Cashflow timing vs. discount-rate timing: A decomposition of mutual fund market-timing skills

Chunhua Lan[1] and Russ Wermers[2]

ABSTRACT

This paper decomposes the measurement of market timing skills into talents that exploit aggregate (1) cashflow news and (2) discount-rate news, the two components of market returns. This differentiation reveals that the average U.S. domestic equity mutual fund has economically and statistically significant timing skills of about 1.2% per year: cashflow timing contributes 2% per year in abnormal returns, while discount-rate timing generates -0.8% per year. Our timing metrics identify a subset of funds with superior timing abilities that persist. For example, funds in the best timing quintile (those having the highest sum of the two timing ability components) exhibit about 2.5% total market timing abnormal returns over the next year. Our findings suggest that the misspecification of market timing skills accounts for the failure of prior research to properly identify funds with timing abilities.

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[1] School of Banking and Finance, University of New South Wales, Sydney, Australia 2052; Tel: (612) 9385 5952; Fax: (612) 9385 6347; email: c.lan@unsw.edu.au. [2] Smith School of Business, University of Maryland at College Park, College Park, MD, USA 20742; Tel: (301) 405-0572; Fax: (301) 405-0359; email: wermers@umd.edu. We are grateful to Jonathan Berk, Stephen Brown, John Campbell, Roger Edelen, Allaudeen Hameed, Neal Stoughton, and seminar participants at 2016 Finance Down Under conference for their valuable comments.

1 Introduction

Market timing is one major dimension through which professional fund managers can add value for their investors. A skilled manager can strategically increase the market exposure of her fund portfolio before market upswings and decrease it before market declines. However, the prevailing literature suggests that the average mutual fund exhibits little or even negative market-timing ability.[1] A plausible reason for such a finding is that the typical approaches used to measure market-timing skills lack power, because the market return is treated as an undifferentiated object of market-timing efforts.

Indeed, stock market prices vary because of two main factors: changing expectations of future cash flows and/or changing expectations of future discount rates. A growing asset pricing literature recognizes the importance of separating cashflow risk and discount-rate risk in explaining cross-sectional and time-series return anomalies, and shows that cashflow risk plays an important role in driving aggregate stock price movements.[2] Active fund managers, as sophisticated investors, are likely to recognize cash flows and discount rates as different drivers of price variability, and exploit their cashflow and discount-rate information differently.[3] Yet, to our knowledge, there is no existing study that investigates cashflow versus discount-rate timing abilities of professional fund managers.

It is intuitive that fund managers exploit cashflow and discount-rate information differently, since corporate profits covary positively with macroeconomic activity.[4] In choosing their securities, skilled fund managers can be expected to use their insights about economic developments to form

[1]See, for example, Treynor and Mazuy (1966), Henriksson and Merton (1981), Ferson and Schadt (1996), Graham and Harvey (1996), Becker et. al (1999).

[2]For evidence on how cashflow risk explains anomalies, see Campbell and Vuolteenaho (2004), Lettau and Wachter (2007), Hansen, Heaton, and Li (2008), and Da and Warachka (2009). For evidence on how cashflow risk drives aggregate stock prices, see Bansal and Yaron (2004), Ang and Bekaert (2007), Larrain and Yogo (2008), Binsbergen and Koijen (2010), Koijen and van Nieuwerburgh (2011), and Chen, Da, and Priestley (2012).

[3]Relatedly, classic security analysis involves separately estimating future expected cash flows and their market-determined discount rates, as if different forces determine each. See, for example, Graham and Dodd (1934).

[4]Lucas (1977) lists the cyclicality of profits as one of the seven main features of macroeconomic fluctuations. Blanchard and Perotti (2002) show that corporate profits comprise an important portion of GDP, roughly 10%.

their views of market-level cashflows.[5] Alternatively, they can purchase cashflow forecasts from third parties, such as sell-side analysts. In contrast, discount-rate predictability is much harder to exploit. Despite of a great amount of evidence for return predictability, some parallel studies cast doubt on its statistical inference and point out issues, such as biased regression coefficients, in-sample instability of estimates, and poor out-of-sample forecasts.[6]

In this paper, we analyze timing skills of U.S. domestic equity mutual fund managers, using a set of enhanced models that separately measure cashflow timing and discount-rate timing. By distinguishing cashflow and discount-rate components of the market return, we find that many equity mutual fund managers possess significant market-timing skills due to their superior ability in shifting their portfolio exposures to aggregate cash flows (but not to discount-rates). Specifically, a U.S.-domiciled equity mutual fund, on average, generates significant market-timing abnormal returns of 1.2% per year, in which 2% comes from timing market cashflow news and -0.8% from timing market discount-rate news. This finding suggests that many mutual fund managers are able to forecast and use aggregate cashflow information profitably in choosing their stocks, but are not able to profit from their forecasts of changing discount rates.

A cross-sectional examination of the equity funds reveals striking and contrasting patterns for cashflow timing versus discount-rate timing. We find positive and significant cashflow timing gains for most of funds, and no evidence of significantly negative cashflow timing. In contrast, we find evidence of negative and significant discount-rate timing, but no evidence of significantly positive discount-rate timing. Because cashflow timing gains are, on average, larger in magnitude than discount-rate timing losses, the cross-sectional patterns for overall timing performance are similar to those for cashflow timing. Moreover, we find that cashflow timing ability is persistent, but there is no evidence of persistence in either positive or negative discount-rate timing performance. These results suggest that some fund managers possess cashflow timing talents, and manage to avoid eliminating this cashflow-based performance with their (potentially negative) discount-rate timing.

Key to our approach is that, through separating cashflow timing and discount-rate timing, we

[5] As an illustration, the well-known division of stocks into "defensive" vs. "procyclical" is an attempt to classify stocks by their exposure to changes in macroeconomic conditions, including market-level cashflows.

[6] See, for example, Nelson and Kim (1993), Stambaugh (1999), Valkanov (2003), Goyal and Welch (2003, 2008).

add power to the identification of fund managers with timing skills. If, instead, we measure timing as the ability to forecast (unexpected) market returns (the sum of cashflow and discount-rate market return components) as one-piece, as conducted in the prior literature, we find no timing ability for the average fund, but significantly negative timing performance for some funds, consistent with prior research.

To identify funds with superior timing talents, we propose a timing metric—past-year total timing performance, defined as the sum of past-year performances for both cashflow timing and discount-rate timing.[7] We choose this metric because when managers strategically shift the exposure of their funds to aggregate cashflows, the exposure of their funds to market discount rates is often simultaneously altered. Therefore, a manager with superior timing skills, when making her timing decisions, should take into account the likelihood of timing losses due to the resultant shifting exposure to discount rates.

Using this total timing metric, we are able to identify funds with superior market-timing skills, and the superiority stems from cashflow timing prowess. Specifically, funds in the quintile with the best past-year total timing performance exhibit significant cashflow timing abnormal returns of roughly 3.5% over the next year. Although discount-rate timing reduces their timing profits, the total timing gain for this group of funds, on average, is about 2.5% over the next year. Both are economically and statistically significant. Moreover, funds in the best quintile, consistent with their superior cashflow timing gains, considerably shift their cashflow betas in response to future market cashflow movements, but funds in the worst quintile do not. Even so, the time-series average of cashflow betas is very close to 1 across different quintiles. Therefore, it is time-variation in cashflow betas, not higher unconditional levels of these betas, that generate superior timing performance for top market-timers.

Since we find aggregate-cashflow-timing skills for a subset of funds, we conjecture that shifts in the cashflow betas of the top market timers would be informative about future aggregate cash flows and macro activities. To test this conjecture, we construct a time series of aggregate differential

[7] Note that we separately measure the cashflow and discount-rate timing, then sum them. This is very different from past research, which attempts to measure total timing without separate estimations of the cashflow and discount-rate return components.

cashflow beta as the average of differential cashflow betas (a fund's cashflow beta in excess of its target beta that is calculated as the average of its past cashflow betas) across all funds in the top decile sorted each period on past-year total timing performance (measured as the sum of cashflow and discount-rate timing). This aggregate variable positively and significantly predicts future marketwide cashflow news as well as macro variables, such as GDP growth, over the next few quarters. This result confirms that top timers possess superior skills in forecasting future market-level cash flows.

Furthermore, we find that superior market timing skills are possessed by a correlated, but somewhat different set of managers, relative to the set that possesses top stock-selection skills. The spread of fund portfolio returns between the best and worst timing quintiles is 2.9% and 3% over the next year, based on fund net returns and fund holding-based returns, respectively. Although stock-selection abilities (measured by fund portfolio DGTW-adjusted returns) are higher for top market-timers, the difference between the best and worst timing quintiles is about 1% over the next year, far less than the differences in fund portfolio returns and timing profits mentioned above. These findings indicate that skilled managers, in picking stocks, consider both forecasts of marketwide cashflows (and the corresponding exposure of a stock) and cashflow forecasts for individual securities or industries that are orthogonal to these marketwide forecasts. However, since the above-noted 1% per year is less than the difference between the groups with the best and worst stock-picking skills that have been documented in the literature, our results suggest that one should separately look for the best managers in each dimension (market timing vs. stock selection) in order to form the best overall portfolio of managers.

Finally, we propose an explanation for negative discount-rate timing that is based on the impact of fund flows from investors. Aggregate fund net flows can be correlated with the market return and its cashflow and discount-rate return components because of the information content of flows (Warther, 1995) or because aggregate flows reflect investor sentiment (Ben-Rephael et. al, 2012). The latter interpretation has a testable implication: as investor sentiment or price pressure fades away, a reversal will occur in marketwide equity returns.[8] We find that aggregate net flows contain

[8]Consistent with these two prior studies, we find that aggregate net flows are positively contemporaneously correlated with the unexpected market return that does not exhibit pronounced reversion later. Ben-Rephael et. al

macro-level cashflow information, as they are positively correlated with both concurrent and next-quarter cashflow return components; aggregate net flows also reflect investor sentiment and exert price pressure, as the discount-rate return component reverts significantly in the next quarter. It is intuitive that discount-rate expectations are easily subject to price pressure, while cashflow expectations are not, because frequently announced macroeconomic data provide an objective gauge to adjust cashflow expectations quickly but there is no similar gauge for discount-rate expectations.

We find supporting evidence that negative discount-rate timing takes place when discount-rate reversals occur. If the average mutual fund manager must respond to the flows of retail investors, and cannot easily change discount-rate exposure to exploit the negative timing of flows (perhaps because this would lead to further outflows as investors see a fund increasing its exposure to the aggregate market), then flows will drive discount-rate exposure of funds.[9] We find that the differential discount-rate beta for the average mutual fund significantly decreases with aggregate net flows. This significant decrease, coupled with pronounced next-quarter discount-rate reversal (an increase) generates negative discount-rate timing, as a second-order polynomial of aggregate net flows significantly and negatively affect discount-rate timing performance. Moreover, including the second-order polynomial in the regression of discount-rate timing increases the intercept from significantly negative to insignificantly positive. In contrast, aggregate net flow or its second order has no relation with cashflow beta shifting and cashflow timing performance for the average mutual fund.

This paper makes a few contributions to the literature. First, it offers a novel approach in measuring market-timing skills through separating market cashflow and discount-rate timing com-

(2012) find a subset of aggregate net flows—shifts between bond funds and equity funds—that capture significant market-return reversal in the following months. One possible reason is that discount-rate expectations are subject to price pressure but cashflow expectations are not, so mixing the two components together clouds detection of sentiment-driven market-return reversals.

[9]Note that, in the main tests, we measure timing ability using the changing cashflow and discount-rate exposure of stocks only in a portfolio, and do not consider the changing cash holdings of a fund in order to focus on the fundamentals that drive timing-oriented stock selection by a manager. As a robustness check, we find time-variation in cash holdings has a very small impact on timing performance, as cash holdings can be driven by many other factors, such as a decrease in market liquidity or a perceived increase in investor flow volatility.

ponents. As a result, we provide evidence of positive timing ability for the average mutual fund, in contrast to past studies, which find either little or negative timing abilities.[10]

Second, using our total timing measure as a metric, we are able to identify, ex-ante, a subset of funds that earn impressive abnormal returns from the implementation of timing strategies. This metric complements those in the mutual fund literature that are used to identify a subset of funds with stock-selection abilities, such as industry concentration and return gap (Kacperczyk, Sialm, and Zheng, 2005, 2008), active share (Cremers and Petajisto, 2009), R-squared from benchmark regressions (Amihud and Goyenko, 2013), peer tracking records (Cohen, Coval, and Pástor, 2005), or network connections (Cohen, Frazzini, and Malloy, 2008). More importantly, the difference in abnormal returns between the best and the worst timing groups is comparable to that between the best and the worst stock-picking groups. Our evidence suggests that market timing is a profitable investment strategy as important as stock selection in adding values to managed assets.

Finally, unlike adopting stock-selection techniques that require exploiting firm-specific information with an exposure to high idiosyncratic risk, implementing market-timing strategies involves exploiting systematic factors with a time-varying exposure to systematic risk. Because systematic risk is an important component of investors' marginal utility, identifying and studying a subset of investors with timing skills on systematic factors enables us to better understand the heterogeneity of professional investors and lays an empirical foundation for building richer theoretical models.

Our paper proceeds as follows. Sections 2 and 3 discuss our empirical methodologies and the data sets that we use, respectively. Section 4 presents our main empirical findings on cashflow timing and discount-rate timing. Section 5 examines the detection of a subset of funds with good timing abilities. Section 6 investigates an explanation of negative discount-rate timing. Section 7 summarizes additional tests and robustness checks. We conclude in the last section.

[10]Exceptions are Bollen and Busse (2001), Elton, Gruber, and Blake (2012), Jiang, Yao, and Yu (2007),and Kacperczyk, Nieuwerburgh, and Veldkamp (2014, 2016).

2 Methodology

Prior studies investigating marking-timing skills, starting with Treynor and Mazuy (1966) and Henriksson and Merton (1981), conventionally examine whether a fund manager holds a greater proportion of the market portfolio when the market return is high and a smaller proportion when the market return is low. Put differently, their research interest is whether a fund portfolio's CAPM beta at the beginning of a holding period positively covaries with the holding period market return. These studies implicitly assume the market return as an one-piece object of market-timing efforts. The prevailing view in this literature is that there is little or even negative market-timing ability.

