Cashflow timing vs. discount-rate timing: An examination of mutual fund market-timing skills

Chunhua Lan[1] and Russ Wermers[2]

ABSTRACT

We measure the ability of professional investment managers in timing cashflow vs. discount-rate news, the two components of market returns. We find that the average U.S. equity mutual fund exhibits cashflow-timing skills of 2.12% per year, but discount-rate timing of -0.84%; cashflow-timing skills strongly persist over future quarters. The misspecification of market-timing skills accounts for the failure of prior research to locate skilled timing funds; such managers predict low-volatility cashflow news in the face of high-volatility discount-rate news, making skills difficult to detect with traditional models. Importantly, we find that value funds outperform growth funds in timing cashflow news.

Keywords: Cashflow timing, discount-rate timing, market timing

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[1] Faculty of Business Administration, University of New Brunswick, Fredericton, NB, Canada, E3B5A3; Tel: (506) 453-4942; email: clan@unb.ca. [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, Philip Dybvig, Roger Edelen, Allaudeen Hameed, Jennifer Huang, Min Kim, Neal Stoughton, Stijn Van Nieuwerburgh, Chengdong Yin, and seminar participants at the Institute of Financial Studies at Southwestern University of Finance and Economics (Chengdu, China), Peking University, the 2016 Finance Down Under conference, Financial Management Association 2016, American Finance Association 2017, and Asian Finance Association 2017 (Seoul) meetings for their valuable comments.

1 Introduction

Market timing is one important dimension through which professional fund managers can add value for their investors. A skilled manager, when implementing timing, can strategically increase the market exposure of her fund portfolio in anticipation of market upturns, and decrease it in anticipation of market declines. Empirically, the prevailing literature suggests that the average mutual fund exhibits little, or even negative market-timing ability.[1] One reason for such a finding, as we show in this paper, 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, it is well known that stock market prices vary either because of changing expectations of future cashflows 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 a central role in driving aggregate stock price movements.[2]

Active fund managers, as sophisticated investors, may recognize cashflow expectation changes and discount-rate changes as different drivers of price variability, and accordingly exploit their cashflow and discount-rate information differently. Indeed, aggregate cashflow news is fundamentals-related and covaries positively with macroeconomic activities, whereas discount rates are sentiment-related. In the finance industry, most security analysts and active portfolio managers are well-trained (e.g., through the CFA certification) in forecasting cashflows to evaluate stocks, either individually or for the aggregate market. But, they rely on simple models, such as the CAPM, to project discount rates and these projections are typically non-time-varying.

Discount-rate changes, as prior studies show, are not only difficult to forecast in real time, but also much more volatile than expected cashflow changes. That is, unexpected market

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

[2]For evidence on how differential exposure to cashflow risk helps to explain stock return 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 price variation, see Bansal and Yaron (2004), Ang and Bekaert (2007), Larrain and Yogo (2008), van Binsbergen and Koijen (2010), Koijen and van Nieuwerburgh (2011), and Chen, Da, and Priestley (2012).

returns are composed of a high-volatility, discount-rate component and a low-volatility, cashflow component[3]. As a result, skills in timing cashflows, if they exist among professional managers, are extremely difficult to detect when timing is measured through an econometric model that packages market cashflow and discount-rate return components into one factor, since high-volatility discount-rate changes act as noise in this one-factor setting. Put differently, if managers chiefly have skills in forecasting changes in cashflows, separating timing efforts into cashflow vs. discount-rate timing has the potential to add statistical power in detecting fund manager market-timing talents. Yet, to our knowledge, there is no existing study that separately measures cashflow versus discount-rate timing abilities of professional fund managers.

In this paper, we analyze the timing skills of actively managed U.S. equity mutual funds, using a set of enhanced models that separate cashflow timing from discount-rate timing. By separately measuring the cashflow and discount-rate components of the market return, we find that a substantial fraction of equity mutual fund managers possess significant market-timing skills due to their superior ability in shifting portfolio exposures to aggregate cashflows, but not to discount rates. For example, in our main tests in which the cashflow return component is constructed using changes in sell-side analysts' earnings forecasts as changes in cashflow expectations, the average fund generates market-timing abnormal returns of 1.28% per year, of which 2.12% comes from timing market cashflow news and -0.84% from timing market discount-rate news.[4] This finding suggests that mutual fund managers, on average, are able to forecast and profitably use aggregate cashflow information in choosing their stocks, but are unable to do so through forecasts of changing discount rates. This conclusion is robust to various alternative decomposition approaches that decomposes the market return into cashflow and discount-rate components, including a VAR model with price ratios as state variables.

[3]Several papers document that changing expectations of market-level discount rates exhibit a much higher level of volatility than changing expectations of market-level cashflows. See, for example, Table 3 of Campbell and Vuolteenaho (2004).

[4]In Section 6.3, we show that negative discount-rate timing returns can be attributed to equity mutual fund managers shifting their portfolios in the same direction as investor sentiment, in order to attract investors flows (or to stem outflows), which exposes the fund to a reversal in market discount rates during the following quarters due to mean-reversion in the investor sentiment. That is, funds' discount-rate betas shift in a direction opposite to a following-period discount-rate reversal, leading to a negative discount-rate timing return component.

A cross-sectional examination reveals further striking and contrasting patterns of cashflow timing versus discount-rate timing. For cashflow timing, we find significantly positive abnormal returns for most funds, and no evidence of significantly negative abnormal returns for others. In contrast, for discount-rate timing, we find significantly negative abnormal returns for some funds, but no evidence of significantly positive performance for others. Because cashflow timing returns are, on average, larger in magnitude than (negative) discount-rate timing returns, the cross-sectional patterns for overall timing performance (the sum of cashflow timing and discount-rate timing) are similar to those for cashflow timing. Additionally, cashflow timing ability is strongly persistent, but there is little evidence of persistence in either positive or negative discount-rate timing performance. These results suggest that many fund managers possess cashflow timing talents, and, because of their inability to time discount rates, their overall market timing return is reduced but not eliminated.[5]

Different characteristics associated with cashflows and discount rates help explain the preceding different timing patterns. Cashflows are fundamentals-related, and covary positively with macroeconomic activities.[6] In choosing securities, skilled fund managers can potentially use their insights about economic developments to form their views of market-level cashflows. In contrast, discount rate predictability is much harder to exploit in real time. Despite some evidence in favor of discount rate 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 especially poor out-of-sample forecasts, which indicate that professional managers may face enormous difficulties in timing discount rates.[7]

We further investigate the mechanism through which U.S. equity fund managers tilt their portfolios to execute cashflow timing. We find that skilled managers use both diversified

[5]In the cross-section of stocks, there is a negative correlation between cashflow beta and discount-rate beta, so a professional manager, when selecting stocks to increase her fund's cashflow beta in anticipation of good cashflow news, is likely to (mechanically) lower her fund's discount-rate beta (i.e., make it more negative). As market-level cashflow news and discount-rate news are positively correlated (Campbell and Vuolteenaho, 2004; Lettau and Ludvigson, 2005), if a portfolio manager's cashflow anticipation is correct, then positive cashflow timing returns are expected to be (mechanically) accompanied by some level of negative discount-rate timing performance for her fund. However, this mechanical effect is relatively small.

[6]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%.

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

sector “bets" and individual security “bets". In particular, skilled market-timers implement industry rotation by strategically tilting their portfolios toward high (low) cashflow-sensitivity industries in anticipation of positive (negative) changes in aggregate cashflows. They typically increase their portfolio weights in cyclical sectors before an upswing in aggregate cashflows, and in defensive sectors before a decline. Within an industry, they tilt toward (away from) value stocks and relatively small-capitalization stocks when anticipating good (poor) aggregate cashflow news due to the high cashflow sensitivities of these two types of stocks (Campbell and Vuolteenaho, 2004).

Key to our approach is that, through separating cashflow timing and discount-rate timing, we 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 undifferentiated factor, as conducted in the literature, we find insignificant timing ability for the average fund, consistent with prior research. Because market returns consist of a low-volatility cashflow component and a high-volatility discount-rate component, our approach allows a careful extraction of skills in forecasting the low-volatility cashflow component, in contrast to prior approaches.

We next investigate the predictability in funds having timing skills. We propose a simple timing metric—past-year total timing performance, defined as the sum of past-year cashflow and past-year discount-rate timing abnormal returns, which is different from timing performance measured using a single, undifferentiated factor. Using this metric, we identify funds with superior overall market-timing skills; such superiority mostly stems from their cashflow-timing talents. Specifically, funds in the quintile with the best past-year total timing performance earn a significant cashflow timing abnormal return of 3.57% over the next year, which is 3.58% higher than that earned by funds in the worst quintile. Even though discount-rate timing partially reduces their performance, the annual total timing return for this best group is 2.49%, which is 1.86% higher than that of the worst group. These timing spreads between the two extreme fund quintiles are not only economically significant, but also statistically significant. Consistently, the best-quintile funds exhibit a significant ability to shift their cashflow betas in response to future market cashflow movements, while the worst-quintile funds do not. Therefore, our evidence shows that time variation in cashflow betas generates superior and persistent timing performance for top market-timers.

We also use several performance metrics to demonstrate that, compared with bottom timers, top market timers generate superior overall fund portfolio performance, and that market-timing is a dominant contributor to this outperformance. For example, using either fund net returns after expenses or fund gross returns before expenses, the spread of fund portfolio returns between the best and the worst timing quintiles is roughly 3% over the following year, which is much larger than the spread of 1% per year between these two extreme fund groups in terms of their stock-selection ability measured by fund portfolio DGTW-adjusted returns. This above-noted 1% spread is also less than the return difference between the groups with the best and worst stock-picking skills that have been documented in the literature. Thus, our findings also suggest 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.

In our main tests we construct cashflow news based on direct, model-free market prevailing cashflow expectations (Pástor, Sinha, and Swaminathan, 2008; Da and Warachka, 2009), and then back out discount-rate news. Using analyst forecasts as a proxy for market expectations of cashflows has been the standard in the accounting literature since the work of Fried and Givoly (1982) (Kothari, 2001; Kothari, So, and Verdi, 2016)). This standard is consistent with the asset management industry's practice of widely using sell-side analyst forecasts for security evaluation. Chen, Da, and Zhao (2013) find that cashflow innovations derived from analyst earnings forecasts explain a large portion of stock return variability at both the market and stock levels. The reason for adopting this decomposition approach is to avoid the misspecification sensitivity that traditional VAR-based decomposition methods face.[8] Such misspecification sensitivity can pose a serious problem when comparing the relative importance of cashflow vs. discount-rate news in explaining stock return variations (Chen and Zhao, 2009). Nevertheless, it is less of an issue in our context, as we measure *shifts* in mutual fund loadings on cashflow and discount-rate news, which are a function of VAR state variables; *changes* in fund portfolio weights are unlikely to be related to VAR

[8]In addition, misspecification errors in one-period VAR-based return expectations amplify in multiperiod expectations through the iterative process used in return decomposition when using a one-period VAR model.

specification errors, so VAR misspecification essentially has a small effect on timing performance when measured as the change in fund loadings multiplied by decomposed return components derived from the VAR specification. In addition, a placebo test demonstrates that index funds exhibit no timing skills, which suggests that our evidence of timing ability for actively managed mutual funds is not a result of any potential biases captured in our timing measures.

