06)	(0.01)	

Panel B. Fixed Fund Effects

LNTNA	NUM	EXP	12B1	TURN	FLD	DLD	YLD	YREND	CF	CFSTD	LRET	R^2
-0.524	-0.060	1.125	-1.112	-0.091	0.101	-0.495	0.550	-0.554	0.410		0.272	0.49
(0.01)	(0.01)	(0.01)	(0.19)	(0.52)	(0.30)	(0.36)	(0.01)	(0.01)	(0.01)		(0.31)	
-0.537	-0.063	1.191	-1.027	-0.124	0.104	-0.550	0.564	-0.554		1.710	0.572	0.48
(0.01)	(0.01)	(0.01)	(0.23)	(0.39)	(0.29)	(0.31)	(0.01)	(0.01)		(0.01)	(0.03)	

where *MKT*, *SMB*, *HML*, and *UMD* are the market factor, size factor, book-to-market factor, and the momentum factor respectively. I note that the one-factor market model and the Fama-French three-factor model are both nested in the above four-factor model.

To account for time-varying risk premiums and time-varying betas, Ferson and Schadt (1996) propose a conditional performance evaluation model based on pre-determined conditioning variables. They show that conditional alphas can differ significantly from unconditional alphas. As a robustness check, I also estimate the following conditional performance evaluation model.

$$r_{p,t} - r_{f,t} = \alpha + b_1 MKT_t + b_2 \cdot DP_{t-1} \cdot MKT_t + b_3 \cdot DEF_{t-1} \cdot MKT_t + b_4 \cdot TERM_{t-1} \cdot MKT_t$$
$$+ b_5 \cdot TB3M_{t-1} \cdot MKT_t + s \cdot SMB_t + h \cdot HML_t + u \cdot UMD_t + e_t \tag{14}$$

where *DP* is the S&P 500 index dividend yield, *DEF* is the default spread, *TERM* is the term premium, and *TB3M* is the three-month T-bill rate. These conditioning variables are differences from their respective unconditional means.

In this model, I allow the market beta to be a linear function of pre-determined variables. Alternative specifications of the conditional model do not affect the qualitative results.

Table V reports the results for fund performance across fund cash portfolios. The results indicate that there is a substantial spread in cash holdings between low-cash funds and high-cash funds. The average cash holding for funds in quintile 1 (with least cash) is only 0.19%, but the average cash holding for funds in Quintile 5 (with most cash) is 14.45%.

Nineteen out of 20 alpha estimates are negative and eight of them are statistically significant at the 10% level. This finding is consistent with the existing evidence that actively managed mutual funds generally underperform their passive benchmarks after expenses. For instance, when I use the unconditional four-factor model, I find that quintile 1 underperforms the benchmark by 11.30 basis points per month, while Quintiles 2 through 5 underperform the benchmark by 10.10, 6.11, 15.50, and 4.09 basis points respectively.

There is little evidence of a systematic relation between fund performance and cash holdings. Funds in Quintile 3 (with median cash holdings) and Quintile 5 (with most cash holdings) tend to outperform funds in Quintiles 1, 2 and 4 on a risk-adjusted basis. For instance, when I use the CAPM, Quintile 3 and Quintile 5 each underperforms the market by less than five basis points per month. On the other hand, each of Quintiles 1, 2, and 4 underperforms the market by more than ten basis points per month. This result is also robust to the use of a conditional performance evaluation model. Overall, I find little evidence that risk-adjusted fund performance is systematically related to fund cash holdings.[8]

2. Cross-Sectional Regression Approach

I now use a cross-sectional fund regression approach to further examine the relation between cash holdings and fund performance. I regress one-month-ahead risk-adjusted fund returns (i.e., alphas) for each fund on various fund characteristics including fund cash holdings. Using this approach allows me to control for other fund characteristics that might affect fund performance.

I use a similar approach to Chen et al. (2004) to estimate factor loadings for each fund. I divide all funds into five quintiles by fund cash holdings. I track these five portfolios for one quarter and then use the entire time series of their monthly returns (1992-2001) to estimate the loadings to various risk factors (MKT, SMB, HML, and UMD). For each month, each

[8]A double sort based on fund cash holdings and lagged one-year fund returns produces a similar finding.