In fact, stock market prices vary due to changing forecasts of future aggregate cash flows or changing forecasts of future market discount rates. As Campbell and Vuolteenaho (2004) stress, it is important to recognize the difference of these two components as risk factors because a rational multiperiod investor demands a greater reward for bearing cashflow risk than discount-rate risk. Such a difference in reward is intuitive because a poor current return, if driven by increases in future discount rates, is partially compensated by improved prospects of future returns, while, if driven by decreases in future cash flows, future investment opportunities stay virtually unchanged. Based on this intuition, Campbell and Vuolteenaho (2004) employ an economically motivated two-beta model, which specifies nondiversifiable risk in terms of both cashflow betas and discount-rate betas, and successfully explain the size and value anomalies. Along with this work, a growing literature recognizes the importance of aggregate cashflow risk to explain both cross-sectional and time-series patterns of asset returns as well as some documented return anomalies.[11]

Supporting evidence of separating cashflow and discount-rate risk in the recent literature suggests that superior information about future market returns essentially stems from a deep insight and good anticipation of two types of market movements—aggregate cashflow variations and discount-rate variations. Therefore, separating timing efforts from cashflow and discount-rate perspectives is likely to give us a better understanding of fund managers' marking-timing skills.

Indeed, it is natural for fund managers to gather and exploit cashflow information and discount-

[11] See Bansal and Yaron (2004), Campbell and Vuolteenaho (2004), Da and Warachka (2009), Hansen, Heaton, and Li (2008), Lettau and Wachter (2007), among others.

rate information differently. Aggregate cashflow news is closely related to prospects of future economic growth, aggregate investment efficacy, as well as productivity outlook. As sophisticated investors, fund managers, if skillful, can obtain superior anticipation about future aggregate cash flows by analyzing comprehensive economic and financial data, and developing an insight regarding future economic trends. On the other hand, despite of evidence in favor of return forecastability, a recent literature questions the strength of statistical inference by pointing out issues such as biased coefficient estimates and instable in-sample estimates. Discount rates are also largely affected by changes in investor sentiment, which are hardly forecastable (Baker and Wurgler, 2007). Finally, compared with market discount-rate news, market cashflow news, though less volatile, is associated with a higher reward (Campbell and Vuolteenaho, 2004). Hence, exploiting the latter type of information is likely to generate similar abnormal returns with less volatility or tracking error, an important criterion in evaluating fund performance.

When implementing market-timing strategies, a fund manager typically varies the sensitivity of her managed portfolio to common factors, such as market returns, market cashflow (CF) news, or market discount-rate (DR) news. In doing so, she can switch among securities of the same type but with different sensitivities to the factors, or change allocations to different classes of securities, such as bonds or options. Because we do not have holdings data of other classes of securitie except for common stocks, this paper concentrates on market-timing skills employed in equity portfolios. We also account for cash holdings as additional tests in Section 7.

2.1 Cashflow and discount-rate components of stock market returns

We adopt two approaches in constructing the cashflow and discount-rate components of stock market returns, one based on the Gordon (1962) model and the other based on the Campbell and Shiller (1988) present-value model. The former approach relies on some strong assumptions, nevertheless, it produces simple and intuitive decomposition of stock market returns. The latter model is derived from a dynamic accounting identity with a weak assumption of no price exploration imposed.

Let P_t and e_t be stock market prices and corporate earnings at time t, respectively, and let μ_t and g_t represent the time-t expected return and expected earnings growth in perpetuity, respectively.

The Gordon (1962) model states that

$$P_t = \frac{e_t}{\mu_t - g_t}. \tag{1}$$

This model assumes that g_t is less than μ_t, and that earnings are not reinvested to generate future cash flows. Taking a first-order Taylor expansion of the above equation leads to

$$\frac{\Delta P_t}{P_t} = \frac{-P_t}{e_t}(\Delta\mu_t - \Delta g_t) = \frac{P_t}{e_t}\Delta g_t - \frac{P_t}{e_t}\Delta\mu_t, \tag{2}$$

where $\Delta\mu_t$ and Δg_t are time-t changing expectations of future discount rates and earnings growth in perpetuity, respectively, and $\frac{P_t}{e_t}$ is the time-t aggregate PE ratio. This equation motivates us to separate the stock market return $\frac{\Delta P_t}{P_t}$ into two parts:[12] a cashflow component (or news) $\frac{P_t}{e_t}\Delta g_t$ and a discount-rate component (or news) $\frac{P_t}{e_t}\Delta\mu_t$.

Formalizing the intuition that stock prices fluctuate due to expected cashflow changes, discount-rate changes, or both, Campbell and Shiller (1988) decompose stock returns into a cashflow component ($N_{CF,t+1}$) and a discount-rate component($N_{DR,t+1}$):

$$r_{t+1} - \mathrm{E}_t r_{t+1} = (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{k=0}^{\infty}\rho^k \Delta d_{t+1+k} - (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{k=1}^{\infty}\rho^k r_{t+1+k} = N_{CF,t+1} - N_{DR,t+1} \tag{3}$$

where r_t is a log stock return at time t, Δd_t denotes time-t dividend growth, E_t represents a rational expectation at time t, and ρ is a log-linearization constant. Note that the cashflow and discount-rate return components are changing expectations of future cash flows and discount rates, respectively, over an infinite horizon. Because our main results stay similar using the both proxies of the cashflow and discount-rate return components based on the above two models, for simplicity, we only report the results based on the Campbell and Shiller model in the main body of our paper. The results based on the Gordon model are reported in a separate appendix.

2.2 Measures of market-timing ability

One way of utilizing market-timing technique is to change the sensitivity (beta) of a fund portfolio to systematic factors that affect asset returns. Normally, fund betas can be estimated

[12] We do not distinguish capital gain returns and total returns (including dividends) of the stock market in this approach because their correlation is more than 0.999 in our sample. Although these two return variables have slightly different means, they virtually have the same volatility that is a key element in our study.

by running a time series regression of the excess return on a fund against the excess returns of systematic factors over time. However, if managers engage in market timing, fund betas will vary over time. Without knowing exact timing manner, it is hard to obtain appropriate estimates of fund betas in this way. With holdings data, we can adopt a bottom-up approach to estimate a fund beta at a point in time as the value-weighted average of stock beta for all stocks held in the portfolio, weighted by the percentage of stock values in a fund portfolio at that time. We employ two models to capture systematic risk: a two-factor model with market cashflow and discount-rate news as factors, and a one-factor model based on either unexpected market returns or market excess returns.

Let $r_{i,t}$ be the excess return of stock i at time t, and let $K_{j,t}$ be the return on factor j at time t. To avoid look-ahead bias, we run the following regressions over the past 60-month rolling window, with at least 24-month observations available:

$$r_{i,t} = \alpha_{i,t} + \sum_{j=1}^{J} \beta_{i,j,t} K_{j,t} + \epsilon_{i,t}, \tag{4}$$

where $\beta_{i,j,t}$ is the sensitivity of stock i to factor j at time t, $\alpha_{i,t}$ and $\epsilon_{i,t}$ are the risk-adjusted excess returns and return residuals, respectively, of stock i at time t. If the two-factor model is used in the above regression, cashflow and discount-rate betas for each stock are obtained; If the one-factor model is used, the CAPM beta is obtained.

Fund betas are then calculated as value-weighted average of stock betas for all stocks held in a fund portfolio:

$$\beta_{f,j,t} = \sum_{i=1}^{N_{f,t}} \omega_{i,f,t} * \beta_{i,j,t}, \tag{5}$$

where $\beta_{f,j,t}$ is the time-t sensitivity of fund f to factor j, $\omega_{i,f,t}$ is the time-t portfolio weight of stock i in fund j, and $N_{f,t}$ is the number of stocks held in fund f at time t.

Because the sum of market cashflow news and (minus) discount-rate news is the market return according to the Gordon model (2) or the unexpected market return according to the Campbell-Shiller model (3), it is natural to select the market excess return as one factor for the former model and the unexpected market return for the latter when we compare timing performance between distinguishing cashflow and discount-rate components and treating the (unexpected) market return as one piece. The difference in these two choices of one factor is that the market excess return contains the expected return that can be produced based on public information. Because the expected return accounts for a tiny portion of return volatility, timing performance based on these two choices of one factor is quite similar, as we find in our empirical analysis.

Note that time variations in fund betas can stem from either active fund trading activities or passive portfolio-weight changes due to nonproportional price changes in stocks held in a fund portfolio. To avoid this passive time-variability, which is irrelevant to evaluating timing skills, we keep fund portfolio weights unchanged within a quarter. That is, fund betas are valid at the same frequency as fund holdings data.

2.2.1 Differential return timing measure

Our first timing measure is a differential return measure, analogous and comparable to those used in evaluating stock-selection skills. Similar to Elton, Gruber, and Blake (2012), we define market-timing contribution $tim_{f,j,t}$ for fund f in response to factor j in period t as

$$tim_{f,j,t} = (\beta_{f,j,t-1} - \bar{\beta}_{f,j,t-1})K_{j,t} \tag{6}$$

where $K_{j,t}$ is the period-t return of factor j, $\beta_{f,j,t-1}$ is fund f's beta with respect to factor j at the beginning of period t, estimated according to (5), and $\bar{\beta}_{f,j,t-1}$ is fund f's target beta that is calculated as the average of either the fund's past betas or the fund's betas over the full sample periods. Using either definition of fund target beta delivers quite similar timing results. More importantly, the timing measure based on the former definition can be adopted in real time, so we only report analysis based on this definition. We term $\beta_{f,j,t-1} - \bar{\beta}_{f,j,t-1}$ "differential beta" of fund f in response to factor j.

The timing measure of fund f with respect to factor j is calculated as the sample average of market timing contribution, $tim_{f,j,t}$:

$$tim_{f,j} = \frac{1}{T}\sum_{t=1}^{T} tim_{f,j,t}, \tag{7}$$

where T is the number of periods with valid observations for fund f. This measure simply reflects how well a timing strategy performs on average by varying the sensitivity of a fund portfolio to a given factor compared with simply keeping the sensitivity at its target level. To avoid capturing a spurious effect, we demean factor returns, $K_{j,t}$, using the sample average. Hence, either of two naive cases—a constant beta with random factor returns or random betas with a constant factor return—delivers zero timing measure over the sample period.

2.2.2 TM and HM timing measures

We also examine timing ability in the sprit of the conventional timing measures proposed by Treynor and Mazuy (1966) and Henriksson and Merton (1981). Let $r_{f,t}$ and $r_{m,t}$ denote the time-t excess fund and market returns, respectively. The Treynor-Mazuy (TM) timing measure is the estimated coefficient γ in the regression of

$$r_{f,t} = \alpha + \beta r_{m,t} + \gamma r_{m,t}^2 + e_{f,t} = \alpha + (\beta + \gamma r_{m,t}) r_{m,t} + e_{f,t}, \tag{8}$$

and the Henriksson-Merton (HM) timing measure is the estimated coefficient γ in the regression of

$$r_{f,t} = \alpha + \beta r_{m,t} + \gamma \mathrm{max}(\mathrm{r_{m,t}}, 0) + e_{f,t} = \alpha + (\beta + \gamma I_{r_{m,t}>0}) r_{m,t} + e_{f,t} \tag{9}$$

where $\mathrm{max}(\mathrm{r_{m,t}}, 0)$ equals $r_{m,t}$ if $r_{m,t} > 0$, and zero otherwise, and $I_{r_{m,t}>0}$ is a dummy variable that equals one if $r_{m,t} > 0$, and zero otherwise. As shown by Admati et al. (1986), the TM model is consistent with a manager whose target beta varies linearly with her forecast for the expected market return. The HM model is consistent with a manager who chooses one of two amounts of leverage for her portfolio depending on whether she forecasts that the market return will exceed the risk-free rate or not.

Most prior studies run nonlinear regressions of realized fund returns on contemporaneous market returns to get TM and HM market timing measures, as specified in the first equations of (8) and (9). However, the nonlinear relation between fund returns and market returns can also be induced by factors other than active market timing, such as interim trading and passive timing induced by stocks with option-like feature (Jagannathan and Korajczyk, 1986), therefore leading to biased conclusions. Jiang, Yao, and Yu (2007) provide evidence that such biases can be avoided by running regressions of holding-based fund betas that are constructed based only on *ex ante* information of portfolio holdings.

Motivated by the second equations in (8) and (9), both TM and HM timing measures can be described as comovements between the market excess return $r_{m,t}$ and fund f's holdings-based beta at the beginning of period t, $\beta_{f,m,t-1}$. Equivalently, the TM and HM timing measures, γ, can be estimated by running the following regressions (Jiang, Yao, and Yu, 2007):

$$\beta_{f,m,t-1} = \beta + \gamma r_{m,t} + \eta_{f,t} \quad \text{for the Treynor-Mazuy approach,} \tag{10}$$

$$\beta_{f,m,t-1} = \beta + \gamma I_{r_{m,t}>0} + \eta_{f,t} \quad \text{for the Henriksson-Merton approach.} \tag{11}$$

In the spirit of (10) and (11), we extend TM and HM timing measures with respect to a given factor j, such as the cashflow or discount-rate component of the market return, as the slope coefficient γ estimated in the following regressions

$$\beta_{f,j,t-1} = \beta_0 + \gamma K_{j,t} + \eta_{f,t} \quad \text{for the Treynor-Mazuy approach} \tag{12}$$

$$\beta_{f,j,t-1} = \beta_0 + \gamma I_{K_{j,t}>0} + \eta_{f,t} \quad \text{for the Henriksson-Merton approach} \tag{13}$$

where $I_{K_{j,t}>0}$ is a dummy variable that equals one if $K_{j,t} > 0$, and zero otherwise.

Note that TM and HM timing measures assume that managers implement timing technique in a specific way and may not detect a complex timing manner, whereas the differential return timing measure is not subject to this issue. Moreover, the latter measure is expressed in terms of (differential) returns, and therefore facilitates evaluation of economic significance as well as comparison of value added to managed assets by utilizing timing strategy versus stock-selection technique, the latter technique being studied in a growing literature. Because these timing measures deliver the same conclusions, to save space, we only report results based on the differential return timing measure in the paper. Results based on other measures are presented in a separate appendix.

3 Data and variables construction

Our data of U.S. actively managed equity mutual funds come from the intersection of Thomson Reuters mutual fund holdings database and the Center for Research in Security Prices (CRSP) mutual fund database. Those two databases are linked using MFLINKS from Wharton Research Data Services (WRDS). Thomson Reuters provides information on equity mutual fund holdings of common stocks in a quarterly or semiannual frequency. CRSP provides information on mutual fund net returns, total net assets (TNA), and several fund characteristics such as expense ratio and turnover ratio. The information provided by CRSP is at the share class level. We therefore calculate value-weighted fund net returns and fund characteristics across multiple share classes within a fund using the latest TNA as weights, except that fund age is calculated based on the oldest share class and TNA as the sum of net assets across all share classes belonging to the same fund.