Our paper offers important contributions to the literature. First, it creates a new decomposition approach to measuring market-timing skills through separating market cashflow timing and discount-rate timing. This approach, as we argue, has significant statistical advantages. As a result, we provide evidence that the average equity mutual fund exhibits positive cashflow timing ability, in contrast to past studies, which find either little or negative (unconditional) timing abilities.[9]

Second, this paper segregates the timing skills of funds holding stocks with high book-to-market equity or (relatively) small capitalization, and compares them with growth funds and large-cap funds, respectively. We find strong evidence that value funds, and especially those value funds that hold smaller-cap stocks, exhibit substantially higher cashflow timing abnormal returns than their counterparts. These results provide important new evidence to the long-standing puzzle that value funds are much less likely to add value than growth funds in terms of stock-selection abilities (e.g., Kosowski, et al. (2006)). Our findings are the first in the literature to indicate that value funds, and especially smaller-capitalization value funds, add substantial value through a different channel: timing market cashflow news.

Third, using our total timing measure as a metric, we identify, ex ante, a subset of funds that earn significant 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

[9]While Bollen and Busse (2001), Elton, Gruber, and Blake (2012), Jiang, Yao, and Yu (2007), and Kacperczyk, van Nieuwerburgh, and Veldkamp (2014, 2016) document some market-timing skills of professional managers, none of these papers deliver insights on how market timing is done by professional managers through cashflow, instead of discount-rate, timing, which is important both from an econometric point of view, and for an understanding of the source of economically significant timing skills. In addition, our paper is the first to provide strong predictive power of market-timing skills through our proposed timing metric, and the first to demonstrate that market-timing is a strategy as profitable as stock-selection in adding value to managed assets in terms of a differential return timing measure.

(Kacperczyk, Sialm, and Zheng, 2005, 2008), active share (Cremers and Petajisto, 2009), R-squared from benchmark regressions (Amihud and Goyenko, 2013), peer track-records (Cohen, Coval, and Pástor, 2005), or network connections (Cohen, Frazzini, and Malloy, 2008). Further, the abnormal return spread between the best and the worst timing groups is comparable to that between the best and the worst stock-picking groups of funds. Our evidence suggests that market timing is a profitable investment strategy, and is as important as stock selection in adding value to managed assets.

Finally, unlike adopting stock-selection techniques that require exploiting firm-specific information with an exposure to potentially high idiosyncratic risk, implementing market-timing strategies involves exploiting systematic factors with a time-varying exposure to systematic risk. Because such time-varying 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 mechanisms used by professional investors, and lays an empirical foundation for building richer theoretical models of active fund skills.

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 further characterizes cashflow vs. discount-rate timing. Section 7 summarizes additional tests and robustness checks. We conclude in the last section.

2 Methodology

Prior studies investigating market-timing skills, starting with Treynor and Mazuy (1966) and Henriksson and Merton (1981), examine whether a fund manager increases her portfolio's market exposure in anticipation of an upswing in the stock market, and scales it down in anticipation of a decline. Put differently, their research explores whether a fund portfolio's CAPM beta at the beginning of a holding period covaries positively with the holding period market return. These studies implicitly assume that the market return is a one-piece object of market-timing efforts and reach the prevailing view that there is little or even negative market-timing ability.[10]

It is well known that stock market prices vary due to changing forecasts of future aggregate cashflows or changing forecasts of future market discount rates. As Campbell and Vuolteenaho (2004) stress, it is important to recognize the difference in these two components as risk factors since a rational multiperiod investor demands a greater reward for bearing cashflow risk than for bearing 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 cashflows, wealth decreases but future investment opportunities are virtually unchanged. Along with Campbell and Vuolteenaho (2004), a growing literature recognizes the importance of separating cashflow risk from discount-rate risk to explain both cross-sectional and time-series patterns in asset returns as well as some documented return anomalies.[11]

As sophisticated investors, mutual fund managers likely understand the importance of these two drivers of market return variation to their fund portfolios, and exploit cashflow information and discount-rate information differently. Aggregate cashflows are fundamental-related and covary positively with macroeconomic activities. In choosing securities, skilled fund managers can use their insights about economic growth as well as macro-level corporate productivity and investments to form their views of future market-level cashflows. In contrast, it is very hard to forecast variations in discount rates in real time.[12] Hence, separating timing efforts from cashflow and discount-rate perspectives can shed new light on our understanding of fund managers' market-timing skills.

When implementing market-timing strategies, a fund manager can vary 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

[10]Another line of research, including Ferson and Schadt (1996), argues that the negative market timing claimed by these studies is due to errors in measuring the CAPM beta.

[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.

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

classes of securities, such as bonds or options. Our paper concentrates on market-timing skills employed by U.S. equity mutual funds, thus, we measure how equity managers shift their equity portfolios to implement such timing strategies, including shifting their portfolios toward different sectors over time, as well as holding varying amounts of cash.

2.1 Cashflow and discount-rate components of market returns

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

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

where r_t is the log stock market return at time t, Δd_t denotes time-t aggregate 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 cashflows and discount rates, respectively, over an infinite horizon. For robustness, we also employ the Gordon (1962) model to construct the cashflow and discount-rate components of the market return in Section 7, and our main results stay similar.

2.2 Construction of fund beta

One way of implementing market-timing is to vary the sensitivity (beta) of a fund portfolio, in response to variations in conditioning variables, to systematic factors that affect asset returns. Without knowing the exact conditioning variables that a fund manager may employ and how they are used, however, identification of such timing abilities is difficult.[13] To avoid the need to choose such variables, we adopt a bottom-up approach, with fund holdings data, to estimate a fund beta at a point in time as the value-weighted average of stock betas for all stocks held in the fund portfolio. This approach has the advantage of not imposing a

[13]We note that some papers use a small set of macroeconomic variables, applied to returns-based regression models, as proxies for these conditioning variables, with some success, including Ferson and Schadt (1996) and Avramov and Wermers (2006). Our paper contributes to this literature and suggests that shifts in betas in response to macroeconomic conditions can be traced to shifts in cashflow betas, rather than discount-rate betas.

particular structure on the dynamic beta shifting of a portfolio manager, whether in response to publicly observable state variables or to private information. By facilitating precise measurement of dynamic beta shifts by fund managers, this bottom-up approach is crucial to our identification of cashflow vs. discount-rate timing.

We first calculate stock betas by employing two models to capture systematic risk: a two-factor model with market cashflow and discount-rate return components as factors, and a one-factor model based on either unexpected market returns or market excess returns. Let $r_{i,t}$ be the time-t excess return on stock i, and let $K_{j,t}$ be the time-t return on factor j. To avoid look-ahead bias, we run the following regressions over the past 60-month rolling window, with at least 24 monthly observations available:

$$r_{i,t} = \alpha_i + \sum_{j=1}^{J} \beta_{i,j,t} K_{j,t} + \epsilon_{i,t}, \tag{2}$$

where $\beta_{i,j,t}$ is the time-t sensitivity of stock i to factor j, α_i and $\epsilon_{i,t}$ are the risk-adjusted excess returns and return residuals, respectively, of stock i over the window ending at time t. If the two-factor model is used in the above regression, cashflow and discount-rate betas for each stock are obtained;[14] If the one-factor model is employed, the CAPM beta is obtained.

Fund f's time-t sensitivity to factor j, $\beta_{f,j,t}$, is then calculated as the value-weighted average of stock betas across all stocks held by fund f:

$$\beta_{f,j,t} = \sum_{i=1}^{N_{f,t}} \omega_{i,f,t} * \beta_{i,j,t}, \tag{3}$$

where $\omega_{i,f,t}$ is the time-t portfolio weight of stock i in fund f, and $N_{f,t}$ is the number of stocks held by fund f at time t.[15]

Because fund holdings data are available at a quarterly frequency at most, following the convention in the mutual fund literature, we assume that fund holdings are valid starting at the end of a quarter until the end of the next quarter when fund holdings are updated.[16]

[14] Note that cashflow and discount-rate betas of Campbell and Vuolteenaho (2004) are univariate betas rather than two-factor betas.

[15] Note that we do not attempt to estimate the weight of cash, fixed-income, and other non-U.S. equity securities due to the incomplete information in CRSP on such holdings. In a later section, we test our results for robustness on the sample of funds that have CRSP data on cash holdings.

[16] If a fund reports its holdings semi-annually, we assume that fund holdings reported in a quarter stay the

Accordingly, in this paper we examine quarterly market-timing abnormal returns stemming from quarterly shifts in fund betas.

2.3 A differential return timing measure

Similar to Elton, Gruber, and Blake (2012), we define the market-timing contribution $tim_{f,j,t+1}$ for fund f in response to factor j in period $t+1$ as

$$tim_{f,j,t+1} = (\beta_{f,j,t} - \bar{\beta}_{f,j,t})K_{j,t+1} \tag{4}$$

where $K_{j,t+1}$ is the return on factor j in period $t+1$, $\beta_{f,j,t}$ is fund f's beta with respect to factor j at the end of period t, estimated according to (3), and $\bar{\beta}_{f,j,t}$ is fund f's target beta, which is defined as the average of the fund's beta over either the past or the full sample periods. We find that employing either definition of fund target beta delivers similar timing results. Because the timing measure based on the average of past betas can be adopted in real time, we report results based only on this definition.[17] $\beta_{f,j,t} - \bar{\beta}_{f,j,t}$ is called the "differential beta" of fund f in response to factor j. If a fund manager has superior skill in anticipating an upward (downward) movement in next-quarter factor returns, then she will shift her fund's exposure to the factor above (below) its target level at the end of the current quarter to attempt to achieve timing abnormal returns.

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

$$tim_{f,j} = \frac{1}{T}\sum_{t=1}^{T} tim_{f,j,t}, \tag{5}$$

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. Because the mean factor return has no effect on fund beta variation and should not impact

same in the next quarter if it lacks a new portfolio report.

[17]For a given fund, we require at least eight quarter-end estimated fund betas available in the past to calculate the time-series average as its target beta.

timing ability, to improve the power of our measure, we demean factor returns, $K_{j,t}$, by the time-series average before calculating the timing measure. Accordingly, two naive cases—not only a constant beta with random factor returns but also random betas with a constant factor return—should result in a zero timing measure over the sample period after demeaning the factor return.

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. These two databases are linked using MFLINKS from Wharton Research Data Services (WRDS). Thomson Reuters provides information on equity mutual fund holdings of common stocks at 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 observations where the year for the observation is prior to the reported fund-starting year, or where the name of the fund is 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 MFLINKS used in this paper. All the other data cover the sample period of January 1982 to December 2011.