Table V. Fund Cash Holdings and Risk-Adjusted Fund Performance, 1992-2001

This table presents the performance of fund portfolios sorted by cash holdings. The sample period is 1992-2001. I obtain fund characteristics from the CRSP Survivor-bias Free Mutual Fund Database. In each year, I rank all funds according to their cash holdings. I form five quintiles. Quintile 1 contains funds with the least cash holdings. Quintile 5 contains funds with the most cash holdings. I update the cash-holding portfolio each year and construct portfolio returns using the TNA-weighted average returns. Alpha is the intercept term of the regression of portfolio returns on factors. The one-factor model is the CAPM. The three-factor model is the Fama-French (1993) three-factor model. The four-factor model is the Fama-French three-factor model augmented with a momentum factor. The four-factor conditional model allows market beta to be a linear function of predetermined instruments. Fama-French factors and the momentum factor are from Kenneth French's website. Numbers in parentheses are *p*-values.

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Average Cash Holding (%)	0.19	2.10	4.00	6.74	14.45
Alpha – CAPM (basis point)	-15.20	-12.90	-4.41	-10.10	-3.32
	(0.01)	(0.08)	(0.49)	(0.18)	(0.66)
Alpha – Three-Factor Model	-7.73	-12.10	0.79	-9.81	-3.88
(basis point)	(0.16)	(0.08)	(0.89)	(0.16)	(0.55)
Alpha – Four Factor Model	-11.30	-10.10	-6.11	-15.50	-4.09
(basis point)	(0.04)	(0.15)	(0.24)	(0.02)	(0.54)
Alpha – Conditional Four	-12.50	-12.20	-6.91	-17.40	-3.44
Factor Model (basis point)	(0.03)	(0.10)	(0.22)	(0.01)	(0.63)

fund inherits the loadings of one of these five fund cash holding quintiles to which it belongs. I then calculate the one-month-ahead expected fund return by using the above factor loadings along with the realized factor returns (including return on the risk free asset) for the next month. Finally, I calculate the risk-adjusted return as the difference between the realized fund return and the expected fund return.

To gauge the robustness of my results to various asset pricing models, I again consider four different models, the CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and a conditional four-factor model. However, for brevity, I only report results on the Fama-French three-factor alpha and Carhart four-factor alpha. The results for the CAPM alpha and the conditional 4-factor alpha are qualitatively similar and are available on request.

The specification of the cross-sectional regression is as follows:

$$\begin{aligned}\alpha_{i,t} &= a + b_1 CASH_{i,t-1} + b_2 LOGTNA_{i,t-1} + b_3 LOGFAM_{i,t-1} + b_4 EXP_{i,t-1} + b_5 LOGAGE_{i,t-1} \\ &+ b_6 TURNOVER_{i,t-1} + b_7 LOAD_{i,t-1} + b_8 LAGFLOW_{i,t-1} + b_9 LAGFUNDRET_{i,t-1} + e_{i,t}\end{aligned} \tag{15}$$

where a_t is the one-month-ahead risk-adjusted fund return, CASH is fund cash holding, LOGTNA is the logarithm of fund TNA, LOGFAM is the logarithm of the fund family's TNA, EXP is the fund's expense ratio, LOGAGE is the logarithm of the fund's age, LOAD is the fund's total load, LAGFLOW is the lagged 1-year fund flow, and LAGFUNDRET is the lagged 1-year fund return. These control variables follow from Chen et al. (2004).

I use the Fama-MacBeth (1973) approach to estimate the above cross-sectional regression each month, and report the time-series average coefficients. The statistical significance of the average coefficient is based on Newey-West adjusted standard errors.

Table VI reports the results. Regardless of which alpha measure I use, three-factor or four-factor, net returns or gross returns, I find a negative relation between fund cash holding and fund performance. This result is consistent with my model's prediction. However, none of the coefficients on CASH is statistically significant. The coefficients on other fund characteristics are generally consistent with Chen et al. (2004). For example, fund size is significant and negatively related to fund performance while fund family size is significant and positively related to fund performance.

Overall, using both a portfolio approach and a cross-sectional regression approach, I find little evidence of a systematic relation between fund cash holdings and fund performance. This result does not support a prediction of my model that more skilled managers tend to hold less cash.