We follow a similar procedure as Kacperczyk, Sialm, and Zheng (2008) adopt to select our sample. In particular, we exclude funds that do not invest primarily in equity securities, funds that hold fewer than 10 stocks, or those that, in the previous month, manage assets of less than US$5 million. To address the incubation bias (Evans, 2010), we further exclude the observations where the year for the observations is prior to the reported fund-starting year, or where the names of the funds are missing in the CRSP database. Finally, we exclude index funds using both fund names and the sample of index funds identified by Cremers and Petajisto (2009) and available at www.sfsrfs.org/addenda_viewpaper.php?id=379.

Stock returns, prices, and shares outstanding come from CRSP. Accounting data, such as book values of equity, are obtained from COMPUSTAT. Analyst earnings forecasts come from the Institutional Broker's Estimate System (IBES) summary unadjusted file. The final sample includes 2942 equity funds over a sample period of January of 1982 to December of 2010. This end date is due to the data availability in the version of MFLINK used in this paper. All the other data cover the sample period of January of 1982 to December of 2012.

3.1 Construction of market return components and fund betas

Monthly analyst earnings forecasts allow us to measure cashflow news at the monthly frequency. Let $A1_t$ ($A2_t$) be market-level earnings forecasts for the current (next) fiscal year as the sum of corresponding firm-level earnings forecasts across all firms, where t denotes when a forecast is employed. Let LTG_t be market-level long-term growth forecasts as the value-weighted average of firm-level forecasts across all firms using firms' latest market capitalization as weights. LTG_t represents an annualized percentage growth rate and pertains to the next three to five years. These forecasts are available on consensus forecast issuance date, typically the third Thursday each month. We call the span between two consecutive consensus forecast issuance dates an IBES month. Accordingly, we calculate an IBES-monthly (excess) return as cumulative daily returns (in excess of daily interest rates that are available from French's web site) within an IBES month.

In the return decomposition (2) based on the Gordon (1962) model, we use IBES-monthly changes of LTG_t as a proxy of Δg_t, then multiplied by PE ratio $\frac{P_t}{e_t}$ to obtain the cashflow component $\frac{P_t}{e_t}\Delta g_t$, where $\frac{P_t}{e_t}$ is the ratio of the market cap at the end of IBES month t divided by past-year aggregate earnings. The discount-rate component is then backed out as $\frac{P_t}{e_t}\Delta g_t - \frac{\Delta P_t}{P_t}$, where $\frac{\Delta P_t}{P_t}$ is IBES-monthly stock market returns.

To construct the aggregate cashflow component $N_{CF,t+1}$ in (3) based on the Campbell and Shiller (1988) decomposition, we follow Da and Warachka (2009), Balduzzi and Lan (2014), and Da, Liu, and Schaumburg (2014), and apply analyst earnings forecasts in a three-stage earnings growth model by taking advantage of multiple earnings forecasts for different maturities. Let $X_{t,j}$ denote the time-t expectations of future earnings in the next j^{th} year, where the first subscript is in months, and the second one is in years because we use only annual forecasts to avoid the seasonality issue.

In the first stage of the earnings growth model, expected earnings are computed directly using analyst forecasts:

$$X_{t,1} = A1_t, \quad X_{t,2} = A2_t, \tag{14}$$

$$X_{t,j} = X_{t,j-1}(1 + LTG_t), \quad j = 3, 4, 5. \tag{15}$$

In the second stage, expected earnings are assumed from year six to year 10 to converge to a steady-state growth rate $\bar{g}_t$ that is the cross-sectional average of firm-level long-term growth forecasts:

$$X_{t,j+1} = X_{t,j}[1 + LTG_t + \frac{j-4}{5}(\bar{g}_t - LTG_t)], \text{ for } j = 5, \ldots, 9. \tag{16}$$

Under the assumption that cashflow payout is equal to a fixed portion (Ψ) of the ending-period book value, the clean surplus accounting identity implies that the evolution of expected book value is $B_{t,j+1} = (B_{t,j} + X_{t,j+1})(1 - \Psi)$. The parameter Ψ is set to 5% since this percentage is close to the average payout rate for the firms in our sample. In the third stage, expected earnings growth stays at $\bar{g}_t$, which implies expected accounting returns to be $\frac{\bar{g}_t}{1-\Psi}$ beyond year 10. The expected log return on book equity $\theta_{t,j}$ is estimated at time t as:

$$\theta_{t,1+j} = \left\{ \begin{array}{ll} \log(1+\frac{X_{t,1+j}}{B_{t,j}}) & \text{for } 0 \leq j \leq 9 \\ \log(1+\frac{\bar{g}_t}{1-\Psi}) & \text{for } j \geq 10 \end{array} \right. \tag{17}$$

The three-stage growth model implies expected future cash flows:

$$E_t \sum_{j=0}^{\infty} \rho^j \theta_{t,1+j} = \sum_{j=0}^{9} \rho^j \theta_{t,1+j} + \frac{\rho^{10}}{1-\rho} \log(1+\frac{\bar{g}_t}{1-\Psi}), \tag{18}$$

where ρ is a log-linearization constant (Campbell and Shiller, 1988) and equals 0.96 in our sample. As Vuolteenaho (2002) shows, cashflow news at time $t+1$, $N_{CF,t+1}$, can be represented as the difference between cash flow expectations over two consecutive months, with replacement of log dividend growth in (3) by log returns on book equity:

$$N_{CF,t+1} = E_{t+1} \sum_{j=0}^{\infty} \rho^j \theta_{t,1+j} - E_t \sum_{j=0}^{\infty} \rho^j \theta_{t,1+j}. \tag{19}$$

To obtain a proxy of the discount-rate market return component, we first follow Campbell and Vuolteenaho (2004) and forecast the market return in IBES month $t+1$ using four instruments—the market excess return in IBES months, the yield spread between long-term and short-term bonds, the market's smoothed price-earnings ratio, and the small-stock value spread, where these instruments are available at the end of IBES month t. We then back out the market discount-rate news in IBES month $t+1$, $N_{DR,t+1}$, as suggested in equation (3), as the cashflow news minus unexpected market returns, $N_{CF,t+1} - (r_{t+1} - \mathrm{E_t r_{t+1}})$. The Appendix provides full details for our data items.

Because cashflow and discount-rate market return components are available in IBES months, we accordingly calculate cashflow and discount-rate betas as well as CAPM betas using IBES monthly data for every stock that belongs to our sample of mutual funds, as described in (4). Since fund holdings are available at the quarterly frequency, we assume that these holdings are valid at the end of IBES quarters (the third Thursday of the last month of each calendar quarter). Fund betas are then calculated as the average of stock betas weighted by fund portfolio weights at the end of IBES quarters, as specified in (5). Although we employ fund betas at the IBES-quarterly frequency in this study, stock betas are estimated based on IBES-monthly data to improve estimation precision.

As a robustness check, we also calculate stock betas using data in calendar months and accordingly obtain fund betas in calendar quarters, and our conclusions remain the same. Through the rest of the paper, quarters are referred to IBES quarters without explicitly stating "IBES" for simplicity, unless confusion emerges

4 Empirical analysis of timing performance

In this section, we provide evidence of cashflow and discount-rate timing abilities as well as their persistency. To show the importance of distinguishing cashflow and discount-rate return components in evaluating market-timing skills, we compare the timing performance with such distinction versus the timing performance of treating the (unexpected) market return as one piece. We also examine how the performances of these timing strategies vary with the business cycle.

4.1 Cashflow timing and discount-rate timing

Table 1 presents timing performance in terms of the differential return timing measure specified in (7). It focuses on the cross-sectional statistics of mean, median, and the 5th, 10th, 25th, 75th, 90th, and 95th percentiles of this measure. These cross-sectional statistics shed light on timing ability of not only an average fund but also funds at extreme percentiles.

To test statistical significance of these cross-sectional statistics, we follow a bootstrap approach that is developed by Kosowski, etc. (2006) and employed by Jiang, Yao, and Yu (2007) and Elton, Gruber, and Blake (2012). This approach accounts for the likelihood of correlated fund betas and correlated fund timing performance across funds as well as the finite sample property of the test statistics. In the bootstrap procedure, for each actual quarter, we choose all systematic factors (the cashflow and discount-rate market return components and the unexpected market return) in a randomly selected quarter, and multiply these quarterly factor returns by the actual differential betas (fund betas in excess of their targets) calculated at the beginning of the actual quarter for each fund. The time series average of these multiplications produces a bootstrap timing measure for each fund. Because of the random assignment of factors each quarter, bootstrap timing measures are expected to be zero. The bootstrap not only maintains the covariance structure across fund betas and the contemporaneous correlation among systematic factors, but also captures the complex shape of the entire cross-sectional distribution of timing statistics under the null hypothesis of no timing ability. Statistical inference is then based on the probability that actual timing statistics at any point of the cross-sectional distribution could have arisen by chance. See the Appendix for details.

We also report t-statistics of the timing measure at these different percentiles for robustness. As discussed by Kosowski, etc. (2006), a fund that has a short life or engages in high risk-taking generally exhibits high variance of its abnormal return distribution, so its abnormal return measure is likely to be a spurious outlier in the cross section. The t-statistic provides a correction for such a spurious outlier by normalizing the timing measure by the corresponding standard deviation of timing abnormal returns. The t-statistic, as a pivotal statistic, also has better sampling properties and is hence more robust than the timing measure of abnormal returns.

Clearly, most funds exhibit cashflow timing prowess, as illustrated in Panel A of Table 1. The average fund adds value of 53 basis points per quarter, or about 2% per year, for timing aggregate cash flows. This gain is not only economically significant but also extremely unlikely to be produced solely through luck. According to bootstrap p-values for both the timing measure and t-statistics, less than 1% of bootstrap samples generate a mean value higher than 53 basis points per quarter. Funds ranked in the top decile achieve an abnormal return at least of 1.57% per quarter, or around 6% per year. On the other hand, the funds in the 10th or even the 5th percentile experience negative but insignificant abnormal returns, so there is no evidence of negative cashflow timing.

In contrast, Panel B shows that the average fund suffers losses, 21 basis points per quarter, or 0.84% per year, for timing discount rates. Funds in the right-tail distribution of the discount-rate timing measure, including the 75th, 90th, and 95th percentiles, experience positive but insignificant abnormal returns, so there is no evidence of positive discount-rate timing ability. On the other hand, funds in the left-tail distribution exhibit economically and statistically significant, negative timing performance. For instance, funds in the bottom decile experience a loss at least of -78 basis point per quarter. We reject the null hypothesis that such negative performance could arise by chance.

Adding together cashflow timing and discount-rate timing, termed “total timing”, for each fund, the cross-sectional statistics of this total timing performance, as summarized in Panel C of Table

1, lie in between those of cashflow timing and discount-rate timing. Note that the statistics of this total timing performance are not simply the sum of corresponding statistics in Panels A and B, except for the mean statistics, because the fund with the best cashflow timing skill is not necessarily the fund with the best discount-rate timing ability. We notice that the total timing performance for the average fund is 32 basis points per quarter, or 1.28% per year, which is both statistically and economically significant. Funds in the top decile achieve at least a 1.1% abnormal return per quarter, while there is no evidence of negative total timing performance even for funds with low rankings.

To demonstrate the importance of differentiating between cashflow timing and discount-rate timing in evaluating timing skills, Panel D of Table 1 presents the results for timing the unexpected market return as one piece. Different from the results in Panel C, the average fund exhibits no timing ability. Even funds in the right tail of the cross-sectional distribution of this timing measure deliver insignificant timing performance, whereas funds in the left tail suffer a significant loss. Overall, the message for timing the market unexpected return as two components (Panel C) versus one piece (Panel D) is quite different. This comparison suggests that it is important to distinguish strategic shifts in risk exposure to market-level cashflow news and discount-rate news when evaluating fund managers' timing skills.

4.2 Persistence of timing ability

As discussed in Section 2, the cashflow component of the market return is fundamental-related. Fund managers, if skilled, are likely to develop superior anticipation about its future movements. On the other hand, forecasting and exploiting discount rates are a quite tough task. Due to the differential characteristics of these two systematic factors, we would expect that cashflow timing performance is likely to persist for fund managers who truly possess such skills, while discount-rate timing performance is hardly to remain. Moreover, the cashflow return component is less volatile than the discount-rate component, so the latter largely determines movements of unexpected market returns (Campbell and Vuolteenaho, 2004). Therefore, performance of timing unexpected market returns is also unlikely to persist.

To test the persistence of timing ability, each quarter we sort all funds in our sample into deciles according to their past timing measures (6) due to shifting their exposure to market cashflow news, discount-rate news, or the unexpected market return. We then compute the average of the corresponding timing measures in the next quarter across funds in each decile. Table 2 presents the time-series averages across sorting quarters of these averaged timing measures in each decile. The last two rows exhibit the difference in timing performance between past winner deciles and past loser deciles.

Panel A confirms our intuition: Positive cashflow timing performance is quite persistent. Funds in the best cashflow timing deciles, sorted on the past 1-, 3-, or 5-year performance, generate timing abnormal returns of 1.38%, 0.99%, and 0.89% per quarter, respectively, which are statistically and economically significant. In contrast, funds in the worst deciles, ranked on the past 3- or 5-year performance, deliver insignificant cashflow timing performance. The spreads of timing gains between these two extreme deciles are also significant.

On the other hand, Panel B shows no evidence of persistence in discount-rate timing. All deciles exhibit insignificant abnormal returns for timing discount rates. Panel C also presents little evidence of performance persistence for timing market unexpected returns. Although the winner (loser) deciles continue to perform the best (worst) with positive (negative) abnormal returns, these timing measures are not significant, neither are the spreads of the abnormal returns for the two extreme deciles.

4.3 Timing ability over the business cycle

Timing performance is likely to vary with economic environments due to differing opportunities. The stock market is more volatile and risk aversion becomes higher during stress periods than normal periods. Under such circumstances, obtaining macro information is more valuable to reduce portfolio risk and generate timing profits during economic downturns (Kacperczyk, Nieuwerburgh, and Veldkamp, 2016). Taking either the market return or macro fundamental (industrial production) as one-piece market-timing efforts, Kacperczyk, Nieuwerburgh, and Veldkamp (2014, 2016) provide evidence that skilled fund managers choose to focus on market timing in recessions. To understand how cashflow timing and discount-rate timing vary over the business cycle, Table 3 presents timing performance in NBER-recognized recessions and expansions separately.