3.1 Construction of market return components and fund betas

The traditional approach in finance estimates a VAR model to decompose the market return into cashflow news and discount-rate news as functions of state variables. In this approach, expectations of market returns in the distant future are imputed from the one-period forecast relation estimated from a VAR model. Then, discount-rate news is calculated as the revision in future discount rate expectations, using an iterative process on the one-period results, over an infinite horizon. Because predicting the equity premium from a pure time-series regression is a difficult task (Goyal and Welch, 2003, 2008), misspecification error in model-based return expectations is likely large and tends to amplify in multiperiod expectations through the iterative process. As a result, the traditional approach is quite sensitive to the choices of predictive variables and sample periods, which has been addressed by a recent line of research (Chen and Zhao, 2009; Chen, Da, and Zhao, 2013; Koijen and van Nieuwerburgh, 2011). Such misspecification sensitivity can be a serious problem when comparing the relative importance of cashflow and discount-rate return components in explaining cross-sectional or time-series return variations (Chen and Zhao, 2009). It is, however, less of an issue in our context because professional managers would not have an ability to time noise in a proxy of cashflow and discount-rate news. If a decomposition approach captured just random noise, then it would prevent us from finding timing ability. Robust evidence based on the traditional VAR decomposition approach will be discussed later in the paper.

Nevertheless, to avoid the effect of model-based misspecification sensitivity, we construct cashflow news using direct, model-free market prevailing cashflow expectations, similar to Pástor, Sinha, and Swaminathan (2008), Da and Warachka (2009), and Chen, Da, and Zhao (2013), and then back out discount-rate news. Using analyst forecasts as a proxy for market expectations, though still debated, has been the standard in the accounting literature since the work of Fried and Givoly (1982) (for review articles see Kothari (2001), Bradshaw (2011), and Kothari, So, and Verdi (2016)).[18] This standard is consistent with the asset management industry's practice of widely using sell-side analyst forecasts for security evaluation. Chen, Da, and Zhao (2013) find that cashflow innovations derived from analysts' earnings forecasts explain a large portion of stock return variability at both the market and stock levels. Moreover, compared with forecasts from time-series models relying on publicly observed signals, analysts' earnings forecasts bring investors incremental information (Lang and Lundholm, 1996; Bowen, Davis, and Matsumoto, 2002). This information advantage is reflected in the fact that prices, trading activity, and liquidity all change around analysts' forecast revisions (Lys and Sohn, 1990; Asquith, Mikhail, and Au, 2005; Frankel, Kothari, and Weber, 2006). Importantly, forward-looking information from analysts' forecasts does not involve predictive regressions and therefore does not rely on coefficient stability and historical data; and the choice of state variables is a non-issue either. Both features help avoid the sensitivity issue the VAR-based approach faces. In addition, if our approach relying on analysts' earnings forecasts could not separate true cashflow news from discount-rate news to some extent, it would be difficult for us to detect timing skills, because mixing cashflow and discount-rate news is similar to treating the unexpected market return as a one-piece timing object, which, as prior research shows, leads to little timing ability.

Monthly analysts' earnings forecasts allow us to measure cashflow news at a 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 average of firm-level forecasts, weighted by firms' latest market capitalization. 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 dates, typically the third Thursday of 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 cumulative daily interest rates that are available

[18]Bradshaw et al. (2012) find that analysts' forecasts are inferior to random walk time-series forecasts for smaller or younger firms. This finding has little effect on our use of aggregated analysts' forecasts because small and young firms take quite small weights at the market level. Moreover, our results remain quite similar if we use analyst-forecasted earnings on the S&P500 index as a proxy for aggregate cashflow in order to exclude small or young firms.

from Kenneth French's web site) within an IBES month.

To construct the cashflow component of the market return $N_{CF,t+1}$ in (1), we employ a three-stage earnings growth model, similar to Da and Warachka (2009) and Pástor, Sinha, and Swaminathan (2008), to take advantage of analysts' earnings forecasts for different maturities. Let $X_{t,j}$ denote month-t expectations of future earnings in the next j^{th} year. Here we use only annual forecasts to avoid the seasonality issue.

In the first stage of the earnings growth model, expected earnings are obtained directly from analysts' forecasts:

$$X_{t,1} = A1_t, \quad X_{t,2} = A2_t, \tag{6}$$

$$X_{t,j} = X_{t,j-1}(1 + LTG_t), \quad j = 3,4,5. \tag{7}$$

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:

$$X_{t,j+1} = X_{t,j}[1 + LTG_t + \frac{j-4}{5}(\bar{g}_t - LTG_t)], \text{ for } j = 5,\ldots,9. \tag{8}$$

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. Together, the time-t expectation of log return on book equity $\theta_{t,j}$ in the next j^{th} year is:

$$\theta_{t,1+j} = \begin{cases} \log(1 + \frac{X_{t,1+j}}{B_{t,j}}) & \text{for } 0 \le j \le 9 \\ \log(1 + \frac{\bar{g}_t}{1-\Psi}) & \text{for } j \ge 10 \end{cases} \tag{9}$$

With replacement of log dividend growth in (1) by log returns on book equity under the assumption that the clean-surplus identity is satisfied, Vuolteenaho (2002) shows that cashflow news in month $t+1$, $N_{CF,t+1}$, can be represented as the difference between cashflow expectations over two consecutive months:[19]

$$N_{CF,t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \tilde{\theta}_{t,1+j}, \tag{10}$$

where $\tilde{\theta}_{t,j}$ is the log return on book equity in the next j^{th} year from month t, ρ is a log-linearization constant and equals 0.96 in our sample, and expected future cashflows implied from the three-stage growth model is:

$$E_t \sum_{j=0}^{\infty} \rho^j \tilde{\theta}_{t,1+j} = \sum_{j=0}^{9} \rho^j \theta_{t,1+j} + \frac{\rho^{10}}{1-\rho} \log(1 + \frac{\bar{g}_t}{1-\Psi}). \tag{11}$$

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.[20] To keep the decomposition identity in (1), we back out the market discount-rate news in IBES month $t+1$, $N_{DR,t+1}$, as the cashflow news minus unexpected market returns, $N_{CF,t+1} - (r_{t+1} - \mathrm{E_t r_{t+1}})$. Appendix A provides details for our data items.

Although we construct cashflow and discount-rate news using an approach different from the traditional VAR method, our conclusions are robust to VAR-based decompositions, which will be discussed in Section 7. The Internet Appendix shows that the correlation of cashflow news generated using these two methods is 0.75 (0.92 for discount-rate news), when similar forecasts for future cashflows are used. The high correlations suggest that the decompositions using the three-stage growth model vs. VAR model, though implemented differently, produce similar results. We further find that analysts' earnings forecasts, in aggregate, are a better predictor of future market-level cashflows than forecasts implied from

[19]Even if the levels of earnings forecasts are subject to optimistic biases, as long as such biases are slow-moving as documented by Mendenhall (1991) and Abarbanell and Bernard (1992), among others, the forecast revisions essentially reflect actual cashflow news. Nevertheless, we show in Section 7 that our results are robust to the adjustment of optimistic earnings forecasts.

[20]Forecasts are based on a rolling regression of past 60-month data with at least 24 monthly observations. Additionally, our results are similar if we use the smoothed PE ratio, the term spread or the dividend yield as the market return predictor, or if we impose the constraint of a non-negative expected market return.

the VAR model. These findings combined suggest that our proxy of cashflow and discount-rate news is a good alternative to the traditional VAR-based decomposition, which faces a model-based misspecification sensitivity issue.

Next, we estimate stock betas using IBES monthly data according to (2). Here, we assume that calendar quarter-end reported fund share holdings are valid at the IBES quarter-end (the third Thursday of the same month). Then, fund betas are calculated as the average of stock betas weighted by fund portfolio weights at the end of IBES quarters, as specified in (3). Even though IBES-quarterly fund betas are employed in this study, stock betas are estimated using IBES-monthly data to improve estimation precision. As a robustness check, we also calculate these betas using data in calendar dates, and our conclusions remain the same. Throughout the rest of the paper, for simplicity, we do not explicitly state "IBES" for IBES dates unless necessary for clarity.

Panel A of Table 1 presents standard deviations of the unexpected market return and its two components as well as correlations of these return components. Consistent with Campbell, Giglio, and Polk (2013)(Table 4), the standard deviation of discount-rate news roughly doubles that of cashflow news, and is slightly larger than that of unexpected market returns because cashflow news and discount-rate news are positively correlated. The correlation of IBES-quarterly cashflow news and discount-rate news is 0.54, comparable to 0.58 reported by Campbell, Giglio, and Polk who use calendar-quarterly data.[21] Moreover, the unexpected market return is strongly correlated with discount-rate news in magnitude but weakly correlated with cashflow news, which implies that discount-rate news dominates cashflow news in determining market return variability.

Panel B presents summary statistics of cashflow betas, discount-rate betas, and CAPM betas at both the stock and fund levels. A few points are noteworthy. First, discount-rate betas are negative because an increase in future discount rates decreases current stock prices, therefore lowering current returns. Second, all these three betas in magnitude are close to 1. Third, stock-level cashflow beta and discount-rate beta are negatively correlated, which indicates that a stock with high cashflow exposure generally has a high discount-

[21] Campbell and Vuolteenaho (2004) reports standard deviations and correlation of calendar-monthly cashflow and discount news, which are also comparable to summary statistics of our IBES-monthly cashflow news and discount-rate news.

rate exposure (a more negative discount-rate beta). When a manager strategically selects some stocks to shift her portfolio's cashflow exposure, her portfolio's discount-rate exposure (in magnitude) expands away from, or shrinks toward, zero when the cashflow exposure expands away from, or shrinks toward, zero, respectively—which is confirmed by the negative correlation between fund-level cashflow beta and discount-rate beta. Finally, the discount-rate beta (in magnitude) is highly correlated with the CAPM beta, because the discount-rate return component comprises a large portion of variability in the unexpected market return, consistent with prior research (e. g. Campbell and Vuolteenaho, 2004; Campbell, Giglio, and Polk, 2013).

4 Empirical analysis of timing performance

In this section, we provide evidence of cashflow and discount-rate timing abilities, as well as the importance of distinguishing between these two types of timing performance in evaluating market-timing skills of professional fund managers.

4.1 Cashflow timing and discount-rate timing

Table 2 presents timing performance in terms of the differential return timing measure specified in (5). 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 the average fund but also funds at extreme percentiles.

To test the statistical significance of these cross-sectional statistics, we follow a bootstrap approach that is developed by Kosowski, et al. (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 properties 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 bootstrapped factor returns by the corresponding 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 factor returns 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 Appendix B for details.

We also report t-statistics of the timing measure at these different percentiles for robustness. As discussed by Kosowski, et al. (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 in terms of abnormal returns.

Clearly, a substantial fraction of funds exhibit cashflow timing skills, as illustrated in Panel A of Table 2. The average fund adds value of 53 basis points per quarter, or 2.1% per year, for timing aggregate cashflows. 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 generated under the null of no timing ability produce a mean value higher than the actual value. Funds ranked in the top decile achieve an abnormal return of at least 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 (perverse) negative cashflow timing.

In contrast, Panel B shows that the average fund loses 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 90th and 95th percentiles, generate positive but insignificant abnormal returns, indicating no evidence of positive discount-rate timing ability.

On the other hand, funds in the left-tail distribution exhibit significantly negative timing performance. For instance, funds in the bottom decile experience a loss of at least 78 basis point per quarter.