IV. Aggregate Fund Cash Holdings

Here, I examine the determinants and predictive ability of aggregate cash holdings by equity mutual funds. This analysis provides additional insights into the predictions of models of optimal cash holdings. Further, an examination of aggregate fund cash holdings helps answer the following questions: Do equity funds engage in positive-feedback trading at the market level? Do equity mutual funds as a whole have market timing skills?

A. Summary Statistics for Aggregate Cash Holdings and Predictive Variables

I obtain monthly aggregate cash holdings of US equity funds from the Investment Company Institute for the period 1970-2001. I obtain three-month T-bill rates, ten-year T-bond yields, and Baa corporate bond yields from the Federal Reserve Bank of St. Louis' website. I obtain dividend yields of the S&P 500 index from Robert Shiller's website, and value-weighted market index returns from CRSP. I calculate default spread as the difference between Baa corporate bond yields and ten-year T-bond yields. I calculate term spread as the difference between ten-year T-bond yields and three-month T-bill rates.

Table VII presents the summary statistics for aggregate cash holdings. The average aggregate cash holding for the sample period is 7.93%. The highest aggregate cash holding is 12.9%, which occurred in October 1990. The lowest is 3.9%, occurring in May 1972. Aggregate cash holding is extremely persistent, with a first-order autocorrelation coefficient of 0.96. Figure 2 plots aggregate cash holding and shows that there is substantial time-series variation in aggregate cash holdings.

Table VII also presents summary statistics for market excess returns and several macroeconomic predictive variables. The average market excess return is 0.49% per month, which translates to an equity premium of approximately 6% per year. The average default spread over the sample period is 2%. The average dividend yield is 3.4%. The average three-month T-bill rate is 6.53%. The average term spread is 1.55%. All of the predictive variables are extremely persistent, each with a first-order autocorrelation coefficient of 0.93 or higher.

B. Determinants of Aggregate Cash Holdings

The results contained in Panel A of Table VIII indicate that aggregate cash holdings are highly persistent. This finding is consistent with the prediction of the dynamic model of

Table VI. Cash Holdings and Fund Performance – Cross-Sectional Regressions

This table examines the relation between fund cash holdings and fund performance. The sample period is 1992-2001. I obtain fund characteristics are from the CRSP mutual fund database. The sample includes all funds with an investment objective code of “AG” (aggressive growth), “LG” (long-term growth), or “GI” (growth and income). I exclude index funds. I combine different share classes into a single fund. I estimate the three-factor alphas using the Fama-French (1993) three-factor model, and estimate the four-factor alphas using the Carhart (1997) four-factor model. I estimate a cross-sectional regression of risk-adjusted returns on fund characteristics month-by-month. I use the Fama-MacBeth (1973) method and report the average regression coefficients. Numbers in parentheses are *t*-statistics which adjust for serial correlation using the Newey-West method.

	Dependent Variable							
	3-factor net alpha		4-factor net alpha		3-factor gross alpha		4-factor gross alpha	
Intercept	-0.37	(1.18)	-0.33	(1.07)	-0.35	(1.10)	-0.31	(0.99)
Cash	-0.28	(0.77)	-0.27	(0.74)	-0.29	(0.79)	-0.28	(0.76)
Log TNA	-0.04	(2.64)	-0.05	(3.29)	-0.04	(2.74)	-0.05	(3.37)
Log Family TNA	0.03	(3.59)	0.02	(3.54)	0.03	(3.58)	0.03	(3.53)
Expense Ratio	-0.04	(0.48)	-0.04	(0.47)	0.04	(0.47)	0.04	(0.47)
Log Fund Age	0.01	(0.41)	0.01	(0.54)	0.01	(0.42)	0.01	(0.55)
Turnover	0.02	(0.75)	0.02	(0.76)	0.02	(0.77)	0.02	(0.78)
Total Load	-0.01	(1.25)	-0.01	(1.31)	-0.01	(1.10)	-0.01	(1.16)
Lagged Fund Flow	-0.09	(2.26)	-0.09	(2.31)	-0.09	(2.26)	-0.09	(2.31)
Lagged Fund Return	0.03	(3.27)	0.03	(3.27)	0.03	(3.23)	0.03	(3.23)
Average R^2	0.20		0.20		0.20		0.20	

optimal cash holdings described in Section I.D. Aggregate cash holding is significantly and negatively related to lagged market excess returns. This result could arise if equity funds as a whole engage in positive feedback trading at the market level.