Consistent with Kacperczyk, Nieuwerburgh, and Veldkamp (2016), the first panel shows that implementing cashflow timing is more profitable in recessions than in expansions. Specifically, the median fund earns considerable abnormal returns of 1.75% per quarter during economic downturns, much higher than abnormal returns of 0.24% per quarter during normal periods.[13] Because of much higher volatility during stress periods, the cross-sectional distribution of cashflow timing performance is considerably wider. For instance, the performance spread between the 90th and 10th percentiles is 7.3% per quarter in recessions, far larger than 1.47% per quarter in expansions.

In contrast, the median fund exhibits no discount-rate timing ability during normal periods, while it suffers a discount-rate timing loss of 1.5% per quarter during stress periods, as summarized in the second panel. The cross-sectional distribution of discount-rate timing performance is also wider in recessions.

Adding together cashflow timing and discount-rate timing performance for each fund, the third panel of Table 3 suggests that the median fund's total timing performance is significantly positive in expansions, but insignificantly positive in recessions due to large market volatility.[14] Nevertheless, premier market-timers earn considerable timing profits in recessions, which is economically more significant. Our results extend the evidence in the work of Kacperczyk, Nieuwerburgh, and Veldkamp (2014) and suggest that skilled managers implement timing strategies during recessions in anticipation of fundamental news instead of discount-rate changes.

[13]Our proxy of the aggregate cashflow factor summarizes earnings information over all future periods that is reflected in the stock market return, while Kacperczyk, Nieuwerburgh, and Veldkamp (2016) adopt one-period industrial production as a proxy. This difference in the proxies possibly explains that we document higher cashflow-timing profits than they do as the stock market return contains aggregate cash-flow information spread in different future periods.

[14]Although the bootstrap p-values for the timing measure are very small, the bootstrap p-values for t-statistics are large because recessions account for a small fraction of our sample periods and market volatility is high during downturns.

5 Identifying funds with timing skills

Although the average fund makes profits by implementing timing technique, there is a wide variation in timing performance across funds. Therefore, it is tempting to identify funds that possess superior market timing ability. Based on our timing evidence discussed before, we propose past-year total timing ability (the sum of past-year cashflow timing and past-year discount-rate timing) as a metric to identify funds in real time with market-timing talents. We choose this metric because when a fund's exposure to market cashflow news changes, its exposure to market discount-rate news is likely to be altered at the same time, and vice versa. As we have discussed, the average fund suffers a loss by timing discount-rate news, so a manager with superior information about future cash flows, when making timing decisions, should take into account the likelihood of the perverse effect due to simultaneous shifts in discount-rate betas. In this section, we examine future timing performance as well as overall fund portfolio returns for funds sorted in real time according to this metric. We also exploit the informativeness of shifts in cashflow betas aggregated from top market-timers about future aggregate cash flows.

5.1 Characteristics of funds ranked on past-year total timing ability

We first compare fund characteristics across fund quintiles sorted on funds' past-year total timing ability. These fund characteristics include fund age, fund size (measured by log TNA), fund expense ratio, past-year fund flow (as a fraction of lagged fund TNA), flow volatility (the volatility of monthly fund flows over the past year), fund return volatility (the volatility of monthly fund net returns over the past year), and the most recently available CRSP turnover ratio. We average these fund characteristics across funds in each quintile and each sorting quarter and then take a time-series average across sorting quarters for each quintile.

A few points are noteworthy in Table 4. First, top market timers are long-established funds, 2.6 years older than poor timers. Second, they exhibit higher portfolio turnover (100% per year), consistent with the evidence that they frequently shift fund portfolios' exposures to time aggregate cash flows, which we will show in Section 5.3. Finally, they receive larger inflows of new asset to manage and experience higher fund flow volatility, presumably a market-based recognition of their performance.

5.2 Timing performance for funds sorted on past-year total timing

Panel A of Table 5 presents future timing performance for fund quintiles ranked on funds' past-year total timing ability. Specifically, in one of the subsequent four quarters, we calculate the average of a quarterly timing measure (cashflow timing, discount-rate timing, or total timing) across funds in each quintile. Then, the time-series average across ranking quarters of the timing measure for each quintile and each of the subsequent four quarters is reported.

Note that future cashflow timing performances line up with quintile rankings, and these performances are striking for funds with good past-year total timing ability. For example, top timers (quintile 5) produce cashflow timing profits of 1.14% and 0.67% in the first and fourth quarters, respectively, after the ranking quarter. These abnormal returns are both statistically and economically significant. Cumulating them over the subsequent four quarters yields an impressive timing gain of 3.57%. In contrast, poor timers (quintile 1) exhibit insignificantly small cashflow timing performance. The performance spreads between the two extreme quintiles are also significantly positive in the next four quarters.

Different from the pattern in cashflow timing, there exists a perverse and weak relation between discount-rate timing and quintile rankings based on past-year total timing ability. Top timers produce a insignificantly small discount-rate timing loss over the next four quarters, whereas bottom timers generate a insignificantly small gain.

Nevertheless, top timers continue to yield the best total timing performance in the subsequent four quarters because their discount-rate timing losses are much smaller than their cashflow timing gains. Meanwhile, poor timers remain the worst. Top timers produce 0.91% and 0.41% total timing profits in the next first and fourth quarters, respectively, after the formation quarter. Cumulating these profits over the subsequent four quarters yields 2.49% total timing gain, 1.86% higher than that for poor timers.

Because our metric—past-year total timing ability—is likely to be measured with noise, the top and the bottom quintiles might be populated not only by the best and the worst market timers, but also by funds that have the highest estimation error in this metric. To alleviate this issue, we follow the suggestion of Mamaysky, Spiegel, and Zhang (2007) and apply a back-testing procedure in which a modest, ex ante filter is used to eliminate funds for which past-year total timing performance likely derives primarily from estimation error. Specifically, we keep funds for which quarter-t total timing performance has the same sign as accumulative total timing performance over quarters $[t-5, t-1]$. Thus, in this back-testing procedure, we consider only funds for which past-year total timing performance exhibits some predictive success in the past. We then sort the remaining funds into quintiles on their past-year total timing ability and study future timing performance of each fund quintile as we did above.

Our results, summarized in Panel B of Table 5, show that both the cashflow and the total timing performance spreads between the top and the bottom quintiles widen after applying the back-testing procedure, especially in the next one and two quarters after the sorting period. For instance, the total timing performance spread increases from 1.03% to 1.42% per quarter in the first quarter. After applying the filter, top timers also perform slightly better by generating large cashflow timing abnormal returns and total timing abnormal returns.

5.3 Strategic shifts in fund betas

To further confirm that timing ability comes from strategic shifts in fund betas, we examine the direct relation between a next-quarter market return component and its associated differential fund beta (a fund's beta with respect to this return component in excess of the fund's target beta—the average of the fund's past betas). Specifically, we first sort funds into quintiles on their past-year total timing ability. We then run four regressions of the average of differential fund betas across funds in each quintile in the subsequent four quarters, with one regression for one quarter. The independent variable is a dummy variable that is defined on the next-quarter market return component, as specified in (13) in the spirit of the Henriksson and Merton (1981) model.[15] Table 6 reports the results.

We notice strong evidence that superior market timers skillfully shift their cashflow betas. The coefficient estimates on the dummy variables increase monotonically with fund ranking quintiles

[15] We also run similar regressions with the independent variable defined according to (12) in the spirit of the Treynor and Mazuy (1966) model, and conclusions stay unaltered.

(Panel A). Funds in the best timing quintile, on average, increase their cashflow betas by 0.21 relative to their targets when next-quarter market cashflow news is positive. Compared with the average fund cashflow betas of roughly 1 (Panel C of Table 6), this positive shift is both statistically and economically significant, generating the cashflow timing profit of 1.14% in the first quarter (Panel A of Table 5). Even in the forth quarter after the sorting period, funds in the best quintile on average increase their cashflow betas by 0.14 relative to their targets when market cashflow news in the fifth quarter is positive. In contrast, we see no evidence of strategically varying cashflow betas for funds in the worst quintile, nor we see evidence in Panel B of Table 6 of skillfully shifting discount-rate betas.

Panels C and D of Table 6 report that, on average, target cashflow beta is very close to 1 and target discount-rate beta is very close to -1 for each quintile.[16] Nevertheless, we notice slightly higher cashflow and discount-rate risk exposure in two extreme quintiles—a slight, hump-shaped pattern of fund target betas. This pattern is quite different from what is illustrated in Panel A. These different patterns suggest that cashflow timing skill comes from superior information about future cash flows instead of the consequence of high target cashflow betas.

5.4 Shifts in cashflow betas from top market timers

As we just showed, skilled market-timers strategically shift their fund portfolios' cashflow exposure and make timing profits. We would expect that differential cashflow beta aggregated from top market timers is informative about future aggregate cash flows.

To test this conjecture, we first equally weight differential cashflow betas across top timers in each quarter and obtain a time series aggregated differential cashflow beta ($ADCFbeta$), where top timers are classified as funds in the top decile sorted on past-year total timing performance. To reduce potential estimation error, we also construct another time-series $ADCFbeta$ by applying a back-testing procedure, which described in Section 5.2, in selecting top timers. Next, we run the following regression:

$$X_{t+1,t+j} = a + bADCFbeta_t + cX_{t-j+1,t} + \epsilon_{t+1,t+j}, \tag{20}$$

[16] A positive discount-rate shock reduces current stock returns, so discount-rate betas are negative.

where $X_{t+1,t+j}$ is cumulative aggregate cashflow news starting from the beginning of quarter $t+1$ to the end of quarter $t+j$, j is a look-ahead horizon and equal to 1, 2, 3, or 4 quarters, and $ADCFbeta_t$ is quarter-t aggregated differential cashflow beta. Table 7 reports the regression results.

Regardless of controlling for lagged cumulative cashflow news, for all four look-ahead horizons and for both proxies of $ADCFbeta$, $ADCFbeta$ significantly and positively forecasts future aggregate cashflow news.[17] For example, when $ADCFbeta$ is a sole predictor, a one-standard-deviation increase in $ADCFbeta$ (0.37) is expected to raise next-quarter cashflow news by 3.7%, which is both statically and economically significant, compared with the standard deviation of quarterly cashflow news being 7.2%. Moreover, the coefficient estimates on $ADCFbeta_t$ increase with the look-ahead horizon. These results provide further evidence that top market timers possess superior information about future market-level cash flows.

An alternative explanation is that the above positive predictability by $ADCFbeta$ is somehow mechanical because sell-side analysts incorporate fund holdings information into earnings forecasts and $ADCFbeta$ is also constructed based on fund holdings. If it was the case, then we would see cashflow reversals over longer horizons after earnings are revealed. To test this reversal story, we run regressions of cumulative cashflow news at horizons of 1-5 years or annual cashflow news in the 2nd, 3rd, 4th, and 5th year into the future, with an independent variable being $ADCFbeta$ and with or without controlling for past-year cashflow news. The results, summarized in Table 8, show no evidence of cashflow reversals, regardless of applying a back-testing procedure in the construction of $ADCFbeta$. The coefficient estimates on $ADCFbeta$ are either positive or slightly negative, but none of them is significantly negative.

We also examine whether $ADCFbeta$ is informative about future macro activities that are closely related to stock-market cash flows. We run similar regressions of (20), where X is one of macroeconomic variables, including GDP growth, industrial production (IP) growth, and the Chicago Fed National Activity Index (CFNAI), which are available from the Federal Reserve Bank of St. Louis. The results, reported in Table 9, show that $ADCFbeta$ positively predicts future macro activities over the next few quarters. This evidence suggests that top timers' differential cashflow beta, reflecting their superior anticipation about stock-market cash flows, is also a good

[17] As expected, an unreported table shows that $ADCFbeta$ has no forecasting power for market excess returns.

signal of future movements of macro fundamentals. This evidence also helps to invalidate the above alternative explanation that the predictive relation between $ADCFbeta$ and future cashflow news is mechanical, because no forecast is involved in the dependent variables in these regressions of macro variables.

5.5 Other dimensions of fund portfolio performance

In this section, we conduct a simple investigation whether top market timers produce superior overall fund portfolio returns and whether they exhibit impressive stock-selection talents. To do so, we first sort funds into quintiles on their prior-year total timing performance. We then calculate the average across funds in each quintile of fund net returns after expenses, fund holding-based returns before expenses, and fund DGTW adjusted abnormal returns in each of the subsequent four quarters after the formation period.[18] Table 10 reports the time-series average across sorting quarters of these averaged quarterly fund returns in each quintile.

Clearly, both fund net returns and holding-based returns increase monotonically with past timing performance. In the first quarter, top market timers (quintile 5) outperform poor timers (quintile 1) by 0.73% and 0.79% in terms of quarterly net returns and holding-based returns, respectively. Even in the forth quarter after the sorting period, these quarterly return differences are still large, being 0.54% and 0.62%, respectively. These results suggests that overall fund portfolio returns of top market timers are pretty good.

On the other hand, DGTW adjusted abnormal returns, a proxy of stock-picking ability, are insignificantly positive for top timers and insignificantly negative for bottom timers. The difference in these risk-adjusted returns is 0.29% in the first quarter after the formation period, less than half of the return differences in terms of net returns, holding-based returns, or total timing abnormal returns. This difference is also much smaller than the return spread between the best and the worst stock-picking groups, around 3% per year according to prior studies (Kacperczyk, Sialm, and Zheng, 2008; Cremers and Petajisto, 2009). Therefore, although superior market timers have some stock-picking skills, they are a correlated but somewhat different set of managers, relative to the

[18]Note that there is a gap of around one week between the end of the sorting IBES quarter (for timing performance) and the beginning of the look-ahead calendar quarter (for fund returns).

group that possess striking stock-selection skills.

6 An explanation for negative discount-rate timing

We have provided evidence that the average mutual fund manager is able to time aggregate cashflow information profitably, but encounters a loss for discount-rate timing. If a fund manager had no ability to time discount rates, the discount-rate timing measure of her fund is expected to be zero. It is not clear how mutual fund managers, as a group of sophisticated investors, suffer discount-rate timing losses on average. This section provides an explanation that is based on the impact of aggregate fund flows.

Aggregate fund net flows can be correlated with the market return and its return components because of their informational revelation (Warther, 1995) or reflection of investor sentiment (Ben-Rephael et. al, 2012). Aggregate fund net flows are informative if mutual fund investors, in aggregate, possess information, or if they trade mutual fund shares in the same direction as informed investors. For example, fund investors chase funds with recent good performance (Sirri and Tufano, 1998). If managers of some of these funds earn profits based on their good understanding of macro fundamentals that unfold over time, then aggregate fund net flows contain market-level cashflow information.