The preceding different timing patterns are likely associated with different characteristics of cashflow information versus discount-rate information. 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 skilled, can obtain superior anticipation about future aggregate cashflows by analyzing comprehensive economic and financial data, and developing their own insights regarding future economic trends. On the other hand, despite evidence in favor of return (discount rate) forecastability, a recent literature questions the strength of statistical inference by pointing out issues such as biased coefficient estimates, unstable in-sample estimates, and poor out-of-sample return forecasts. Discount rates are also largely affected by changes in investor sentiment, which are hard to predict (Baker and Wurgler, 2007).

Adding together cashflow timing and discount-rate timing, which we call "total timing", for each fund, Panel C shows that this total timing performance is significantly positive for the average fund, of 32 basis points per quarter, or 1.28% per year. Note that the statistics of this total timing measure 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 also notice that funds in the right-side distribution of this measure, including the 75th, 90th, and 95th percentiles, achieve both economically and statistically significant and positive timing abnormal returns. For example, funds in the top decile achieve at least a 1.1% abnormal return per quarter. In contrast, there is no evidence of significantly negative total timing returns, 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 presents the results for timing the unexpected market return as one piece, as done by prior studies.[22] The difference between Panels C

[22] We find a similar level of timing performance whether taking the market excess return or the market unexpected return as a one-piece timing object.

and D is dramatic; when timing is measured using the undifferentiated market return, even funds in the right-tailed cross-sectional distribution deliver insignificant timing performance, whereas funds in the left tail exhibit significantly negative returns. The reason for such a dramatic difference is that the discount-rate market return component is more volatile than the cashflow component, so that skills in timing cashflows, by strategically shifting funds' cashflow exposure in response to anticipated future aggregate cashflow movements, are very difficult to detect through an econometric model that treats the (unexpected) market return as an undifferentiated object of marketing-timing efforts. Note that although cashflow news and discount-rate news add up to the unexpected market return, cashflow beta and discount-rate beta bear no simple linear relation with the CAPM beta (using the unexpected market return as the market factor),[23] because cashflow news and discount-rate news are not perfectly correlated. As a result, cashflow timing and discount-rate timing combined is not equal to unexpected-market-return timing. These results suggest that it is important to separately measure strategic shifts in risk exposure to market-level cashflow news and discount-rate news when evaluating fund managers' timing talents; otherwise, mutual funds tend to exhibit no market timing ability, as claimed by many prior studies.

4.2 Persistence of timing ability

We have shown that fund managers, if skilled, have a superior ability to achieve positive abnormal returns for timing aggregate cashflows, but have difficulty to do so in timing discount rates. Accordingly, we would expect that cashflow timing returns are persistent for skilled managers, but it is not the case for discount-rate timing performance. Compared with the cashflow return component, the discount-rate component comprises a larger portion of variability in the unexpected market return (Campbell and Vuolteenaho, 2004), so performance due to timing the unexpected market return as a one-piece object, similar to discount-rate timing performance, is unlikely to persist.

[23] Note that cashflow beta and discount-rate beta in this paper are calculated as standard two-factor betas with cashflow news and discount-rate news being two factors. On the other hand, Campbell and Vuolteenaho (2004) calculate cashflow beta and discount-rate beta as the covariance of stock returns with cashflow news and discount-rate news, respectively, then divided by variance of market unexpected returns. So, their cashflow beta and discount-rate beta add up to be CAMP beta, but this is not the case for our betas.

To test this persistence conjecture, each quarter, we sort all funds in our sample into deciles according to their past 1-, 3-, or 5-year timing performance, as specified in (4), separately for (i) cashflow timing, (ii) discount-rate timing, and (iii) unexpected-market-return timing. We then compute the average of the next-quarter abnormal returns of the corresponding timing measure across all funds in each decile. Table 3 presents the time-series averages across sorting quarters of these decile-averaged timing measures. The last two rows exhibit the timing return spread between past winner and past loser deciles.

Panel A demonstrates that cashflow timing performance is persistent. Next-quarter cashflow timing abnormal returns increase monotonically with past cashflow timing performance. Funds in the best deciles, formed on their past 1-, 3-, or 5-year performance, generate significant abnormal returns of 1.38%, 0.99%, and 0.89% per quarter, respectively. The decline in persistence as the look-back horizon increases indicates that timing skills deteriorate over time, possibly because investors are able to identify superior timers and the diseconomy-of-scale effects modeled by Berk and Green (2004) reduce abnormal returns. In contrast, funds in the worst deciles deliver poor cashflow timing performance. As a result, the return spreads between these two extreme deciles are both economically and statistically significant.

On the other hand, Panels B and C show little evidence of persistence in discount-rate timing and unexpected-market-return timing. Next-quarter timing abnormal returns do not monotonically increase with past performance for either of these two timing measures. Although the winner deciles continue to perform better than the loser deciles, the performance spreads between the two extreme deciles are not significant.

5 Identifying funds with timing skills

There exists a wide range of timing performance across funds, as we have shown, so identifying funds with market-timing skills, ex ante, is an important task for fund investors. For this purpose, we choose prior-year total timing performance, defined as the sum of past-year cashflow timing and past-year discount-rate timing abnormal returns, as a metric. The reason for this choice is that shifting a fund's cashflow exposure is likely to simultaneously alter its discount-rate exposure, and vice-versa. Therefore, a fund manager with superior information about future aggregate cashflows, when making timing decisions, should take into account a potentially adverse effect stemming from resulting shifts in discount-rate betas. In this section, we examine timing abnormal returns as well as overall fund portfolio performance for funds sorted on their past-year total timing ability in real time.

5.1 Characteristics of funds ranked on past-year total timing

We start by summarizing fund characteristics across fund quintiles formed on funds' past-year total timing ability. 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), the most recently available CRSP turnover ratio, and Active Share (Cremers and Petajisto, 2009). We also consider portfolio-weighted market capitalization of equity holdings and portfolio-weighted book-to-market equity (B/M) ratios of holdings, which are defined as the average of market-cap and B/M decile numbers, respectively, for all stocks held by a given fund, weighted by the fund's portfolio weights, after we rank all CRSP-listed common stocks each quarter into market-cap deciles and, separately, B/M deciles using breakpoints based on NYSE stocks. Using decile ranking is to reduce the influence of outliers and time trends in these two stock characteristics. We then average these fund characteristics across funds in each quintile for each sorting quarter, and take a time-series average across sorting quarters for each quintile.

A few points are noteworthy in Table 4. First, although top market timers manage smaller total net assets than other groups, fund size is not monotonically related to timing ability. Second, top timers exhibit somewhat higher portfolio turnover (98% per year), consistent with the evidence that they frequently shift fund portfolios' cashflow exposures, which we will show in Section 5.3. Nevertheless, top timers exhibit Active Share similar to that for poor timers, consistent with the finding that Active Share captures only stock-selection talents instead of skills in timing systematic factors. Third, top timers receive substantially larger inflows from investors, reinforcing our prior message that the diseconomy-of-scale effects modeled by Berk and Green (2004) ultimately lead to a deterioration in top market timers' ability to deliver net-of-fee abnormal returns. Finally, top market timers tend to tilt toward value stocks, consistent with the fact that compared with growth stocks, value stocks have higher cashflow betas (Campbell and Vuolteenaho, 2004), which facilitate value funds' exploitation of cashflow timing.

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

Each quarter we rank funds into quintiles based on their past-year total timing ability (the sum of cashflow timing and discount-rate timing performance). In each of the subsequent four quarters after the ranking quarter, we calculate the average cashflow timing, discount-rate timing, and total timing measures across funds in each quintile. Then, the time-series average across all ranking quarters of each timing measure for each quintile and for each of the subsequent four quarters is reported in Panel A of Table 5.

Note that cashflow timing performance is monotonically increasing with past-year total timing ability. For example, top timers (quintile 5) generate cashflow timing abnormal returns 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 over the next four quarters.

Different from the pattern in cashflow timing, there exists a weak and negative relation between discount-rate timing and past-year total timing rankings. Top timers produce insignificantly small and negative discount-rate timing returns over the next four quarters, whereas bottom timers generate insignificantly small and positive returns. One reason for this result is that a stock's cashflow beta and discount-rate beta are generally negatively correlated, as discussed in Section 3.1 (Table 1). When anticipating a rise in aggregate cashflows, a skilled manager shifts upward her fund portfolio's cashflow exposure by tilting toward stocks with high cashflow betas, and her fund portfolio's discount-rate beta is likely to become more negative due to the negative correlation. As a result, if her anticipation is correct, her fund earns cashflow timing gains, but experiences poor discount-rate timing performance because the market cashflow and discount-rate return components are positively correlated (Campbell and Vuolteenaho, 2004; Lettau and Ludvigson, 2005).

Nevertheless, this negative effect is small; top timers continue to produce the best total timing performance, as their cashflow timing gains are much larger than their negative discount-rate timing returns in magnitude. This evidence suggests that skilled managers are able to overcome the adverse effect from (mechanical) simultaneous shifts in discount-rate exposure possibly because they understand when cashflow news is expected to be significant enough to overwhelm the potential negative effect of correlated discount-rate news. Meanwhile, poor timers remain the worst. Top timers produce 0.91%, 0.65%, 0.52%, and 0.41% total timing returns over the following four quarters after the formation quarter. Cumulating these returns 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, respectively, but also by funds that have the highest estimation error in this metric. To alleviate this concern, 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, show that after applying the back-testing procedure, top market timers outperform bottom timers by an even larger amount in terms of both cashflow timing and total timing performance, especially in the first quarter after the sorting period. For instance, the total timing profit produced by top timers increases from 0.91% to 1.09% in the first quarter. After applying the filter, both the cashflow and total timing performance spreads between the two extreme quintiles also widen.

5.3 Strategic shifts in fund betas

If timing ability stems from strategic shifts in a fund beta, then we would expect that the fund beta with respect to a systematic factor shifts above (below) its target when an upward (downward) movement in the factor return is anticipated. To obtain direct evidence, we first sort funds each quarter into quintiles based on their past-year total timing ability, and then calculate the average of differential fund betas (the fund beta in excess of its historical average) across funds in each quintile and for each of the subsequent four quarters. Next, for each quintile we run four regressions, with one regression for one of the subsequent four quarters:

$$\tilde{\beta}_{q,k,t+i-1} = b_0 + \gamma I_{K_{t+i}>0} + \eta_{q,k,t+i-1}, \tag{12}$$

where $\tilde{\beta}_{q,k,t+i-1}$ is the averaged differential beta in quintile q ($q = 1,...,5$) at the beginning of i^{th} ($i = 1,...,4$) quarter after the sorting quarter t, k is CF (DR) if K_t represents the quarter-t cashflow (discount-rate) return component, and $I_{K_t>0}$ is a dummy variable that equals one if $K_t > 0$ and zero otherwise. The coefficient of interest is γ.

Panel A of Table 6 shows strong evidence that superior market timers successfully shift their cashflow exposure. Funds in the best timing quintile, on average, increase their cashflow betas by 0.21 relative to their targets before good cashflow news in the next quarter. Compared with the average fund cashflow beta of 1.07 in this group (Panel C), 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 fourth quarter after the sorting period, the average fund in the best quintile still increases its cashflow beta by 0.14, relative to its target, before good cashflow news in the fifth quarter. In contrast, we see no evidence of strategically varying cashflow betas for funds in the worst quintile, nor do we see evidence, in Panel B of Table 6, of skills in strategically shifting discount-rate betas.