Aggregate cash holding is not significantly related to predetermined macroeconomic variables. This finding suggests that fund managers do not adjust their cash holdings based on these predictors of market returns. Finally, I find that as a whole, equity funds hold 0.46% less cash in December than in other months. This finding is consistent with the cross-sectional results presented earlier in the paper, and again is likely attributable to dividend and capital gain distributions in December and window dressing by fund managers.

To examine the relation between aggregate cash holdings and aggregate fund flows, I obtain aggregate fund flows to equity funds from the Investment Company Institute. Unfortunately, this data is not available prior to 1984. Therefore, I run separate regressions of fund cash holdings for the period 1984-2001.

Panel B of Table VIII presents the results. As in Panel A, I find that aggregate cash holdings are highly persistent and negatively related to lagged market returns. More important, I find that aggregate fund cash holdings are significant and positively related to lagged fund flows. This result is consistent with dynamic models of optimal cash holdings.

C. Forecasting Market Returns using Aggregate Cash Holdings

Here, I examine whether aggregate cash holdings forecast future market returns. If equity mutual funds’ managers as a whole have market timing skills, then large aggregate cash holdings will tend to be followed by low market returns, and small aggregate cash holdings will tend to be followed by high market returns. I regress one-month-ahead market excess

Table VII. Summary Statistics for Aggregate Fund Cash Holdings and Predictive Variables, 1970-2001

This table presents the summary statistics for aggregate cash holdings and various predictive variables. The sample period is 1970-2001. All variables are monthly and are expressed in percentage terms. AGGCASH is aggregate cash holdings by equity funds. DEF is the default spread, which I calculate as the difference between Moody's Baa corporate bond yields and 10-year Treasury bond yields. DP is the dividend yield of the S&P 500 index. MKTRF is the value-weighted market return in excess of risk-free rate. TB3M is the three-month Treasury bill rate. TERM is the term spread, which I define as the difference between 10-year Treasury bond yields and three-month Treasury bill rates. I obtain AGGCASH from the Investment Company Institute, DP from Robert Shiller's website, and all interest rate data from the Federal Reserve Bank of St. Louis. ρ_1 is the first-order autocorrelation coefficient.

Panel A. Univariate Summary Statistics

	Mean	Med.	Max.	Min.	Std. Dev.	ρ_1
Aggregate Cash Holding (AGGCASH) - %	7.93	8.20	12.90	3.90	1.99	0.96
Default Spread (DEF) - %	2.00	1.92	3.82	0.93	0.55	0.93
Dividend Yield (DP) - %	3.40	3.35	6.24	1.09	1.24	0.99
Market Excess Return (MKTRF) - %	0.49	0.78	16.05	-23.09	4.67	0.05
Three-Month T-bill Rate (TB3M) - %	6.53	5.77	16.30	1.69	2.64	0.97
Term Spread (TERM) - %	1.55	1.64	4.42	-2.65	1.30	0.94

Panel B. Correlations

	AGGCASH	DEF	DP	MKTRF	TB3M	TERM
AGGCASH	1.00					
DEFAULT	0.02	1.00				
DP	0.60	-0.02	1.00			
MKTRF	-0.05	0.18	-0.02	1.00		
TB3M	0.50	-0.08	0.68	-0.12	1.00	
TERM	0.04	0.24	0.01	0.13	-0.48	1.00

returns on lagged aggregate cash holdings and several widely used predictive variables including dividend yield, default spreads, and term spreads.

$$R_{t+1} = \alpha + \beta \times AGGCASH_t + \gamma'\mathbf{z_t} + e_{t+1} \tag{16}$$

where R_{t+1} is the one-month-ahead CRSP valued-weighted index excess returns,[9] *AGGCASH* is the aggregate cash holdings by equity mutual funds, and $\mathbf{z}_t$ is the vector of predetermined predictive variables. To correct for serial correlation and conditional heteroskedasticity, I use Newey-West standard errors.