On the other hand, aggregate fund net flows reflect investor sentiment and exert price pressure, as the media sometimes claims.[19] Ben-Rephael et. al (2012) find that a subset of aggregate net flows—shifts between bond funds and equity funds—is positively contemporaneously correlated with stock market excess returns, which revert significantly in the following months. We would expect that discount-rate expectations are easily subject to price pressure or investor sentiment, while cashflow expectations are not. The reason is that macro fundamentals are revealed frequently over time, so an estimation error in projecting future cash flows is likely to be adjusted accordingly. In contrast, discount rates are unobservable, so underestimation or overestimation about them is hard to detect. This price-pressure explanation has a testable implication: as investor sentiment or price pressure fades away, a reversal will occur.

[19]See, for example, Wall Street Journal (WSJ) 9/30/1993, p. C1; WSJ 3/14/1994, p. C1

We conjecture that negative discount-rate timing takes place when a discount-rate reversal occurs. If the average mutual fund manager must respond to the sentiment of retail investors by moving in the same direction (potentially to appeal to the preferences of their investors), then she will shift her fund's discount-rate beta in a wrong direction, leading to discount-rate timing losses.

To provide supporting evidence, we first examine the relation of aggregate fund net flows with the market return and its two components. We calculate fund j's net flow in calendar quarter t, $flow^c_{j,t}$, as the growth rate of the assets under management (TNA) after adjusting for the appreciation of the fund's asset, by assuming that all the cashflow distributions are invested at the end of the period (Kacperczyk, Sialm, and Zheng, 2008)

$$flow^c_{j,t} = \frac{(TNA_{j,t} - TNA^2_{j,t}(1+mret^3_{j,t})) + (TNA^2_{j,t} - TNA^1_{j,t}(1+mret^2_{j,t})) + (TNA^1_{j,t} - TNA_{j,t-1}(1+mret^1_{j,t}))}{TNA_{j,t-1}}, \quad (21)$$

where $mret^i_{j,t}$ and $TNA^i_{j,t}$ are fund j's net return and TNA in the i^{th} month of quarter t. We winsorize this variable at 1% and 99% to diminish the influence of outliers. We then take TNA-weighted average of $flow^c_{j,t}$ across all funds to get aggregate fund net flows $flow^c_t$. Because returns and timing performance in our study are measured in IBES quarters, we convert this flow variable into one in IBES quarter t, $flow_t$, as

$$flow_t = flow^c_{t-1}\frac{nIBESp_t}{n_{t-1}} + flow^c_t\frac{nIBES_t}{n_t},$$

where n_t is the number of days in calendar quarter t, $nIBES_t$ and $nIBESp_t$ are the number of days of IBES quarter t overlapped with calendar quarters t and $t-1$, respectively.[20]

Panel A of Table 11 reports the results of regressions of contemporaneous and next-quarter unexpected market return and its two components on aggregate fund net flows. Consistent with Warther (1995), the concurrent unexpected market return is significantly and positively correlated with aggregate net flows (column 5), and there is no pronounced evidence of next-quarter reversal (column 6). By distinguishing the cashflow return component from the discount-rate component, we notice that both contemporaneous and next-quarter cashflow return components are positively related to net flows (columns 1 and 2), which suggests that aggregate net flows contain macro-level

[20]Since IBES quarters and calendar quarters are overlapped except for roughly a one-week difference, using aggregate net flows in either IBES quarters or calendar quarters produces similar results.

cashflow information. In contrast, aggregate net flows is significantly and negatively correlated with the concurrent discount-rate return component but significantly and positively correlated with the next-quarter discount-rate component (columns 3 and 4)—pronounced evidence of discount-rate reversal due to price pressure. A one-percentage rise in aggregate net flows decreases the concurrent discount-rate return component by 1.11% and increases the next-quarter discount-rate component by 1%, which reverses about 90% of the concurrent drop. Both Warther (1995) and Ben-Rephael et. al (2012) do not find evidence of market-return reversal following aggregate net flows. One possible reason is that discount rates are subject to price pressure but cash flows are not, so mixing the two components together clouds detection of market-return reversal.

The second column of Panel B shows that differential discount-rate beta for the average mutual fund significantly decreases with aggregate net flows. This significant decrease coupled with pronounced next-quarter discount-rate reversal (an increase) generates negative discount-rate timing, as confirmed in Panel C of Table 11. In columns 3 and 4 of Panel C, discount-rate timing performance drops significantly with the square of demeaned aggregate net flows, regardless of controlling for fund characteristics. These fund characteristics are described in Section 5.1. Except aggregate net flows squared, all other explanatory variables are demeaned so that the regression intercepts are not affected by including these control variables. Compared with the average discount-rate timing performance of -17 basis points, significantly negative, (unreported to save space), adding aggregate net flows squared improves the regression intercepts to 6 basis points, positive and insignificant.

The coefficients on demeaned aggregate net flows in columns 3 and 4 are significantly positive for two possible reasons. First, negative (demeaned) net flows drive discount-rate timing performance further down. Second, the square of demeaned aggregate net flows is not a correct functional form of the second-order polynomial of aggregate net flows (up to scale) to explain negative discount-rate timing, so that the first-order aggregate net flows play a role of correction. We thus construct a new variable for the second-order polynomial of aggregate net flows as the fitted value of the next-quarter discount-rate return component shown in column 4 of Panel A, $(1.001flow - 0.016)$, multiplied by minus the fitted value of differential discount-rate beta presented in the second column of Panel B, $(1.093*flow-0.051)$ (taking the minus sign to make the multiplication have the positive sign for net flows squared to facilitate interpretation). The regression results are presented in columns 5 and 6.

The coefficient estimates on the second-order polynomial are significantly negative, similar to those on aggregate net flows squared in columns 3 and 4. The coefficient estimates on demeaned aggregate net flows, though still positive, are much smaller and insignificant. The regression intercepts remain positive and insignificant. These comparisons provide evidence supporting our conjecture that discount-rate reversal due to price pressure is responsible for negative discount-rate timing.

In contrast, the first column of Panel B shows that differential cashflow beta has no relation with aggregate net flows. Accordingly, the first two columns of Panel C demonstrate that cashflow timing performance is not explained by aggregate net flows squared and that the regression intercepts remain significantly positive. As displayed in the last column of Panel B, differential unexpected-return beta is positively related with aggregate net flows, while reversal of next-period unexpected market return is insignificant, as summarized in the last column of Panel A. Accordingly, the last two columns of Panel C show that performance for timing unexpected market returns decreases with aggregate net flow squared but this relation is not significant.

7 Additional analyses and robustness tests

This section summarizes a number of additional analyses and robustness checks, which further strengthen our main conclusion that the average fund possesses timing ability due to timing aggregate cash flows. To save space, we summarize results in this section in a separate appendix.

7.1 Time-varying cash positions

Our main tests have examined how a fund manager times the stock market by shifting her fund's exposure to a systematic factor based on pure equity positions. Alternatively, she can time the market by varying cash positions. For example, when a fund manager intends to lower cash-flow beta of her fund, she can increase cash positions, an alternative approach to tilting towards stocks with low cash-flow beta. Keep in mind that an increase in cash position reduces both cash-flow exposure and discount-rate exposure simultaneously for a fund portfolio. We find that timing performance stays quite similar regardless of accounting for fund cash positions.

Data of cash positions come from CRSP. For each fund we take the TNA-weighted average of cash positions across different asset classes. Top and bottom 1% are winsorized to reduce data error. We notice that cash positions are missing for about 53% observations (fund x quarter) in all three months within a quarter. Based on the sample with a valid value of cash position, funds hold about 4.25% of their managed assets in cash on average. Time variation in cash positions with respect to next-quarter market return components is quite small. A one-standard-deviation decrease in the next-quarter cash-flow return component (0.081) raises cash position by 0.08% (0.01×0.081), which just slightly reduces a fund's cash-flow beta after accounting for cash positions, compared with the average fund's cash-flow beta in equity portfolios close to 1. A one-standard-deviation increase in the next-quarter discount-rate return component (0.124) reduces cash position by 0.31% (-0.025×0.124). A rise in discount rate is poor news, so decreasing discount-rate exposure (a less negative value of discount-rate beta) is a preferable timing strategy. Instead, we find a lower cash position that increases a fund portfolio's discount-rate beta in magnitude and potentially leads to negative discount-rate timing. This change in discount-rate exposure is also very small compared with the average fund's discount-rate beta in equity portfolios of roughly -1.

To avoid losing many observations in calculating timing performance, we assume a fund's cash position to be zero if it is missing. This assumption possibly introduces noise if a cash position is actually nonzero but reported as missing by CRSP. For this reason, our main tests focus on a fund's betas that are calculated based on pure equity positions. In a table reported in a separate appendix, we notice that the cross-sectional distribution of timing performance is almost identical to those exhibited in Table 1, which is consistent with a small time-variation in cash positions.[21]

7.2 Multivariate regression approach

We further examine whether past-year timing ability has forecasting power for future timing performance, after controlling for other fund characteristics. We run both pooled panel regressions and Fama-MacBeth regressions using either next-quarter or next-year cashflow, discount-rate, or total timing abnormal returns as the dependent variable. In addition to different fund character-

[21] Since changes in cash positions in a wrong direction are quite small for timing discount rates, the economic value of such changes is also very small—discount-rate timing performance reduces at most a couple of basis points per quarter when time-varying cash positions are considered.

istics that we discussed in Section 5.1, the independent variable includes past-year timing ability ranking—a decile ranking obtained by sorting funds each quarter according to their past-year total timing ability.

We find that past-year timing ability has a significant predictive power for future cashflow and total timing performance, even after controlling for other fund characteristics. For instance, ceteris paribus, compared with funds in the bottom decile, funds in the top decile on average earn 1.4–1.8% more cashflow timing abnormal returns or 1–1.4% higher total timing abnormal returns in the next quarter. Moreover, turnover has a significantly positive relation with timing performance, primarily because skilled market timers need to strategically shift their exposure to systematic factors frequently.

7.3 Using different proxies of market return components

We adopt two additional proxies of the cashflow and discount-rate components of the market return to reexamine cross-sectional statistics of fund timing abilities, as we did in Section 4.1. One proxy is based on the Gordon (1962) model, as discussed in Section 2.1. The other proxy is based on first-stage earnings forecasts of the three-stage earnings growth model, which is described in Section 3.1. The cashflow return component is constructed as $E_{t+1}\sum_{j=0}^{5}\rho^j\theta_{t,1+j} - E_t\sum_{j=0}^{5}\rho^j\theta_{t,1+j}$, and the discount-rate component is then backed out according to equation (3). This second proxy intends to rule out the possibility that the assumptions in the second and third stages of the three-stage model have a material impact on measuring cashflow and discount-rate timing performances. We find that adopting these two proxies of market return components yields timing evidence similar to that in our main test reported in Table 1.

7.4 Manipulation-proof timing measure

Ingersoll et. al (2007) illustrate that conventional fund performance measures unfortunately can be subject to manipulation. That is, fund managers can intentionally improve their performance scores by applying static or dynamic manipulation that does not produce or deploy value-relevant information about the underlying assets in their managed portfolios. To avoid the effect of manipulation, according to the work of Ingersoll et. al, performance measures must be (a) increasing in returns, (b) concave to avoid static manipulation by simply leveraging or trading derivatives, and (c) have an additively time-separable representation to prevent dynamic manipulation that induces time variation in return distributions based on past performance rather than on new information to influence measures.

Our differential return timing measure satisfies (a) and (c), and therefore shields from dynamic manipulation. Since U.S. domestic equity mutual funds generally do not trade derivatives, nor do they generally use leverage (including short-selling securities), static manipulation has at most a limited impact on this timing measure. Moreover, the market-timing literature shows little or even negative market-timing performance, so fund managers seem not to manipulate their performance along this dimension.

Nevertheless, we follow the suggestion of Ingersoll et. al and adopt the following manipulation-proof timing measure for fund f with respect to factor j, $MPTM_{f,j}$, to reexamine mutual fund timing skills:

$$MPTM_{f,j} = \frac{1}{(1-\eta)\Delta h} \ln\left(\frac{1}{T}\sum_{t=1}^{T}(1 + tim_{f,j,t})^{1-\eta}\right), \tag{22}$$

where $tim_{f,j,t}$ is the market-timing contribution of fund f in response to factor j in period t, as specified in (6), T is the total number of observations of fund f, Δh is the length of time between consecutive observations in the unit of year and serves to annualize the measure, and η is relative risk aversion in power utility. Following Ingersoll et. al (2007), we chose $\eta = 3$. $MPTM_{f,j}$ is an estimate of the portfolio's premium return for timing factor j after adjusting for risk. It can be interpreted as an annualized continuously compounded certainty equivalent excess return.

Employing this manipulation-proof measure paints a similar picture about mutual fund timing abilities. The average fund and the fund at the 90th percentile earn annualized certainty equivalent excess returns of 1.49% and 5.25%, respectively, from timing cash flows, and earn -1.26% and 0.74%, respectively, from timing discount rates. Because this manipulation-proof measure is concave, so it punishes discount-rate timing to a larger extent due to high volatility of discount rates. Even based on this measure, the total timing performances for the average fund and the fund at the 90th percentile are 0.43% and 3.28%, respectively, in terms of annualized certainty equivalent excess returns, which are statistically significant.

7.5 Other tests

We also examine fund timing skills according to the extended Treynor-Mazuy and Henriksson-Merton timing measures, as specified in (12) and (13), respectively. Our conclusions stay the same. The average fund exhibits significant cashflow timing talents, as estimates of γ are significantly positive. Moreover, there is no evidence for negative cashflow timing. In contrast, funds on the left side of the cross-sectional distribution have significantly negative timing measures for timing either discount-rate news or unexpected market returns, but there is no evidence of significantly positive measures for these two types of timing.

We convert the cashflow and discount-rate market-return components in IBES months into those in calendar months. Specifically, we divide each of the variables by the number of days in each IBES month to get daily values, then sum the daily values in each calendar month to get the variable in calendar months. Following Section 2.2, we use stock returns in calendar months to obtain cashflow beta and discount-rate beta for each stock and then calculate fund betas in calendar quarters. In applying the differential return measure, as specified in (6), factor returns are also in calendar quarters. Because a calendar quarter and a IBSE quarter are overlapped for more than 11 weeks, with only about one week difference, the results based on calendar dates are similar to those in our main test.