Panels C and D show that target cashflow betas and target discount-rate betas are close to each other across different quintiles. Nevertheless, we notice slightly higher cashflow and discount-rate risk exposure (in magnitude) in the two extreme quintiles—i. e., a slight, U-shaped pattern of fund target betas across quintile portfolios. This pattern is quite different from what is illustrated in Panel A. This difference suggests that cashflow timing skill comes from strategic shifts in cashflow betas in response to superior information about future cashflows instead of from high (long-term) target cashflow betas.

5.4 Other dimensions of fund portfolio performance

It is important to determine whether top market timers deliver superior overall fund portfolio returns, and whether they exhibit stock-selection skills as well. To do so, we first sort funds each quarter into quintiles according to their prior-year total timing performance. We then calculate the average across funds in each quintile of fund gross returns before expenses (compounding monthly net returns plus 1/12 expense ratios in a calendar quarter), fund net returns after expenses, and fund DGTW adjusted abnormal returns in each of the subsequent four calendar quarters after the formation period.[24] Table 7 reports the time-series average across sorting quarters of these quintile-averaged quarterly fund returns for each quintile and for each of the subsequent four quarters (untabulated results with the application of a back-testing filter are similar).

Clearly, top market timers outperform bottom timers in terms of overall fund portfolio returns. Regardless of using fund gross returns or net returns as the performance measure, top timers (quintile 5) earn significantly higher quarterly returns than bottom timers by roughly 0.73%, 0.81%, 0.82%, and 0.54% over the next four quarters, respectively. Cumulating these return differences produces around 3% outperformance over the next year.

On the other hand, DGTW adjusted abnormal returns, a proxy for stock-picking ability, are insignificantly positive for top timers and insignificantly negative for bottom timers. The difference between these two groups is insignificant, of 0.29%, in the first quarter after the formation period, less than half of the return spreads in terms of fund gross returns, fund net returns, or total timing abnormal returns. Even though this difference becomes statistically significant in the third quarter, it is still 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

[24]Note that there is a gap of around 10 days between the end of the sorting IBES quarter (for past-year timing performance) and the beginning of the look-ahead calendar quarter (for fund returns).

different set of managers, relative to the group that possess striking stock-selection skills.

Using five factors including Carhart's (1997) four factors plus Pastor and Stambaugh's (2003) liquidity factor, the last two panels of Table 7 display five-factor alphas associated with fund gross returns and net returns over the subsequent four quarters. Clearly, these abnormal returns increase monotonically with past-year total timing performance. Gross alphas are significantly positive for funds in the top timing quintile for all following four quarters, and insignificantly negative (close to 0) for the bottom quintile. Net alphas (after expenses), on the other hand, are insignificantly positive for top timers, with a magnitude less than 40% of the corresponding gross alphas, while net alphas for bottom timers are significantly negative. Regardless of using fund gross or net returns, the alpha spreads between the two extreme quintiles are statistically and economically significant, of at least 0.48% per quarter, or about 2% over the next year. These results suggest that top market-timers earn positive timing abnormal returns but keep a large portion of the gains themselves and leave only a small portion to investors, and that fund investors are better off to avoid investing in funds with poor market-timing abilities. Note that estimation of these five-factor alphas assumes constant exposures to the systematic factors, which is a typical, implicit assumption used in the detection of abnormal returns in the mutual fund literature. In the next section, we consider time-varying risk exposures to identify the contributor to good performance of top market timers.

5.4.1 Using other risk models

Using Campbell and Vuolteenaho's (2004) two-factor (cashflow and discount-rate) model to properly account for the risk premium associated with time-varying risk exposure, we confirm that market timing is a dominant contributor relative to stock selection to the top timers' outperformance in their fund portfolio returns. Specifically, we define a dummy variable $Di_{f,t}$, $i = 2,3,4,5$, to be 1 if fund f is ranked in quintile i according to its past-year total timing ability in the most recent quarter, and 0, otherwise. Then, we run the following panel regression of the calendar-monthly fund net return in excess of the one-month Tbill rate, $r_{f,t+1}$:

$$r_{f,t+1} = \alpha_1 + \alpha_2 D2_{f,t} + \alpha_3 D3_{f,t} + \alpha_4 D4_{f,t} + \alpha_5 D5_{f,t} + \sum_{k=1}^{J} \lambda_k \beta_{f,k,t} + \sum_{c=1}^{C} \theta_c X_{f,c,t} + \epsilon_{f,t+1}, \quad (13)$$

where $\beta_{f,k,t}$ is fund f's sensitivity to factor k, and $X_{f,c,t}$ is fund f's characteristics described in Section 5.1. The advantage of running a panel regression is to allow us to control for fund characteristics that potentially affect fund returns according to prior studies. In the regression, demeaned fund characteristics are included so that α_1 can still be interpreted as alpha for funds ranked in quintile 1 (the base level of alpha) even after controlling for these characteristic variables. The alpha difference of best timers over worst timers, α_5, is a coefficient of major interest. If market timing is a dominant strategy contributing to top timers' outperformance in their fund returns, then significantly positive α_5 would decrease and become insignificant after including the risk premium reflecting time-varying systematic risk exposure ($\sum_{k=1}^{J} \lambda_k \beta_{f,k,t}$) due to strategic beta shifting.

Column 3 of Table 8 confirms that this is the case. α_5 becomes insignificant, being 9.4 basis points per month, a two-thirds decline from 27 basis points when the risk premium term ($\sum_{k=1}^{J} \lambda_k \beta_{f,k,t}$) is excluded from the regression (column 1). In stark contrast, if the model accounts for only time-invariant systematic risk exposure, as in column 5 where the time-series averages of fund betas are used for each fund instead, then we see α_5 barely changed and still significantly positive, and just the base level of alpha α_1 reduces. Controlling for fund characteristics does not alter the message at all.

Alternatively, we account for risk premia associated with time-varying exposures to four factors (Carhart, 1997) or five factors (with an additional Pástor and Stambaugh's (2003) liquidity factor). Because daily factor returns are available,[25] we estimate betas for each stock using daily data within a calendar month to improve accuracy (Merton, 1980), before taking the value-weighted average of betas for stocks held in a fund to compute fund betas. As demonstrated in columns 7 and 9, although α_5 just slightly declines, by 1 basis point, compared with the result in column 1, including these time-varying exposures indeed

[25]Daily returns on the four factors are downloaded from Kenneth French's web site. We construct daily returns on the liquidity factor following Pástor and Stambaugh (2003), except that we calculate value-weighted daily returns instead of monthly returns for the two extreme liquidity deciles.

considerably reduces the base level of alpha, α_1. This contrast with the case accounting for time-varying cashflow and discount-rate two-factor exposures suggests that the four- and five-factor models essentially fail to capture top timers' strategic shifts in cashflow sensitivities. Therefore, selecting a proper pricing model to account for time-varying risk exposures is important to correctly infer differerential stock-selection skills versus market-timing talents of one group over another.

6 Further characterizing cashflow vs. discount-rate timing

In this section, we further explore the mechanism that funds use to successfully time market cashflow news as well as the characteristics of these funds' equity holdings. In exploring the mechanism, we are motivated by prior research indicating that industry rotation is a chief mechanism through which mutual funds respond to time-varying macroeconomic conditions (Avramov and Wermers, 2006). In exploring the stock characteristics of fund holdings, we are guided by previous research showing that certain types of stocks—small-cap and high book-to-market stocks—are more sensitive to cashflow news (Campbell and Vuolteenaho, 2004). Finally, we discuss an aggregate-flow-based explanation for negative discount-rate timing.

6.1 Industry rotation

Sector rotation is a widely used technique in the fund industry. To investigate whether and how funds rotate their portfolio allocations across industries in response to their forecasts of future market-level cashflow and discount-rate variations, we first calculate industry cashflow and discount-rate betas for each fund in our sample as the weighted average of industry-level portfolio betas:

$$\beta^I_{f,j,t} = \sum_{k=1}^{N^I_{f,t}} \omega^I_{f,k,t} \beta^I_{k,j,t}, \tag{14}$$

where $\omega^I_{f,k,t}$ is fund f's portfolio weight in industry k at the end of period t, $N^I_{f,t}$ is the number of industries held by fund f, and $\beta^I_{k,j,t}$ is industry k's sensitivity to factor j (cashflow or discount-rate), calculated using 60-month rolling regressions of industry excess returns on cashflow and discount-rate news ending at period t, according to (2). IBES-monthly excess returns on 48 industry portfolios are compounded from daily returns on these industry portfolios, which are available at Kenneth French's web site, in excess of IBES-monthly risk-free rates. Then, the differential return timing measure specified in (5) can be decomposed into two parts due to industry rotation (the first sum) or intra-industry allocations (the second sum):

$$\frac{1}{T}\sum_{t=1}^{T}(\beta_{f,j,t}-\bar{\beta}_{f,j,t})K_{j,t+1}=\frac{1}{T}\sum_{t=1}^{T}(\beta^I_{f,j,t}-\bar{\beta}^I_{f,j,t})K_{j,t+1}+\frac{1}{T}\sum_{t=1}^{T}(\beta_{f,j,t}-\bar{\beta}_{f,j,t}-\beta^I_{f,j,t}+\bar{\beta}^I_{f,j,t})K_{j,t+1}, \tag{15}$$

where $\bar{\beta}^I_{f,j,t}$ is the average of past industry betas for fund f, $\beta^I_{f,j,s}, s<t$. Table 9 reports this decomposition.

The decomposed cashflow-timing performance reported in Panels A1 and A2 suggests that rotating portfolios across industries is a key mechanism for mutual fund managers to achieve cashflow-timing abnormal returns. Of 0.53% quarterly cashflow-timing gains achieved by the average fund (Panel A of Table 2), 0.38% is attributable to industry rotation and 0.15% to intra-industry allocations. Moreover, industry rotation produces significant and positive cashflow timing returns for some funds but no evidence of significant and negative returns for others, the same pattern demonstrated in Panel A of Table 2 (without distinguishing industry rotation versus intra-industry allocations).

In untabulated results, we find further evidence that fund managers achieve superior cashflow timing by strategically tilting toward high (low) cashflow-sensitivity industries in anticipation of positive (negative) aggregate cashflow changes. Funds typically increase their portfolio weights in cyclical sectors, such as Manufacturing and Financials, before an upswing in aggregate cashflows, and increase their portfolio weights in defensive sectors, such as Healthcare and Consumer NonDurables, before a decline in aggregate cashflows.

One explanation for cashflow timing gains from intra-industry allocation in Panel A2 is that skilled managers, when implementing timing, tend to tilt toward value stocks and relatively small-cap stocks because these two types of stocks are highly sensitive to aggregate cashflow variations (Campbell and Vuolteenaho, 2004). This explanation is also consistent with the evidence that the top market timers tend to tilt toward these two types of stocks in their fund portfolios relative to other funds (Table 4). We explore this potential explanation in the next section. Overall, our evidence suggests that mutual fund managers use both diversified sector “bets" and individual security “bets" to exploit aggregate cashflow information.