It is possible that changes in aggregate cash holdings might be more informative about future market returns than the level of aggregate cash holdings. To test for this possibility, I estimate the following model:

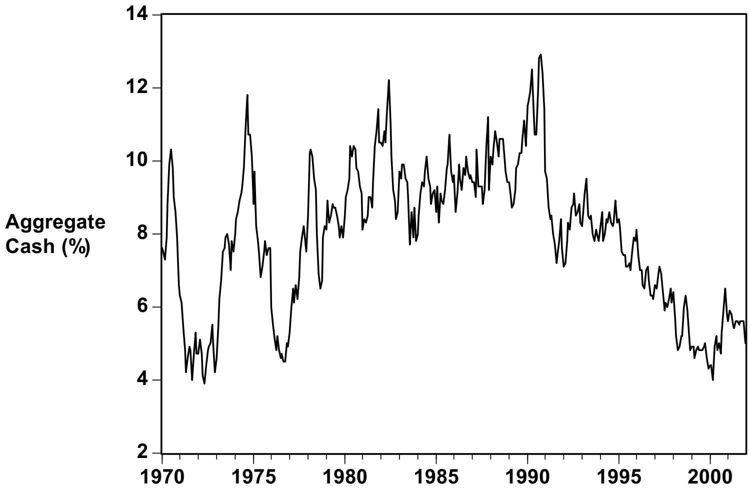
$$R_{t+1} = \alpha + \beta \times \Delta AGGCASH_t + \gamma'\mathbf{z_t} + e_{t+1} \tag{17}$$

In Table IX, Panel A presents the results for the regression Equation (16) and Panel B

[9]Using one-quarter-ahead market excess returns yields qualitatively similar results.

Figure 2. Aggregate Cash Holdings by US Equity Mutual Funds, 1970-2001

This figure plots the monthly percentage aggregate cash holdings by US equity mutual funds for the period from 1970 to 2001. The data are from the Investment Company Institute.



presents the results for the regression Equation (17). Overall, neither lagged cash holdings nor changes in lagged cash holdings reliably forecast future market excess returns. For the full sample period 1970-2001, I find that lagged aggregate cash holdings are positively related to future market excess return. This relation is statistically significant at the 5% level, and implies negative market timing ability by equity fund managers. However, subperiod results indicate that this relation is not robust. In fact, the coefficient changes sign in the second half of the period. None of the coefficients on the changes in aggregate cash holdings is statistically significant. Overall, these results suggest that as a whole, mutual fund managers do not have significant market timing skills. If anything, there is weak evidence of negative market timing skills for equity fund managers as a whole.

V. Conclusion

This article examines the determinants and implications of equity mutual fund cash holdings. I develop a static model of optimal cash holdings, in which a fund faces the trade-off between the opportunity cost of cash and transaction costs associated with selling stocks to meet redemptions. Among other things, the model predicts that funds with less-liquid stock holdings hold more cash, and funds with more-volatile fund flows hold more cash.

Empirical analysis of fund-level cash holdings shows evidence that is consistent with the model predictions. I find that small-cap funds, which tend to have higher transaction costs, hold more cash. I also find that funds with more-volatile fund flows hold more cash. In addition, funds that had large recent fund inflows hold more cash. This result is consistent with dynamic models of optimal cash holdings, in which funds adjust their cash holdings only infrequently.

Because the opportunity cost of holding cash is higher for managers with better stock-picking skills, I might expect that these managers hold less cash. However, the results from

Table VIII. Determinants of Aggregate Fund Cash Holdings

This table presents the results on the determinants of aggregate fund cash holdings. The sample period is 1970-2001 in Panel A and 1984-2001 in Panel B. All variables are monthly and are expressed in percentage terms. AGGCASH is aggregate cash holding by equity funds. DEF is the default spread, which I calculate as the difference between Moody's Baa corporate bond yields and 10-year Treasury bond yields. DP is the dividend yield of the S&P 500 index. MKTRF is the value-weighted market return in excess of the risk-free rate. TB3M is the three-month Treasury bill rate. TERM is the term spread, which I define as the difference between 10-year Treasury bond yields and three-month Treasury bill rates. YEAREND is dummy variable for the month of December. AGGCF is the aggregate fund flows to equity mutual funds and is expressed in percent. I obtain AGGCASH and AGGCF from the Investment Company Institute, DP from Robert Shiller's website, and all interest rate data from the Federal Reserve Bank of St. Louis. In each regression, the first row gives the OLS coefficient estimate. The second row gives the *p*-value, which is based on Newey-West standard errors.