In the conventional Treynor-Mazuy model and Henriksson-Merton model, as specified in (8) and (9), respectively, α is an indication of superior stock selection and γ is considered as a sign of market-timing ability. As shown by Jagannathan and Korajczyk (1986), simply trading options or option-like securities, such as common stocks with highly leveraged firms, can produce positive γ and negative α, or vice versa. To rule out this alternative explanation for our evidence of timing skills, we run regressions, according to (8) or (9), of the average of quarterly fund returns (net returns or holdings-based returns) across funds in each quintile sorted on past-year total timing ability. If this alternative story could explain our results, we would see a strong negative relation between estimates of γ and α in the top quintile with the best timing performance. But we barely see it.[22]

[22] In Section 5.5, we already showed that top market timers generally have slightly better stock-selection abilities than other groups.

8 Conclusions

This paper studies market timing skill by separating two market return components: cashflow news and discount-rate news. It finds significant and positive market skill for an average fund, about 1.2% per year. Such positive timing performance comes from 2% cashflow timing gain and -0.8% discount-rate timing loss. We further find that cashflow timing skill is persistent but not discount-rate timing performance. Aggregate cashflow news is related to economic fundamentals, so skillful managers are able to gain superior information about future aggregate cash flows. In contrast, aggregate discount-rate news is positively related with changes in investor sentiment, which is hardly predictable, leading to loss in timing market discount-rate news. Finally, we propose to use our timing measure to detect a subset of funds with superior timing abilities. For example, funds in the best quintile sorted on our timing measure exhibit about 2.5% timing profit over the next year.

Appendix

A.1 Construction of data items

Market-level earnings forecasts for the current and next fiscal years ($A1_t$, $A2_t$) and market-level long-term growth forecast (LTG_t): We keep consensus earnings forecasts for the current and subsequent fiscal years ($FE1_t$, $FE2_t$), along with a long-term growth forecast (LG_t) for each firm with valid $FE1_t$, where t denotes when a forecast is employed. The earnings forecasts are denominated in dollars per share. The long-term growth forecast represents an annualized percentage growth rate and pertains to the next three to five years. If $FE2_t$ is missing, then we can replace with $FE2_{t-1}$; if $FE2_{t-1}$ is also not available, then we take $FE1_t * (1 + LG_t)$. Our results are very similar if we define the consensus forecast as the median forecast instead of the mean forecast. To get $A1_t$ ($A2_t$), we first multiply $FE1_t$ ($FE2_t$) by time-t shares outstanding for each firm then sum them across all firms. LTG_t is the value-weighted average of LG_t across all firms using firms' market capitalization as weights. To remove the effect of outliers, we winsorize $FE1_t$, $FE2_t$, and LG_t at their 1st and 99th percentiles each month before aggregating them at the market level.

The yield spread between long-term and short-term bonds is computed as the yield difference between ten-year constant-maturity taxable bonds and one-year taxable notes.

The market's smoothed price-earnings ratio is downloaded from Robert Shiller's web site. It is constructed as the price of the S&P 500 index divided by a ten-year trailing moving average of aggregate earnings of companies in the S&P 500 index. We also construct another time series that avoid any interpolation of earnings to ensure that all components of the time-t price-earnings ratio are contemporaneously observable by time t. Using either time series delivers quite similar results in forecasting market returns.

The small-stock value spread is constructed from the data that are available from Kenneth French's web site. The portfolios, which are constructed at the end of each June, are the intersections of two portfolios formed on size (ME) and three portfolios formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in $t-1$ divided by ME for December of $t-1$. The BE/ME breakpoints are the 30th and 70th NYSE percentiles. At the end of June of year t, we construct the small-stock value spread as the difference between the log(BE/ME) of the small high-book-to-market portfolio and the log(BE/ME) of the small low-book-to-market portfolio, where BE and ME are measured at the end of December of year $t-1$. For months from July to May, the small-stock value spread is constructed by adding the cumulative log return (from the previous June) on the small low-book-to-market portfolio to, and subtracting the cumulative log return on the small high-book-to-market portfolio from, the end-of-June small-stock value spread.

A.2 Bootstrap procedure

A bootstrap procedure is used to obtain the empirical distribution of a statistic of interest under the null hypothesis of no timing ability. Each quarter, we first compute differential fund beta for a given fund as the deviation of fund beta from its target beta, which is the average of the fund's past betas. Next, factor returns, including market cashflow news, market discount-rate news, and market unexpected returns, are randomly drawn each quarter from the historical sample with replacement. The bootstrap timing measure is then calculated as bootstrap factor returns multiplied by the corresponding differential fund betas that actually occurred at the beginning of a given quarter for each fund, as described by equation (6). Because bootstrap factor returns are drawn randomly, the expected bootstrap timing measure should be zero across simulations. Note that this simulation approach preserve the cross-sectional patterns of differential fund betas as well as of factor returns. The simulation is repeated 1,000 times. p-values are computed for various statistics of the actual distribution by examining the number of times out of 1000 we get the bootstrap values of that statistic in our simulated samples higher (lower) than the actual value in our historical sample by chance.

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Table 1: Timing ability based on the differential return measure

This table reports point estimates and t-statistics at various points in the cross-sectional distribution of the differential return timing measure that is specified in (7). The timing measure for a given fund with respect to a systematic factor is calculated as the time-series average of the multiplication of the fund's differential beta with respect to this factor and the next-quarter return on this factor. A fund's differential beta is defined as the fund's beta in the current quarter in excess of the average of the fund's betas over all past quarters. Panels A, B, C, and D summarize the results of timing market cash-flow news, discount-rate news, both market cash-flow and discount-rate news, and market unexpected returns, respectively. Bootstrap p-values are reported in parenthesis based on 1000 bootstrap samples. Under the null hypothesis, the expected timing measures are zero. For points above (below) the median, p-value is the probability of a higher (lower) value occurring by chance. For a positive (negative) value of the mean or median of a timing measure, p-value is the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Timing cash-flow news								
Tim(%)	-0.56	-0.30	0.08	0.53	0.44	0.90	1.57	1.99
p-val	(0.11)	(0.38)	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.67	-0.98	0.29	0.99	1.23	1.90	2.50	2.89
p-val	(0.37)	(0.72)	(0.99)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Panel B: Timing discount-rate news								
Tim(%)	-1.06	-0.78	-0.45	-0.21	-0.15	0.06	0.26	0.44
p-val	(0.00)	(0.00)	(0.01)	(0.01)	(0.03)	(0.86)	(0.70)	(0.55)
t-stat	-2.54	-2.01	-1.25	-0.54	-0.49	0.22	0.89	1.36
p-val	(0.01)	(0.02)	(0.06)	(0.05)	(0.10)	(0.90)	(0.82)	(0.69)
Panel C: Timing cash-flow and discount-rate news								
Tim(%)	-0.73	-0.45	-0.04	0.32	0.32	0.66	1.10	1.46
p-val	(0.17)	(0.34)	(0.88)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.50	-0.90	-0.10	0.56	0.67	1.28	1.87	2.26
p-val	(0.51)	(0.76)	(0.91)	(0.08)	(0.06)	(0.07)	(0.06)	(0.06)
Panel D: Timing unexpected market returns								
Tim(%)	-0.74	-0.54	-0.27	-0.09	-0.05	0.13	0.30	0.43
p-val	(0.02)	(0.03)	(0.06)	(0.14)	(0.24)	(0.52)	(0.45)	(0.44)
t-stat	-2.54	-1.97	-1.08	-0.29	-0.22	0.57	1.23	1.69
p-val	(0.01)	(0.03)	(0.13)	(0.19)	(0.29)	(0.60)	(0.50)	(0.35)

Table 2: Persistence of timing ability

Each quarter funds are sorted into deciles according to the average of timing performance, specified in (6), over the past 1, 3, or 5 years. Then the average of this timing measure in the next quarter is calculated across funds in each decile. The time-series average of this quarterly timing measure for each decile is reported with t-statistics in parenthesis. Cash-flow, discount-rate, and unexpected-market-return timing measures are examined in Panels A, B, and C, respectively. The quarterly timing measure for a given fund with respect to a systematic factor is calculated as the fund's differential beta with respect to this factor at the beginning of a quarter multiplied by the quarterly return on this factor, where the fund's differential beta is defined as the fund's beta in the current quarter in excess of the average of the fund's betas over all past quarters.

Deciles	Panel A: Cash-flow news			Panel B: Discount-rate news			Panel C: Unexpected market ret		
	1 year	3 years	5 years	1 year	3 years	5 years	1 year	3 years	5 years
1(low)	-0.51	-0.06	0.06	-0.28	-0.19	-0.13	-0.12	-0.23	-0.18
	(-3.05)	(-0.29)	(0.27)	(-1.00)	(-1.04)	(-0.83)	(-0.57)	(-1.64)	(-1.30)
2	-0.08	0.15	0.24	-0.17	-0.13	-0.06	-0.05	-0.13	-0.08
	(-0.57)	(0.83)	(1.25)	(-0.87)	(-0.87)	(-0.46)	(-0.40)	(-1.54)	(-0.95)
3	0.11	0.26	0.31	-0.10	-0.09	-0.06	0.00	-0.05	-0.04
	(0.68)	(1.48)	(1.70)	(-0.60)	(-0.76)	(-0.46)	(0.03)	(-0.63)	(-0.52)
4	0.23	0.31	0.34	-0.04	-0.08	-0.07	0.04	-0.03	-0.00
	(1.52)	(1.96)	(2.04)	(-0.32)	(-0.62)	(-0.57)	(0.47)	(-0.39)	(-0.04)
5	0.34	0.39	0.40	-0.03	-0.04	-0.08	0.06	0.02	0.02
	(2.25)	(2.49)	(2.21)	(-0.24)	(-0.29)	(-0.60)	(0.66)	(0.28)	(0.23)
6	0.47	0.45	0.45	0.03	-0.07	-0.07	0.09	0.04	0.05
	(2.80)	(2.86)	(2.49)	(0.27)	(-0.52)	(-0.55)	(0.91)	(0.43)	(0.54)
7	0.58	0.51	0.50	0.05	-0.04	-0.05	0.06	0.07	0.10
	(3.14)	(3.04)	(2.88)	(0.38)	(-0.29)	(-0.36)	(0.62)	(0.70)	(0.84)
8	0.70	0.59	0.60	0.04	-0.05	-0.07	0.10	0.10	0.11
	(3.47)	(3.13)	(3.31)	(0.30)	(-0.32)	(-0.43)	(0.76)	(0.79)	(0.87)
9	0.89	0.73	0.70	0.11	-0.06	-0.07	0.16	0.13	0.09
	(3.75)	(3.43)	(3.43)	(0.70)	(-0.33)	(-0.35)	(0.98)	(0.81)	(0.59)
10(high)	1.38	0.99	0.89	0.19	-0.00	-0.10	0.26	0.24	0.17
	(4.13)	(3.75)	(3.59)	(0.74)	(-0.00)	(-0.40)	(1.04)	(1.04)	(0.73)
10-1 spread	1.90	1.06	0.83	0.47	0.19	0.03	0.38	0.46	0.35
	(4.59)	(3.52)	(3.10)	(1.05)	(0.60)	(0.10)	(0.94)	(1.44)	(1.06)

Table 3: Timing ability over the business cycle

This table reports point estimates and t-statistics at various points in the cross-sectional distribution of fund timing measures over the business cycle. For a given fund, each quarter we multiply the fund's differential beta with respect to a systematic factor (market cash-flow news or discount-rate news) by the next-quarter return on this factor. Then, the time-series average of the multiplication is taken across either recession periods or expansion periods. The first, second, and third panels summarize the performance of timing market cash-flow (CF) news, discount-rate (DR) news, and both market CF and DR news, respectively. Bootstrap p-values are reported in parenthesis based on 1000 bootstrap samples. Under the null hypothesis, the expected timing measures are zero. For points above (below) the median, p-value is the probability of a higher (lower) value occurring by chance. For a positive (negative) value of the mean or median of a timing measure, p-value is the probability of a higher (lower) value occurring by chance.

	Recession								Expansion							
CF news	5%	10%	25%	Mean	Median	75%	90%	95%	5%	10%	25%	Mean	Median	75%	90%	95%
Tim(%)	-3.27	-1.61	0.02	1.87	1.75	3.52	5.69	7.24	-0.58	-0.32	-0.03	0.34	0.24	0.59	1.15	1.65
p-val	(0.00)	(0.01)	(0.87)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.28)	(0.48)	(0.91)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-2.28	-1.19	0.03	0.16	0.85	1.51	2.05	2.81	-2.11	-1.33	-0.16	1.08	1.25	2.42	3.44	4.16
p-val	(0.28)	(0.58)	(0.85)	(0.48)	(0.10)	(0.09)	(0.11)	(0.09)	(0.08)	(0.40)	(0.92)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
DR news	5%	10%	25%	Mean	Median	75%	90%	95%	5%	10%	25%	Mean	Median	75%	90%	95%
Tim(%)	-4.71	-3.85	-2.62	-1.43	-1.50	-0.27	0.87	1.82	-1.00	-0.66	-0.26	0.03	0.04	0.31	0.65	0.95
p-val	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.99)	(0.35)	(0.12)	(0.03)	(0.04)	(0.18)	(0.41)	(0.31)	(0.08)	(0.04)	(0.04)
t-stat	-2.27	-1.99	-1.67	-0.89	-1.17	-0.35	0.76	1.05	-2.88	-2.09	-0.93	0.11	0.18	1.21	2.16	2.71
p-val	(0.23)	(0.11)	(0.05)	(0.07)	(0.03)	(0.99)	(0.89)	(0.89)	(0.00)	(0.01)	(0.23)	(0.39)	(0.32)	(0.08)	(0.01)	(0.00)
CF & DR news	5%	10%	25%	Mean	Median	75%	90%	95%	5%	10%	25%	Mean	Median	75%	90%	95%
Tim(%)	-4.14	-2.84	-1.35	0.44	0.20	1.94	3.98	5.91	-0.77	-0.41	-0.01	0.37	0.32	0.66	1.20	1.74
p-val	(0.01)	(0.01)	(0.05)	(0.15)	(0.32)	(0.00)	(0.00)	(0.00)	(0.36)	(0.63)	(0.95)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.78	-1.24	-0.59	0.09	0.08	0.65	1.29	1.82	-1.72	-1.11	-0.04	1.08	1.00	1.97	2.96	3.72
p-val	(0.49)	(0.51)	(0.53)	(0.42)	(0.44)	(0.45)	(0.43)	(0.44)	(0.34)	(0.64)	(0.95)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)

Table 4: Characteristics of funds sorted on past-year total timing ability

Each quarter funds are sorted into quintiles according to their past-year total timing ability, which is the sum of abnormal returns stemming from both cash-flow timing and discount-rate timing. The table presents the time-series average of equally weighted fund characteristics across funds in each quintile. It also reports the spreads between the two extreme quintiles, with t-statistics for statistical significance of the spreads. Fund characteristics include fund size (total net assets), fund age, the expense ratio, the fund turnover ratio, past-year fund flow (the percentage growth in a fund's new money over the past year), flow volatility (the volatility of monthly fund flows over the past 12 months), and fund ret volatility (the volatility of monthly fund net returns over the past 12 months).