Panels B1 and B2 of Table 9 show that discount-rate timing due to either industry rotation or intra-industry allocations is significantly negative for some funds but at best insignificantly positive for others, the same pattern reported in Panel B of Table 2 without distinguishing these two types of allocations. Clearly, fund managers are not able to time discount rates, either through their industry tilts or individual security tilts.

Adding cashflow timing and discount-rate timing together, as shown in Panels C1 and C2 of Table 9, we see that the majority of total timing gains achieved by the average fund comes from industry rotation. Of 0.32% quarterly total timing abnormal returns (Panel C of Table 2), 0.28% is attributable to rotating portfolios across industries. Moreover, there is no evidence of significantly negative total timing performance from industry rotation.

6.2 Value vs growth, and large-cap vs small-cap mutual funds

Table 10 examines the types of stocks that active equity funds tilt toward (or away from) in order to achieve cashflow timing, which indicates the types of funds that are most prone to exhibiting cashflow timing skills. Specifically, each quarter we sort funds into deciles according to their portfolio-weighted stock characteristics (market cap in Panel A or B/M in Panel B), which are defined in Section 5.1. Then, we run panel regressions to get the averages of next-quarter abnormal returns in each decile stemming from cash-flowing timing, as specified by Equation (4), as well as of the decomposed abnormal returns due to industry rotation and intra-industry allocation. This table also presents, analogously, the results for discount-rate timing and total timing abnormal returns for comparison.

The first column shows that cashflow-timing abnormal returns are higher among funds tilting toward smaller-cap stocks (Panel A) or toward higher book-to-market stocks (Panel B).

Decomposing the cashflow-timing performance by distinguishing industry rotation and intra-industry allocation suggests that the outperformance mainly comes from intra-industry allocation.[26] Funds tilting toward relatively small-cap (value) stocks make significant cashflow-timing gains from intra-industry allocation, as opposed to funds tilting toward large (growth) stocks, as shown in the third column.

In contrast, discount-rate timing results show no clear pattern across funds tilting towards different types of stocks. As a result, the total timing performance, shown in the last three columns of each panel, inherits the pattern of the cashflow timing abnormal returns that we discussed above.

These results add an interesting dimension to the literature in which the common view is that growth funds are more likely to add value than value funds through stock-selection skills (e. g., Kosowski, et al. (2006)). Our findings indicate that value funds (especially, small-cap value funds[27]) add substantial value through a different channel: timing market cashflow news.

6.3 Negative discount-rate timing and aggregate fund net flows

Aggregate fund net flows can be correlated with the stock market return or its return components for two reasons. First, aggregate fund net flows are informative if mutual fund investors, in aggregate, possess information, or otherwise trade mutual fund shares in the same direction as informed investors (Warther, 1995). For example, fund investors chase funds with recent good performance (Sirri and Tufano, 1998). If managers of some of these funds earn abnormal returns based on their ability to predict macro fundamentals that unfold

[26]That is, (almost) all funds exhibit high cashflow timing from their industry tilts, compared with their intra-industry tilts, but, in addition to this effect, funds holding small- and value-stocks also add cashflow timing through their individual stock picks. This result is consistent with these types of stocks having higher exposure to aggregate cashflow news, which gives funds holding these stocks a better opportunity to exploit their cashflow information through timing of their trades of individual small-cap or value stocks.

[27]To save space, we do not report results for double-sorting according to both funds' portfolio-weighted market cap and portfolio-weighted B/M, which deliver a similar message as in Table 10. For example, for cashflow timing, the quarterly abnormal return is 1.42% for funds tilting toward small-cap, value stocks vs. 0.34% for funds tilting toward large-cap, growth stocks; the difference is 1.07% per quarter. This double-sorting difference is roughly the sum of the return differences from the corresponding two single-sorting: As reported in Table 10, the quarterly abnormal return is 0.62% higher for funds tilting toward small-cap stocks vs. large-cap stocks and 0.46% higher for funds tilting toward value stocks vs. growth stocks, the sum of which is 1.08%, close to the above-noted double-sorting return difference.

over time, then aggregate fund net flows may be positively correlated with market-level cashflow information.

Aggregate fund net flows can also reflect investor sentiment that is unrelated to manager skills and may exert price pressure, as the media sometimes claims.[28] As investor sentiment fades away, a reversal is likely to occur (Ben-Rephael et. al, 2012).

We conjecture that negative discount-rate timing by fund managers takes place when a discount-rate reversal occurs. Intuitively, a professional fund manager can make adjustments to his cashflow projections over time, as he learns from evolving fundamental information that is publicly available. However, such a manager may find it much more difficult to make correct discount rate forecasts, and adjustments to forecasts, due to the unobservable nature of the investor sentiment factors that drive such rates. If mutual fund managers must respond to the sentiment of retail investors by changing their fund portfolios in the direction preferred by their investors, potentially to appeal to their investors' preferences to attract fund inflows or avoid outflows, then their funds' discount-rate betas will shift in a direction opposite to the following-quarter discount-rate reversal, leading to negative discount-rate timing returns.

To test the conjecture above, we show how fund net flows are related with the two variables (next-quarter market return components and current-quarter fund differential betas), the product of which is the timing measure. These two relations help us to better understand how fund net flows are associated with next-quarter timing abnormal returns. Because returns and timing performance in our main tests are measured in IBES quarters, we convert aggregate net flows in calendar quarters, $flow_t^c$, to those in IBES quarters, $flow_t$:

$$flow_t = flow_{t-1}^c \frac{nIBESp_t}{n_{t-1}} + flow_t^c \frac{nIBES_t}{n_t}, \tag{16}$$

where $flow_t^c$ is the sum of quarter-t fund net flows over all funds, quarter-t fund net flow for each fund is constructed following Kacperczyk, Sialm, and Zheng (2008), n_t is the number of days in calendar quarter t, and $nIBES_t$ and $nIBESp_t$ are the number of days of IBES quarter t overlapped with calendar quarters t and $t-1$, respectively.[29]

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

[29]Since an IBES quarter and its corresponding calendar quarter are mostly overlapped except for around a

Panel A of Table 11 reports the relation of aggregate fund net flows with the unexpected market return and its two components. 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 a next-quarter reversal (column 6). Interestingly, both contemporaneous and next-quarter cashflow return components are significantly and positively related to net flows (columns 1 and 2), indicating that investor flows respond to improving cashflow news in the economy. In contrast, aggregate net flows have a significantly negative relation with the concurrent discount-rate return component (column 3), as expected since both are sentiment-driven, but a significantly positive relation with the next-quarter discount-rate return component (column 4)—a pronounced reversal. A one-percentage point 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.[30]

The second column of Panel B shows that the differential discount-rate beta for the average fund significantly decreases with increasing aggregate net flows. One explanation, as we discussed before, is that inflows occur when investors have positive sentiment, and portfolio managers then overinvest in stocks that have high discount-rate betas in magnitude (more negative betas) to respond to their investors' preferences in order to attract fund inflows or avoid outflows. This significant decrease in discount-rate beta, coupled with pronounced next-quarter discount-rate reversals (next-quarter discount-rate news increases with aggregate net flows) generates negative discount-rate timing.

7 Additional analyses and robustness tests

This section conducts a number of additional analyses and robustness checks, which further strengthen our main conclusion that the average fund possesses cashflow timing

one-week difference, using aggregate net flows in IBES quarters or calendar quarters produces similar results.

[30]Warther (1995) does not find evidence of a market-return reversal following aggregate net flows. One possible reason is that discount rates are subject to price pressure but cashflows are not, so mixing the two together conceals the detection of a market-return reversal. Using a new measure of aggregate net flows between bond funds and equity funds in the U.S. (aggregate net exchanges of equity funds), Ben-Rephael et. al (2012) find a strong market-return reversal.

skills. We summarize results in this section and present the supporting tables in a separate Internet Appendix.

7.1 Initiating buys and terminating sells

Fund betas can change from two sources: either funds tilt towards or away from stocks whose betas differ from those of existing holdings or their portfolio weights change as the prices of their holdings evolve (even though stock betas stay the same). Although the former is an active decision, the latter can also be taken by a skilled market-timer to implement their timing strategies. For example, a fund manager tends to shift her portfolio's cashflow beta upward in anticipation of an increase in aggregate cashflow news. If her fund holds a stock with a high cashflow beta and the price of this stock has gone up recently, then the manager can take advantage of the change in her fund portfolio weights from this price rise, and achieves her desired fund cashflow beta with a minimal amount of trades, thus, avoiding unnecessary transaction costs. Therefore, it is difficult to discern whether, ex-ante, a shift in fund beta due to holdings' price changes is an active vs. passive decision.

To provide robust evidence that timing ability comes from active decisions, we use the former source of fund beta changes and examine the timing performances of buys that initiate a position and sells that fully liquidate a position in a fund portfolio. In this test, we implicitly assume, as other studies (such as Alexander, Cici and Gibson (2007)) do, that when a fund manager is saddled with excess cash from investor inflows, she will add pro-rata to positions already held in the portfolio if she has no new information. Hence, an initiating buy—the purchase of a stock not currently held—is likely to expressly signal an active implementation of timing from a skilled timer through the stock being added. Similarly, a terminating sell—the sale of the entire position in a currently held stock—is likely motivated by timing by a manager who possesses such skills.

As a result, if a manager is skilled in timing aggregate cashflows, we should see strong and positive cashflow timing returns from initiating buys and little from terminating sells. This conjecture is supported by the evidence summarized in the Internet Appendix that the cashflow timing abnormal return is 62 bp per quarter (statistically significant) from initial purchases for the average fund (higher than 53 bp for the average fund in the full sample) and only 8 bp (statistically insignificant) for liquidation sales. After adding discount-rate timing performance, the total timing abnormal return is significantly positive for initiating purchases but insignificantly negative for terminating sells. This evidence suggests that the average fund add stocks that assist market-timing implementation and get rid of those that do not.

7.2 Time-varying cash positions

To time a systematic factor, an equity fund manager can shift her fund's exposure to this factor either by changing equity positions or by varying cash positions. Because cash position information from the CRSP database is missing for around 53% of fund-quarter observations, our main tests, so far, focus on the former timing technique that is purely based on equity positions. In the Internet Appendix, we provide evidence that accounting for time-varying cash positions does not alter our conclusions because varying cash positions have a small effect on the magnitude of our measured fund timing ability.[31]

This evidence is consistent with small time variation in fund betas due to changes in cash positions. For the sample of funds with non-missing cash positions, they hold, on average, about 4.2% of their managed assets in cash. Importantly, time variation in their cash positions is small with respect to changes in next-quarter market return components. A one-standard-deviation increase in the next-quarter cashflow (discount-rate) return component is associated with a decrease of 0.068% (0.4%) in current-quarter cash position, which just slightly changes a fund's cashflow (discount-rate) beta, compared with the beta for the average fund close to unity in magnitude. This small effect of varying cash positions is possibly because equity fund managers are restricted not to hold a large portion of their managed assets in cash, and/or because managers attempt to quickly bring cash levels back to some target level after receiving inflows or losing outflows; i.e., that cash is mainly used as liquidity insurance.[32]

[31] In the sample of funds with non-missing cash positions, we find that regardless of whether time-varying cash positions are considered in calculating fund betas, cross-sectional distributions of timing performance are almost identical.