Panel A. 1970-2001

Intercept	AGGCASH $_{t-1}$	MKTRF $_{t-1}$	DP $_{t-1}$	TB3M $_{t-1}$	DEF $_{t-1}$	TERM $_{t-1}$	YEAREND	R^2
0.240	0.977	-0.051					-0.432	0.946
(0.01)	(0.01)	(0.01)					(0.01)	
0.351	0.957	-0.049	0.023	0.016	-0.076	0.004	-0.418	0.947
(0.01)	(0.01)	(0.01)	(0.50)	(0.34)	(0.18)	(0.86)	(0.01)	

Panel B. 1984-2001

Intercept	AGGCASH $_{t-1}$	MKTRF $_{t-1}$	AGGCF $_{t-1}$	YEAREND	R^2
0.194	0.983	-0.052		-0.427	0.958
(0.05)	(0.01)	(0.01)		(0.01)	
0.116	0.985	-0.060	0.084	-0.399	0.960
(0.19)	(0.01)	(0.01)	(0.01)	(0.01)	

Table IX. Forecasting One-Month-Ahead Market Excess Returns Using Aggregate Cash Holdings and Changes in Aggregate Cash Holdings

This table presents the results for the predictive ability of aggregate cash holdings. The sample period is 1970-2001. All variables are monthly and are expressed in percentage terms. AGGCASH is aggregate cash holding by equity funds. DEF is the default spread, which I calculate as the difference between Moody's Baa corporate bond yields and 10-year Treasury bond yields. DP is the dividend yield of the S&P 500 index. MKTRF is the value-weighted market return in excess of risk-free rate. TB3M is the three-month Treasury bill rate. TERM is the term spread, which I define as the difference between 10-year Treasury bond yields and three-month Treasury bill rates. I obtain AGGCASH from the Investment Company Institute, DP from Robert Shiller's website, and all interest rate data from the Federal Reserve Bank of St. Louis. In each regression, the first row gives the OLS coefficient estimate. The second row gives the *p*-value, which is based on Newey-West standard errors.

Panel A. Forecasting One-month-ahead Market Excess Returns using Aggregate Cash Holdings

Period	$MKTRF_{t-1}$	$AGGCASH_{t-1}$	DP_{t-1}	$TB3M_{t-1}$	DEF_{t-1}	$TERM_{t-1}$	R^2
1970 - 2001	0.015	0.243	0.615	-0.441	1.050	-0.157	0.049
	(0.78)	(0.05)	(0.08)	(0.01)	(0.02)	(0.61)	
1970 - 1983	-0.059	0.063	2.004	-0.687	1.876	-0.399	0.140
	(0.42)	(0.86)	(0.01)	(0.01)	(0.01)	(0.34)	
1984 - 2001	-0.016	-0.494	3.156	-1.040	-0.262	-1.456	0.040
	(0.80)	(0.18)	(0.05)	(0.04)	(0.72)	(0.08)	

Panel B. Forecasting One-month-ahead Market Excess Returns using Changes in Aggregate Cash Holdings

Period	$MKTRF_{t-1}$	$\Delta AGGCASH_{t-1}$	DP_{t-1}	$TB3M_{t-1}$	DEF_{t-1}	$TERM_{t-1}$	R^2
1970 - 2001	0.005	-0.229	0.744	-0.369	1.076	-0.062	0.045
	(0.93)	(0.61)	(0.03)	(0.02)	(0.02)	(0.83)	
1970 - 1983	-0.053	-0.100	2.152	-0.691	1.949	-0.415	0.149
	(0.55)	(0.88)	(0.01)	(0.01)	(0.01)	(0.32)	
1984 - 2001	-0.013	-0.391	1.769	-0.783	-0.222	-0.994	0.032
	(0.86)	(0.46)	(0.05)	(0.05)	(0.76)	(0.13)	

both a portfolio approach and a cross-sectional regression approach do not provide support for this hypothesis. I find no systematic relation between fund cash holdings and risk-adjusted fund performance.

I also examine the determinants and predictive ability of aggregate cash holdings by equity mutual funds. Aggregate cash holding is persistent and positively related to recent fund flows, which is consistent with dynamic models of cash holdings. Aggregate cash is negatively related to past market returns. This result is consistent with funds engaging in positive-feedback trading at the market level. Aggregate cash holding is not significantly related to future market excess returns, suggesting that equity funds as a whole do not have market timing skills.■

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