	Q1(Low)	2	3	4	Q5(High)	5-1	t-stat
Fund size (million $)	1246.50	1303.70	1365.70	1368.70	1220.10	-26.40	-0.20
Fund age (year)	16.15	17.98	18.98	19.69	18.73	2.58	4.01
Expense ratio (%)	1.28	1.20	1.17	1.18	1.29	0.01	0.56
Turnover	0.86	0.80	0.78	0.84	1.00	0.14	6.14
Fund flow (%)	7.63	9.26	7.78	8.98	11.81	4.18	2.08
Flow volatility (%)	2.98	2.74	2.71	2.70	3.30	0.31	2.34
Fund return volatility (%)	5.04	4.61	4.54	4.67	5.05	0.01	0.04

Table 5: Timing performance of funds sorted on past-year total timing ability

Each quarter funds are sorted into quintiles according to their past-year total timing ability, which is the sum of abnormal returns stemming from both cash-flow (CF) timing and discount-rate (DR) timing. The table presents the time-series average of equally weighted quarterly timing performance across funds in each quintile in one of the subsequent four quarters after the formation period. Quarterly timing performance is calculated as the fund's differential beta in a quarter with respect to a systematic factor (market cash-flow news or discount-rate news) multiplied by the next-quarter return on this factor. A fund's differential beta with respect to a systematic factor is calculated as the fund's beta in the current quarter with respect to this factor in excess of the average of the fund's betas over all past quarters. t-statistics reported in parenthesis are calculated based on Newey-West standard error. Panels A and B present timing performance without and with applying a back testing procedure of Mamaysky, Spiegel, and Zhang (2007), respectively, in selecting funds in each quintile.

Panel A	Timing CF news				Timing DR news				Timing CF & DR news			
	q1	q2	q3	q4	q1	q2	q3	q4	q1	q2	q3	q4
1(Low)	-0.26	-0.05	0.08	0.23	0.14	0.21	0.19	0.08	-0.12	0.16	0.28	0.31
	(-1.45)	(-0.31)	(0.49)	(1.26)	(0.80)	(1.30)	(1.32)	(0.67)	(-0.44)	(0.60)	(1.13)	(1.31)
2	0.15	0.23	0.26	0.31	0.05	0.08	0.08	0.02	0.19	0.30	0.35	0.34
	(0.95)	(1.45)	(1.68)	(1.93)	(0.35)	(0.58)	(0.65)	(0.21)	(0.87)	(1.39)	(1.63)	(1.60)
3	0.39	0.40	0.42	0.42	0.02	0.00	-0.03	-0.09	0.40	0.40	0.39	0.33
	(2.49)	(2.49)	(2.55)	(2.50)	(0.15)	(0.04)	(-0.20)	(-0.70)	(2.01)	(1.99)	(1.88)	(1.61)
4	0.65	0.59	0.54	0.52	-0.07	-0.13	-0.13	-0.15	0.59	0.46	0.41	0.36
	(3.69)	(3.43)	(3.08)	(2.94)	(-0.48)	(-0.86)	(-0.83)	(-0.98)	(2.89)	(2.22)	(1.85)	(1.63)
5(High)	1.14	0.93	0.83	0.67	-0.23	-0.28	-0.31	-0.26	0.91	0.65	0.52	0.41
	(4.59)	(3.97)	(3.69)	(3.30)	(-1.10)	(-1.35)	(-1.33)	(-1.21)	(3.76)	(2.52)	(1.97)	(1.59)
5-1	1.40	0.99	0.74	0.45	-0.37	-0.49	-0.50	-0.35	1.03	0.49	0.24	0.10
	(5.57)	(4.85)	(4.29)	(2.90)	(-1.39)	(-2.02)	(-1.94)	(-1.52)	(3.89)	(2.01)	(1.06)	(0.46)

Panel B	Timing CF news				Timing DR news				Timing CF & DR news			
	q1	q2	q3	q4	q1	q2	q3	q4	q1	q2	q3	q4
1(Low)	-0.39	-0.10	0.03	0.15	0.06	0.19	0.22	0.13	-0.33	0.08	0.25	0.28
	(-2.06)	(-0.58)	(0.17)	(0.79)	(0.36)	(1.15)	(1.47)	(0.98)	(-1.19)	(0.32)	(1.03)	(1.10)
2	0.13	0.24	0.30	0.38	0.01	0.05	0.06	-0.03	0.14	0.29	0.36	0.34
	(0.79)	(1.38)	(1.81)	(2.23)	(0.08)	(0.37)	(0.50)	(-0.28)	(0.64)	(1.26)	(1.68)	(1.60)
3	0.42	0.45	0.46	0.46	0.00	-0.05	-0.03	-0.04	0.42	0.40	0.43	0.42
	(2.77)	(2.82)	(2.78)	(2.79)	(0.03)	(-0.32)	(-0.21)	(-0.28)	(2.29)	(1.88)	(2.11)	(2.07)
4	0.73	0.60	0.58	0.58	-0.10	-0.18	-0.08	-0.15	0.62	0.42	0.50	0.43
	(3.94)	(3.70)	(3.40)	(3.43)	(-0.62)	(-1.04)	(-0.50)	(-0.92)	(3.12)	(1.99)	(2.27)	(1.91)
5(High)	1.30	1.08	0.90	0.75	-0.20	-0.38	-0.36	-0.33	1.09	0.69	0.53	0.42
	(4.98)	(4.33)	(3.85)	(3.58)	(-0.91)	(-1.59)	(-1.52)	(-1.41)	(4.37)	(2.48)	(1.97)	(1.57)
5-1	1.69	1.18	0.87	0.60	-0.27	-0.57	-0.59	-0.46	1.42	0.61	0.28	0.14
	(5.68)	(4.97)	(4.24)	(3.42)	(-0.90)	(-2.07)	(-2.06)	(-1.76)	(4.78)	(2.24)	(1.09)	(0.54)

Table 6: Cash-flow and discount-rate exposure for funds sorted on past-year total timing ability

Each quarter funds are sorted into quintiles according to their past-year total timing performance, which is the sum of abnormal returns stemming from cash-flow (CF) timing and discount-rate (DR) timing. The Henriksson-Merton coefficients for cash-flow timing (Panel A) and discount-rate timing (Panel B) are reported for each fund quintile over one of the subsequent four quarters after quintile formation. Specifically, the dependent variable is the average across all funds in each quintile of differential fund betas (a fund's beta in excess of the average of past betas for this fund) in the i^{th} quarter after quintile formation, where $i = 1, 2, 3, 4$. The independent variable is a dummy variable that is defined on the cash-flow return component (Panel A) or the discount-rate return component (Panel B) in the $i + 1^{th}$ quarter after quintile formation, taking a value of one if the corresponding return component is positive and zero otherwise. Henriksson-Merton coefficients are the regression coefficients on these four dummy variables, with one dummy variable in one regression for one of the subsequent four quarters. t-statistics reported in parenthesis are calculated based on Newey-West standard error. The time-series averages of equally weighted fund cash-flow betas and fund discount-rate betas across funds in each quintile are presented in Panels C and D, respectively, for each of the subsequent four quarters.

	Panel A: Timing CF news				Panel B: Timing DR news			
	q1	q2	q3	q4	q1	q2	q3	q4
1(Low)	-0.05	-0.02	0.00	0.04	0.04	0.03	0.02	0.01
	(-0.95)	(-0.46)	(0.09)	(0.85)	(1.56)	(1.13)	(0.87)	(0.63)
2	0.03	0.04	0.04	0.05	0.03	0.02	0.02	0.02
	(0.63)	(0.82)	(0.95)	(1.03)	(1.29)	(1.02)	(0.87)	(0.86)
3	0.07	0.08	0.08	0.08	0.02	0.01	0.01	0.01
	(1.61)	(1.67)	(1.66)	(1.56)	(0.92)	(0.77)	(0.31)	(0.56)
4	0.13	0.12	0.12	0.10	0.00	0.00	0.00	0.00
	(2.64)	(2.37)	(2.34)	(2.03)	(0.06)	(0.09)	(0.05)	(0.10)
5(High)	0.21	0.20	0.17	0.14	-0.03	-0.02	-0.01	0.00
	(3.39)	(3.39)	(2.88)	(2.46)	(-0.83)	(-0.60)	(-0.38)	(0.02)
5-1	0.26	0.23	0.16	0.10	-0.07	-0.05	-0.03	-0.01
	(3.65)	(3.59)	(2.86)	(1.92)	(-1.68)	(-1.27)	(-0.93)	(-0.43)

	Panel C: Average CF betas				Panel D: Average DR betas			
	q1	q2	q3	q4	q1	q2	q3	q4
1(Low)	1.03	1.04	1.04	1.04	-1.05	-1.05	-1.04	-1.04
2	1.00	1.00	1.00	1.00	-1.01	-1.01	-1.01	-1.01
3	0.99	0.99	1.00	1.00	-1.00	-1.00	-1.00	-1.00
4	1.01	1.01	1.02	1.02	-1.02	-1.02	-1.02	-1.02
5(High)	1.07	1.07	1.07	1.08	-1.08	-1.08	-1.08	-1.08
5-1	0.03	0.03	0.04	0.04	-0.03	-0.03	-0.03	-0.04

Table 7: Aggregated differential cash-flow beta and future aggregate cash-flow news

This table reports the results of predictive regressions of future aggregate cash-flow news as follows:

$$X_{t+1,t+j} = a + bADCFbeta_t + cX_{t-j+1,t} + \epsilon_{t+1,t+j},$$

where $X_{t+1,t+j}$ is cumulative aggregate cash-flow news starting from the beginning of quarter $t+1$ to the end of quarter $t+j$, and $j = 1, 2, 3, 4$ (quarters) is a "look-ahead" horizon. $ADCFbeta_t$ is quarter-t aggregated differential cash-flow beta, calculated as equally weighted differential cash-flow betas (a fund's cash-flow beta in excess of the average of the fund's past cash-flow betas) across funds in the top decile sorted in quarter t on past-year total timing ability. Standard errors are calculated based on the Newey-West approach with a lag of $j-1$. Panels A and B present the results for $ADCFbeta$ that is constructed without and with applying a back-testing procedure, respectively, of Mamaysky, Spiegel, and Zhang (2007) in selecting funds in the top decile.

$X_{t+1,t+j}$	1-q CF news	2-q CF news	3-q CF news	4-q CF news
Panel A: Without back testing				
$ADCFbeta_t$	0.100	0.180	0.231	0.248
	(4.32)	(3.27)	(2.79)	(2.19)
Adj. R-squared	0.254	0.246	0.217	0.165
$ADCFbeta_t$	0.047	0.152	0.232	0.274
	(1.85)	(2.50)	(2.46)	(2.13)
$X_{t-j+1,t}$	0.542	0.164	-0.005	-0.102
	(4.65)	(1.31)	(-0.04)	(-0.59)
Adj. R-squared	0.467	0.258	0.208	0.163
Panel B: With back testing				
$ADCFbeta_t$	0.100	0.183	0.242	0.266
	(4.60)	(3.60)	(3.22)	(2.62)
Adj. R-squared	0.285	0.290	0.271	0.217
$ADCFbeta_t$	0.050	0.161	0.248	0.296
	(2.02)	(2.89)	(2.92)	(2.57)
$X_{t-j+1,t}$	0.522	0.138	-0.027	-0.126
	(4.39)	(1.20)	(-0.23)	(-0.82)
Adj. R-squared	0.478	0.297	0.264	0.221

Table 8: Aggregated differential cash-flow beta and long-term cash-flow news

This table reports the results of predictive regressions of future aggregate cash-flow (CF) news as follows:

$$X_{t+m:t+m-1+n} = a + bADCFbeta_t + cX_{t-3:t} + \epsilon_{t+m:t+n},$$

where X represents aggregate CF news, $m = 1, 5, 9, 13, 17$ quarters, and $n = 4, 8, 12, 16, 20$ quarters. $ADCFbeta_t$ is quarter-t aggregated differential cash-flow beta, calculated as equally weighted differential cash-flow betas (a fund's cash-flow beta in excess of the average of the fund's past cash-flow betas) across funds in the top decile sorted in quarter t on past-year total timing ability. Standard errors are calculated based on the Newey-West approach with a lag of $n-1$. Panels A and B present the results for $ADCFbeta$ that is constructed without and with applying a back-testing procedure, respectively, of Mamaysky, Spiegel, and Zhang (2007) in selecting funds in the top decile.