[32] Mutual fund reporting services, including MorningStar, prominently display the level of cash holdings by equity mutual funds. This is consistent with investors paying attention to such cash holdings. In addition, cash holdings by equity funds directly leads to tracking error relative to their benchmarks, which is also visible to

7.3 A placebo test using index funds

To demonstrate that our timing measures do not mechanically produce timing ability, we run a placebo test using index funds. If our method is subject to a mechanical bias, this would imply that index funds exhibit timing skills even though their fund beta shifts are passive. Index funds in our sample include the S&P 500, S&P 400, S&P 600, Russell 1000, Russell 2000, Russell 2500, Russell 3000, Russell 3000E, Russell top 200, Russell Midcap, Russell Small Cap, Russell Microcap, and the value and growth components of these indexes. Standard & Poor's index fund holdings data come from DataStream, and Russell index fund holdings data come from Frank Russell Co. Most index funds' holdings go as early as our sample starting period, and the others are the earliest possible from the two data sources.

We follow the same procedure to calculate index fund betas and timing measures as we did for our actively managed funds. We find no timing ability for these index funds, as shown in the Internet Appendix. This placebo analysis suggests that our results for actively managed mutual funds are unlikely to be driven by a mechanical bias.

7.4 Multivariate regression approach

In this section, we test whether past-year total timing ability significantly predicts future cashflow and total timing performance of a mutual fund, even 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 the fund characteristics described in Section 5.1, we include, as an independent variable, past-year timing ability ranking—a decile ranking obtained by sorting funds, each quarter, according to their past-year total timing performance. We find that, compared with funds in the bottom decile, funds in the top decile earn 1.4–1.8% higher cashflow timing abnormal returns or 1–1.4% higher total timing abnormal returns in the next quarter. These results are similar to those previously reported in Table 5. Moreover, turnover has a significantly positive relation with timing performance, primarily because skilled market timers need to strategically shift their cashflow exposure frequently.

fund investors.

7.5 Using different approaches to decompose the market return

Here we re-examine fund timing abilities using alternative decomposition approaches to generate the cashflow and discount-rate components of the market return. The first alternative approach relies on the Gordon (1962) model that resorts to some strong assumptions but produces a simple and intuitive decomposition of the stock market return. 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. By assuming that g_t is less than μ_t and that earnings are not reinvested, the Gordon (1962) model states that $P_t = \frac{e_t}{\mu_t - g_t}$. Taking a first-order Taylor expansion of the above equation leads to

$$\frac{\Delta P_t}{P_t} = \frac{-P_t}{e_t}(\Delta\mu_t - \Delta g_t) = \frac{P_t}{e_t}\Delta g_t - \frac{P_t}{e_t}\Delta\mu_t, \tag{17}$$

where Δ represents a one-period change, and $\frac{P_t}{e_t}$ is the time-t aggregate PE ratio. This equation motivates us to separate the IBES-monthly stock market return $\frac{\Delta P_t}{P_t}$ into two parts:[33] a cashflow component $\frac{P_t}{e_t}\Delta g_t$ (using IBES-monthly changes of LTG_t as a proxy of Δg_t) and a discount-rate component $\frac{P_t}{e_t}\Delta\mu_t$ (backed out as $\frac{P_t}{e_t}\Delta g_t - \frac{\Delta P_t}{P_t}$).

The second alternative approach is based on the first-stage forecasts of the three-stage earnings growth model, which is described in Section 3.1, to generate the cashflow market return component over the next five years 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 backed out as the difference between the unexpected market return and the cashflow component. This method rules out the possibility that the assumptions in the last two stages of the three-stage model have a material impact on measuring cashflow and discount-rate timing abilities. Using either of the preceding two alternative approaches, we obtain cross-sectional timing performance similar to our baseline results.

The traditional approach in finance runs predictive regressions and calculate the cashflow and discount-rate return components as functions of the predictive variables appealing to

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

the Campbell-Shiller (1988) return log-linearization relation. Consider the following VAR:

$$Z_t = \Gamma_0 + \Gamma Z_{t-1} + \epsilon_t, \tag{18}$$

where $Z_t = [r_t, \Delta d_t, dp_t, X_t]$, dp_t is the time-t log dividend yield, Δd_t is the 3-month growth rate of the past 12-month dividends (using 12-month dividends to avoid spurious predictability arising from seasonality), r_t is the 3-month market return, and X_t are other state variables. The Campbell-Shiller return log-linearization relation, $r_{t+1} = k + \Delta d_{t+1} - \rho dp_{t+1} + dp_t$, implicitly imposes the following constraints in the VAR model:

$$\begin{aligned} \Gamma^{dp} &= 1/\rho(\Gamma^d - \Gamma^r + e3') \\ \epsilon_t^{dp} &= 1/\rho(\epsilon_t^d - \epsilon_t^r), \end{aligned} \tag{19}$$

where Γ^r, Γ^d, and Γ^{dp} are the first three rows in Γ, ϵ_t^r, ϵ_t^d, and ϵ_t^{dp} are the first three rows in ϵ_t, $e3$ is a vector of zeros except for the third element being one, $\rho \equiv 1/(1+\exp(E(dp)))$, and $k \equiv -log(\rho) - (1-\rho)log(1/\rho - 1)$.

As a result, cashflow and discount-rate news in (1) can be constructed directly as:

$$\begin{aligned} N_{CF,t} &= e2'(I+\lambda)\epsilon_t = N_{DR,t} + \epsilon_t^r \\ N_{DR,t} &= e1'\lambda\epsilon_t = N_{CF,t} - \epsilon_t^r, \end{aligned} \tag{20}$$

where $\lambda = \rho\Gamma(1-\rho\Gamma)^{-1}$, and $e1$ and $e2$ are a vector of zeros except for the first and second element being one, respectively. The constraints (19) make the second equalality hold in both of the preceding equations. That is, directly generated cashflow news is the same as that backed out as the unexpected return plus directly constructed discount-rate news. This feature is important for comparing return decomposition using a VAR model vs. using the three-stage growth model, which constructs cashflow news directly, on an equal footing. It helps rule out the possibility that timing performance is sensitive to which return component—cashflow news or discount-rate news—is constructed directly.

Theoretically, the above VAR-based decomposition works perfectly if the VAR model captures the true return dynamics. Empirically, we do not know the true dynamics and select state variables from the existing literature to capture the dynamics as well as possible. Following Campbell, Giglio, and Polk (2013), we include in X_t the default spread, the term spread, and the small-stock value spread (see Appendix A for definitions). If we substitute the log dividend yield with the price-earnings ratio, results remain similar. As Campbell, Giglio, and Polk note, including the default spread is important to reflect the aggregate default probability that, in turn, reflect news about expected market cashflows and discount rates. Because forecasting the equity premium with a pure time-series regression is a difficult task, we follow Campbell, Giglio, and Polk's approach and estimate the aggregate VAR jointly with the cross-sectional restrictions of the intertemporal capital asset pricing model (ICAPM).[34] Information contained in cross-sectional valuation ratios and returns helps improve the prediction of market returns both in-sample and out-of-sample (Campbell, Giglio, and Polk, 2013; Kelly and Pruitt, 2013). See Appendix C for details about this approach.

As further robustness checks, we implement another three VAR models with different choices of state variables that have been used in the literature. First, for parsimony, we take the log dividend yield as the sole predictor, and estimate the restricted VAR using a long sample of the 1927–2011 period to reduce estimation error (see, for example, Cochrane (2008) and Chen, Da, and Zhao (2013)). If we estimate the VAR model with r_t, Δd_t, and dp_t as the state variables, the results remain similar. Then, we apply the estimated coefficients to the 1977-2011 sample to calculate market-level cashflow and discount-rate news (five extra years of data are needed to estimate betas in a 60-month rolling regression). Second, Lettau and van Nieuwerburgh (2008) show that a structural-break adjustment not only improves the dividend yield's forecasting power for returns, but also makes the return predictability stable over different sample periods. After following their method to adjust structural breaks, we use the break-adjusted dividend yield to forecast returns and dividend growth. Cashflow and discount-rate components of the market return are then constructed according to (20). Third, Chen, Da, and Priestley (2012) provide evidence that dividends are much more smoothed

[34]Cross-sectional information helps to forecast aggregate returns and therefore helps to better decompose the market return into cashflow news and discount-rate news. If we only estimate the VAR without imposing the cross-sectional restriction to decompose the market return, as Campbell, Giglio, and Polk (2013) show, there is no clear negative cashflow news during the recent financial crisis, which is inconsistent with the common view about the crisis. Nevertheless, using this VAR decomposition without imposing the cross-sectional restriction, our main conclusions remain, and just the magnitude of timing performance decreases.

in the post-WWII period, which disguises dividend growth predictability, and therefore aggregate dividends are more likely to be a poor proxy for cashflow in the more recent sample. Following their work, we substitute earnings as a proxy for cashflows,[35] and obtain cashflow and discount-rate news analogously using the log earnings yield as the predictor.[36]

Timing abnormal returns based on these alternatively generated cashflow and discount-rate news are similar to our main results illustrated in Table 2. For example, the average fund generates quarterly cashflow timing abnormal returns of 0.49% (using the Campbell, Giglio and Polk's (2013) approach), 0.47% (the simple VAR long-sample estimation), 0.48% (using the break-adjusted dividend yield), and 0.31% (using earnings as the cashflow measure), compared with 0.53% in our baseline result; quarterly total timing abnormal returns produced by the average fund are 0.25%, 0.27%, 0.46%, and 0.28%, respectively, compared with 0.32% in our baseline finding.[37]

7.6 Analyst forecast bias

As noted earlier, we are interested in the revisions in expected cashflows instead of levels. Still, it is possible that forecast biases may affect revisions. To mitigate this concern, similar to Chava and Purnanandam (2010) and Chen, Da, and Zhao (2013), we construct measures of analyst forecasts that account for the bias issue.

[35] Quarterly earnings from Compustat are aggregated to the market level first, then quarterly growth rates of the past four-quarter earnings are calculated. We assume a constant expected payout ratio here because the R^2 is almost zero in the payout ratio regression.

[36] All of the preceding four methods generate a reasonable cashflow component of the market return. Consistent with Campbell, Giglio, and Polk (2013) and the common view that the prospect of poor economic growth was the main driver of the recent financial crisis, for example, of the roughly −30% market return over the three months during and after the Lehman Brothers bankruptcy, cashflow news was around −20% (using the Campbell, Giglio, and Polk (2013) approach), −21% (using the simple VAR long-sample estimation), and −12% (using the break-adjusted dividend yield), respectively. Cashflow news accounts for −39% when earnings (at the calendar quarter frequency) is used as the cashflow measure, compared with the unexpected market return of −29% in the first calendar quarter after the bankruptcy event.