Panel A: Without back testing									
$X_{t+m:t+m-1+n}$	$X_{t+1:t+4}$	$X_{t+1:t+8}$	$X_{t+1:t+12}$	$X_{t+1:t+16}$	$X_{t+1:t+20}$	$X_{t+5:t+8}$	$X_{t+9:t+12}$	$X_{t+13:t+16}$	$X_{t+17:t+20}$
$ADCFbeta_t$	0.248	0.209	0.180	0.244	0.301	-0.040	-0.014	0.076	0.051
	(2.19)	(1.33)	(1.11)	(1.05)	(1.03)	(-0.43)	(-0.11)	(0.82)	(0.91)
Adj. R-squared	0.165	0.046	0.020	0.042	0.058	-0.007	-0.011	0.003	-0.006
$ADCFbeta_t$	0.248	0.211	0.182	0.246	0.304	-0.040	-0.013	0.075	0.053
	(2.20)	(1.34)	(1.11)	(1.04)	(1.03)	(-0.42)	(-0.10)	(0.80)	(0.93)
$X_{t-3:t}$	-0.021	0.020	0.007	-0.022	0.004	0.028	-0.008	-0.008	0.001
	(-0.21)	(0.24)	(0.09)	(-0.29)	(0.04)	(0.26)	(-0.09)	(-0.08)	(0.01)
Adj. R-squared	0.156	0.036	0.009	0.030	0.047	-0.019	-0.024	-0.012	-0.020
Panel B: With back testing									
$ADCFbeta_t$	0.266	0.232	0.193	0.213	0.229	-0.035	-0.026	0.034	0.011
	(2.62)	(1.58)	(1.37)	(1.05)	(0.90)	(-0.39)	(-0.23)	(0.40)	(0.21)
Adj. R-squared	0.217	0.067	0.030	0.034	0.033	-0.007	-0.010	-0.009	-0.013
$ADCFbeta_t$	0.272	0.240	0.203	0.220	0.242	-0.033	-0.025	0.030	0.016
	(2.65)	(1.61)	(1.42)	(1.07)	(0.92)	(-0.36)	(-0.21)	(0.35)	(0.30)
$X_{t-3:t}$	-0.025	0.017	0.013	-0.016	0.017	0.027	-0.009	-0.003	0.005
	(-0.26)	(0.21)	(0.16)	(-0.21)	(0.17)	(0.25)	(-0.11)	(-0.04)	(0.04)
Adj. R-squared	0.215	0.061	0.022	0.025	0.025	-0.020	-0.023	-0.024	-0.027

Table 9: Aggregated differential cash-flow beta and future macro activities

This table reports the results of predictive regressions of future macro activities as follows:

$$X_{t+1,t+j} = a + bADCFbeta_t + cX_{t-j+1,t} + \epsilon_{t+1,t+j},$$

where $X_{t+1,t+j}$ is a cumulative macro variable starting from the beginning of quarter $t+1$ to the end of quarter $t+j$, and $j = 1, 2, 3, 4$ quarters—a "look-ahead" horizon. $ADCFbeta_t$ is quarter-t aggregated differential cash-flow beta, calculated as equally weighted differential cash-flow betas (a fund's cash-flow beta in excess of the average of the fund's past cash-flow betas) across funds in the top decile sorted in quarter t on past-year total timing ability. Macro variables include GDP growth, industrial production (IP) growth, and the Chicago Fed National Activity Index (CFNAI). Standard errors are calculated based on the Newey-West approach with a lag of $j-1$. Panels A and B present the results for $ADCFbeta$ that is constructed without and with applying a back-testing procedure, respectively, of Mamaysky, Spiegel, and Zhang (2007) in selecting funds in the top decile.

$X_{t+1,t+j}$	GDP growth				IP growth				CFNAI			
	1-q	2-q	3-q	4-q	1-q	2-q	3-q	4-q	1-q	2-q	3-q	4-q
Panel A: Without back testing												
$ADCFbeta_t$	0.004	0.007	0.010	0.010	0.011	0.019	0.025	0.028	1.818	3.376	4.429	4.895
	(2.01)	(1.43)	(1.17)	(0.87)	(2.39)	(1.65)	(1.33)	(1.13)	(2.60)	(1.72)	(1.31)	(1.05)
Adj. R-squared	0.044	0.040	0.036	0.022	0.059	0.063	0.059	0.049	0.072	0.068	0.055	0.039
$ADCFbeta_t$	0.003	0.007	0.010	0.011	0.006	0.019	0.025	0.029	0.413	3.205	4.398	5.018
	(1.33)	(1.46)	(1.20)	(0.91)	(1.80)	(1.63)	(1.39)	(1.16)	(1.17)	(1.69)	(1.38)	(1.07)
$X_{t-j+1,t}$	0.510	-0.156	-0.041	0.011	0.520	-0.169	-0.195	-0.013	0.791	-0.430	-0.382	-0.015
	(5.78)	(-0.61)	(-0.47)	(0.22)	(3.72)	(-1.06)	(-1.34)	(-0.23)	(7.41)	(-1.38)	(-1.28)	(-0.16)
Adj. R-squared	0.290	0.046	0.032	0.015	0.314	0.078	0.083	0.041	0.654	0.106	0.076	0.032
Panel B: With back testing												
$ADCFbeta_t$	0.005	0.008	0.011	0.012	0.011	0.020	0.027	0.031	1.925	3.646	4.877	5.470
	(2.34)	(1.63)	(1.41)	(1.07)	(2.63)	(1.82)	(1.52)	(1.35)	(2.88)	(1.98)	(1.55)	(1.27)
Adj. R-squared	0.066	0.054	0.058	0.037	0.079	0.081	0.081	0.073	0.094	0.094	0.080	0.060
$ADCFbeta_t$	0.003	0.008	0.012	0.013	0.007	0.020	0.029	0.033	0.593	3.624	5.101	5.941
	(1.77)	(1.71)	(1.51)	(1.19)	(2.02)	(1.85)	(1.65)	(1.41)	(1.67)	(2.03)	(1.69)	(1.35)
$X_{t-j+1,t}$	0.500	-0.151	-0.056	0.014	0.514	-0.163	-0.200	-0.015	0.779	-0.429	-0.380	-0.023
	(5.70)	(-0.60)	(-0.61)	(0.29)	(3.66)	(-1.04)	(-1.39)	(-0.27)	(7.39)	(-1.42)	(-1.30)	(-0.25)
Adj. R-squared	0.304	0.066	0.064	0.042	0.322	0.099	0.115	0.073	0.658	0.138	0.110	0.063

Table 10: Other performance measures for funds sorted on past-year total timing ability

Each quarter funds are sorted into quintiles according to their past-year total timing performance, which is equal to abnormal returns from both cash-flow timing and discount-rate timing. This table presents the time-series average of equally weighted quarterly fund portfolio performance across funds in each quintile over one of the subsequent four quarters after the formation quarter. Fund portfolio performance is measured using fund net returns after expenses, fund hold-based returns before expenses, and fund portfolio DGTW-adjusted returns. t-statistics reported in parenthesis are calculated based on Newey-West standard error. Panels A and B present timing performance without and with applying a back testing procedure of Mamaysky, Spiegel, and Zhang (2007), respectively, in selecting funds in each quintile.

Panel A	Net returns				Holding-based returns				DGTW adjusted returns			
	q1	q2	q3	q4	q1	q2	q3	q4	q1	q2	q3	q4
1(Low)	2.14	2.10	2.05	2.24	2.36	2.31	2.25	2.67	-0.09	-0.11	-0.12	-0.04
	(2.20)	(2.17)	(2.12)	(2.40)	(2.19)	(2.13)	(2.07)	(2.58)	(-0.59)	(-0.73)	(-0.75)	(-0.27)
2	2.22	2.30	2.21	2.28	2.45	2.50	2.41	2.70	-0.02	0.01	-0.05	-0.01
	(2.47)	(2.58)	(2.49)	(2.63)	(2.47)	(2.52)	(2.41)	(2.83)	(-0.16)	(0.07)	(-0.46)	(-0.07)
3	2.36	2.51	2.38	2.43	2.54	2.66	2.56	2.88	-0.03	0.04	0.02	0.04
	(2.72)	(2.90)	(2.76)	(2.83)	(2.63)	(2.74)	(2.62)	(3.04)	(-0.23)	(0.34)	(0.18)	(0.36)
4	2.64	2.64	2.65	2.64	2.82	2.82	2.81	3.10	0.14	0.13	0.12	0.13
	(3.04)	(3.00)	(3.02)	(3.07)	(2.95)	(2.87)	(2.86)	(3.28)	(1.14)	(1.01)	(1.05)	(1.25)
5(High)	2.87	2.92	2.86	2.78	3.15	3.11	3.10	3.29	0.20	0.18	0.21	0.13
	(3.14)	(3.19)	(3.12)	(2.99)	(3.15)	(3.09)	(3.03)	(3.26)	(1.36)	(1.33)	(1.63)	(1.03)
5-1	0.73	0.81	0.82	0.54	0.79	0.80	0.85	0.62	0.29	0.29	0.33	0.17
	(2.36)	(2.73)	(3.22)	(2.49)	(2.26)	(2.51)	(2.95)	(2.46)	(1.51)	(1.70)	(2.14)	(1.26)

Panel B	Net returns				Holding-based returns				DGTW adjusted returns			
	q1	q2	q3	q4	q1	q2	q3	q4	q1	q2	q3	q4
1(Low)	2.17	2.07	1.92	2.17	2.40	2.27	2.16	2.61	-0.13	-0.15	-0.18	-0.09
	(2.17)	(2.09)	(1.98)	(2.32)	(2.16)	(2.09)	(1.97)	(2.50)	(-0.70)	(-0.93)	(-0.97)	(-0.54)
2	2.25	2.25	2.23	2.26	2.49	2.47	2.53	2.68	-0.02	-0.02	-0.00	-0.06
	(2.51)	(2.52)	(2.51)	(2.58)	(2.49)	(2.48)	(2.52)	(2.80)	(-0.19)	(-0.13)	(-0.02)	(-0.46)
3	2.33	2.44	2.44	2.58	2.57	2.63	2.65	3.12	0.00	0.03	0.06	0.16
	(2.69)	(2.81)	(2.82)	(3.02)	(2.69)	(2.70)	(2.70)	(3.31)	(0.02)	(0.21)	(0.50)	(1.26)
4	2.58	2.83	2.78	2.68	2.90	2.96	3.02	3.17	0.16	0.17	0.12	0.14
	(3.00)	(3.32)	(3.15)	(3.07)	(3.06)	(3.09)	(3.04)	(3.31)	(1.27)	(1.27)	(0.83)	(1.12)
5(High)	2.88	2.84	3.00	2.76	3.12	3.12	3.12	3.30	0.23	0.24	0.22	0.13
	(3.22)	(3.05)	(3.23)	(2.93)	(3.18)	(3.05)	(3.05)	(3.24)	(1.39)	(1.48)	(1.43)	(0.91)
5-1	0.71	0.77	1.07	0.59	0.72	0.85	0.96	0.69	0.36	0.39	0.39	0.22
	(1.79)	(2.23)	(3.41)	(1.93)	(1.59)	(2.24)	(2.68)	(2.13)	(1.39)	(1.85)	(1.96)	(1.24)

Table 11: Negative discount-rate timing and aggregate fund net flows

Panel A summarizes results of the regressions of the concurrent and next-quarter unexpected market return and its cash-flow and discount-rate return components on aggregate fund net flows. Aggregate fund net flow is defined as inflow minus outflow, in aggregate, from investors to equity funds as a percentage of prior quarter-end aggregate AUM. This variable is then converted in IBES quarters (see Section 6). t-statistics are reported in parenthesis based on Newey-West standard error with a lag of four. Panel B presents the regressions of differential cash-flow beta, differential discount-rate beta, and differential unexpected-market-return beta on aggregate fund net flow. Differential beta is defined as a fund's beta in the current quarter in excess of the average of the fund's beta in previous quarters. Panel C reports the regression results of

$$tim_{f,j,t+1} = b_0 + b_1 flowdm_t + b_2 flowdm_t^2 + b_3 flow2nd_t + b_X X_t$$

where $tim_{f,j,t}$ defined by (6) is timing performance for fund f in response to factor j (cash-flow or discount-rate market return component, or unexpected market return) in IBES quarter t, $flowdm_t$ is demeaned aggregate net flow, $flowdm_t^2$ is the square of demeaned aggregate net flow, $flow2nd_t = (1.001 flow_t - 0.016)(1.093 * flow_t - 0.051)$, $flow_t$ is aggregate net flow, and X_t represent demeaned fund characteristics. Fund characteristics include fund size (measured by log TNA), fund expense ratio, fund age, past-year individual fund net flow, flow volatility (the volatility of monthly fund net flows over the past year), fund return volatility (the volatility of monthly fund net returns over the past year), and CRSP turnover ratio. t-statistics reported in parentheses for Panels B and C are calculated based on heteroskedasticity-robust standard errors clustered by fund and quarter.

Panel A	1	2	3	4	5	6
	Cash-flow component		Discount-rate component		Unexpected return	
	Current qr	Next qr	Current qr	Next qr	Current qr	Next qr
Constant	-0.014	-0.015	0.022	-0.016	-0.036	0.002
	(-1.03)	(-1.13)	(1.23)	(-0.92)	(-2.98)	(0.13)
Aggregate net flows	0.814	0.870	-1.114	1.001	1.928	-0.131
	(1.94)	(2.36)	(-2.09)	(1.80)	(5.15)	(-0.34)
Adjusted R-squared	0.047	0.055	0.030	0.023	0.159	-0.008

Panel B	Cash-flow beta differential	Discount-rate beta differential	Unexpected-return beta differential
Constant	0.012	0.051	-0.045
	(0.43)	(4.39)	(-4.37)
Aggregate net flows	-0.278	-1.093	0.958
	(-0.26)	(-1.93)	(1.84)
Adjusted R-squared	0.000	0.008	0.006

Panel C	1	2	3	4	5	6	7	8
	Cash-flow timing		Discount-rate timing		Discount-rate timing		Unexpected-return timing	
Constant(%)	0.467	0.465	0.060	0.062	0.116	0.123	0.036	0.026
	(2.31)	(2.29)	(0.53)	(0.52)	(0.95)	(0.95)	(0.41)	(0.29)
Agg. net flows (demeaned)	-0.206	-0.242	0.438	0.423	0.113	0.071	0.187	0.142
	(-1.21)	(-1.28)	(2.48)	(2.42)	(1.57)	(0.85)	(1.84)	(1.39)
Agg. net flows squared	1.236	1.260	-9.697	-10.519			-3.412	-3.685
	(0.43)	(0.40)	(-2.14)	(-2.25)			(-1.37)	(-1.43)
2nd-order agg. net flows					-8.861	-9.612		
					(-2.14)	(-2.25)		
Fund size		-0.000		-0.000		-0.000		-0.000
		(-0.41)		(-1.83)		(-1.83)		(-1.10)
Expense ratio		-0.071		0.003		0.003		0.010
		(-1.11)		(0.06)		(0.06)		(0.28)
Fund age		0.000		0.000		0.000		0.000
		(0.93)		(1.89)		(1.89)		(1.57)
Fund flow		-0.000		-0.000		-0.000		-0.000
		(-0.38)		(-1.09)		(-1.09)		(-0.40)
Flow volatility		0.006		-0.002		-0.002		0.001
		(1.12)		(-0.55)		(-0.55)		(0.26)
Fund ret volatility		-0.034		-0.067		-0.067		-0.077
		(-0.56)		(-1.22)		(-1.22)		(-1.76)
Fund turnover ratio		0.001		-0.001		-0.001		0.000
		(2.91)		(-1.60)		(-1.60)		(0.82)
Adjusted R-squared	0.008	0.011	0.060	0.068	0.060	0.068	0.018	0.026