[37] In the same spirit of Campbell, Polk, and Vuolteenaho (2010), we approximate expected future cashflows over an infinite horizon $\mathrm{E}_t \sum_{k=0}^{\infty} \rho^k \Delta d_{t+1+k}$ with realized aggregate dividend growth over the next five years $\mathrm{E}_t \sum_{k=0}^{5y} \rho^k \Delta d_{t+1+k}$, a change of which is a proxy of cashflow news. Similarly, because changes of P/E ratios are mainly driven by changes in expected returns, discount-rates over an infinite horizon $\mathrm{E}_t \sum_{k=1}^{\infty} \rho^k r_{t+1+k}$ are approximated by increments in the market log P/E ratios over the next five years $\mathrm{E}_t \sum_{k=1}^{5y} \rho^k \Delta \ln(P/E)_{t+1+k}$, a change of which is a proxy of discount-rate news. This approach avoids the VAR-based misspecification sensitivity issue, but introduces complications because ex post values are not known in advance. The result using these two measures is also similar to our baseline result.

1. Forecasts adjusted by external financing: Analyst forecasts can be overly optimistic for firms that have large investment banking demand (Rajan and Servaes, 1997; Bradshaw, Richardson, and Sloan, 2006). Investment banking business is measured as the amount of cash raised through external financing (Bradshaw, Richardson, and Sloan, 2006). Then, we rank all firms in each IBES month according to the amount of net external financing (equity and debt issuance) over the past year and calculate the percentile ranking, $Rank_i^{EF}$, for firm i. The external-financing-adjusted forecast is calculated as:

$$EPS_i = Rank_i^{EF} \times LOWEPS_i + (1 - Rank_i^{EF}) \times HIGHEPS_i, \tag{21}$$

where $LOWEPS_i$ and $HIGHEPS_i$ are the lowest and highest forecasts, respectively. This adjustment relies more on the pessimistic estimate if a firm has more investment banking business in a particular year.

2. Forecasts adjusted by recent forecast error: Analyst forecast errors tend to be persistent (Abarbanell and Bernard, 1992). That is, current earnings forecasts are more likely to be optimistic (or pessimistic) if they were optimistic (pessimistic) during the recent past. We thus rank all firms in each IBES month according to the consensus earnings forecast error in the most recent fiscal year and calculate the percentile ranking, $Rank_i^{FE}$, for firm i. The forecast error is defined as the forecast minus the actual scaled by the price at the beginning of the fiscal year. The recent-forecast-error-adjusted forecast is calculated as:

$$EPS_i = Rank_i^{FE} \times LOWEPS_i + (1 - Rank_i^{FE}) \times HIGHEPS_i, \tag{22}$$

This adjustment relies more on the pessimistic estimate if a firm has been associated with optimistic earnings forecasts in the recent past.

We also use the lowest analyst forecasts or the highest forecasts instead of the consensus forecasts in case that the effect of bias on the revision might not be strong if the most pessimistic or optimistic forecasts are used. Regardless of which methods being used to mitigate the bias concern, timing abnormal returns stay similar to our baseline results.

7.7 Timing ability over the business cycle

Kacperczyk, van Nieuwerburgh, and Veldkamp's (2016) model predicts that fund managers will allocate more effort to market-timing during economic downturns, as opposed to economic expansions (during which they allocate more effort to security selection), because of the increased aggregate volatility of the market, amplified by the increased risk-aversion of investors during recessions.

Consistent with their model, our evidence shows that timing aggregate cashflows is more profitable in recessions than in expansions; The quarterly abnormal return earned by the median fund during economic downturns (1.35%) is about five times the return earned during economic expansions (0.24%). In contrast, the median fund exhibits poor discount-rate timing performance over the business cycle, with the magnitude during recessions (-0.54%/quarter) about twice that during expansions (-0.26%/quarter). Adding together cashflow timing and discount-rate timing for each fund, the median fund's total timing abnormal return is significantly positive during recessions, but small and insignificant during expansions.

Our results provide further insight on the detailed mechanism through which fund managers increase their market-timing efforts during recessions, made possible through our decomposition approach. Although both volatility of market cashflow news and volatility of discount-rate news increase during recessions, the former increases to a larger proportion than the latter, which provides skilled fund managers a stronger incentive to implement their cashflow timing technique during recessions. Put differently, skilled market timers can improve their Sharpe ratios during recessions, relative to expansions, because the "signal-to-noise" ratio (i. e., cashflow news variation can be beneficial to skilled market timers, as opposed to discount-rate news variation that brings noise) is much higher during recessions. Our evidence that skilled fund managers take advantage of this "beneficial" opportunity set during recessions provides a detailed mechanism on the Kacperczyk, van Nieuwerburgh, and Veldkamp's model prediction that market-timing becomes a bigger focus due to higher market volatility during recessions. Our evidence suggests that it is cashflow timing, instead of discount-rate timing, that is the focus of skilled managers during recessions.

7.8 Extended Treynor-Mazuy and Henriksson-Merton measures

Most prior studies run the following nonlinear regressions of realized fund excess returns $r_{f,t}$ on contemporaneous market excess returns $r_{m,t}$ to get estimated coefficient γ—Treynor and Mazuy (1966, TM) or Henriksson and Merton (1981, HM) market-timing measure:

$$\text{TM: } r_{f,t} = \alpha + \beta r_{m,t} + \gamma r_{m,t}^2 + e_{f,t} = \alpha + (\beta + \gamma r_{m,t}) r_{m,t} + e_{f,t}, \tag{23}$$

$$\text{HM: } r_{f,t} = \alpha + \beta r_{m,t} + \gamma r_{m,t} I_{r_{m,t}>0} + e_{f,t} = \alpha + (\beta + \gamma I_{r_{m,t}>0}) r_{m,t} + e_{f,t} \tag{24}$$

where $I_{r_{m,t}>0}$ is a dummy variable that equals one if $r_{m,t} > 0$, and zero otherwise. This nonlinear relation, however, can also be induced by factors other than active market timing, such as interim trading or trading option-like securities (Jagannathan and Korajczyk, 1986).

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 (Jiang, Yao, and Yu, 2007). Motivated by Jiang, Yao, and Yu's work, we extend TM and HM timing measures as comovements between the period-t return on factor j, $K_{j,t}$, and fund f's holdings-based exposure to this factor at the beginning of period t, $\beta_{f,j,t-1}$:

$$\text{TM: } \beta_{f,j,t-1} = \beta + \gamma K_{j,t} + \eta_{f,t}, \tag{25}$$

$$\text{HM: } \beta_{f,j,t-1} = \beta + \gamma I_{K_{j,t}} + \eta_{f,t}. \tag{26}$$

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 our differential return timing measure is not subject to this issue. Moreover, our measure is expressed in terms of abnormal returns and therefore facilitates evaluation of economic significance.

Employing either the TM or HM timing measure delivers the same conclusions as applying our differential return timing measure. The average fund exhibits significant cashflow timing talents (significantly positive γ), and there is no evidence for negative cashflow timing. In contrast, when timing either discount-rate news or unexpected market returns is considered, significantly negative but no significantly positive timing measures appear.

7.9 Other tests

Ingersoll et al. (2007) illustrate that conventional fund performance measures 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. As suggested by Ingersoll et al., we adopt the following manipulation-proof timing measure for fund f with respect to factor j, $MPTM_{f,j}$, to reexamine mutual fund timing skills:

$$MPTM_{f,j} = \frac{1}{(1-\eta)\Delta h} \ln\left(\frac{1}{T}\sum_{t=1}^{T}(1+tim_{f,j,t})^{1-\eta}\right), \tag{27}$$

where $tim_{f,j,t}$ is the period-t timing contribution of fund f in response to factor j, as specified in (4), 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 $\eta = 3$ is relative risk aversion in power utility (Ingersoll et al., 2007). $MPTM_{f,j}$ can be interpreted as an annualized continuously compounded certainty equivalent excess return. Employing this manipulation-proof measure does not alter our conclusions.

Finally, in the conventional TM model and HM model, as specified in (23) and (24), 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 sort funds into quintiles based on their past-year total timing performance, then run regressions, according to (23) or (24), of quintile-averaged quarterly fund net returns. If this alternative mechanism is behind our results, we should see a strong negative relation between estimates of γ and α for funds in the best timing quintile, but we do not.[38]

[38] In Section 5.4, we already showed that top market timers generally have slightly better stock-selection abilities than other groups.

8 Conclusions

By separating cashflow timing and discount-rate timing, we find that actively managed U.S. equity mutual funds, on average, exhibit significant market-timing skills due to their superior ability in forecasting and using aggregate cashflow information profitably, but are unable to profit from forecasts of changing discount rates. Key to our approach is to allow a careful extraction of skills in forecasting the low-volatility cashflow return component, in the presence of a high-volatility discount-rate return component. If, instead, the (unexpected) market return (the sum of cashflow and discount-rate market return components) is treated as an undifferentiated object of market-timing efforts, as the literature typically does, we find insignificant timing ability for the average fund, consistent with prior studies.

We further propose past-year total timing performance as a metric, using which we are able to identify, ex ante, a subset of funds that earn impressive abnormal returns from the implementation of timing strategies. Specifically, funds in the best timing quintile according to this metric earn a significant cashflow timing abnormal return of roughly 3.57% over the next year, which is 3.58% higher than that earned by funds in the worst quintile. Even though discount-rate timing partially reduces the abnormal returns, the annual total timing gain for this best group is still 2.49%, which is 1.86% higher than that for the worst group. Our results suggest that market timing is a profitable investment strategy as important as stock selection in adding value to managed assets.

Appendix

A 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 replace with $FE2_{t-1}$; if $FE2_{t-1}$ is also missing, 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 (adjusted for share splits) 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 impact of outliers, we winsorize $FE1_t$, $FE2_t$, and LG_t at their 1% and 99% each month before aggregating them.

The term spread: The yield difference between ten-year constant-maturity taxable bonds and one-year taxable notes.

The market's smoothed price-earnings ratio (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.

The small-stock value spread: 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 book-to-market ratio (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 year $t-1$ divided by ME for December of year $t-1$. 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.

The default spread: The difference between the log yields on Moody's BAA and AAA bonds.

B 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 that 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 (4). Because bootstrap factor returns are drawn randomly, the expected bootstrap timing measure should be zero across simulations. Note that this simulation approach preserves 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.

C Campbell, Giglio, and Polk's (2013) approach

Following Campbell, Giglio, and Polk (2013), we impose the cross-sectional restriction of the ICAPM in a generalized method of moments (GMM) estimation of a VAR system. Let K be the dimension of the VAR system $Z_t = \Gamma_0 + \Gamma Z_{t-1} + \epsilon_t$, where Z_t represents state variables, Γ_0 is a $K \times 1$ vector, and Γ is a $K \times K$ slope matrix. The ICAPM conditions require that the risk premium on any asset i satisfies

$$E_t[r_{i,t+1}] - r_{f,t+1} + \frac{\sigma^2_{i,t}}{2} = \gamma \text{cov}(r_{i,t+1}, r_{m,t+1} - \text{E}_t r_{m,t+1}) + (1-\gamma)\text{cov}(r_{i,t+1}, N_{m,DR,t+1}),$$

where $r_{i,t}$ and $r_{m,t}$ are period-t returns on asset i and the market, respectively, $\sigma^2_{i,t}$ is the variance of returns on asset i, $N_{m,DR,t}$ is the period-t market discount-rate return component, and γ is the coefficient of relative risk aversion.

The GMM problem can then be written as

$$\min(\tfrac{1}{T}\textstyle\sum_t g_t(\Gamma_0, \Gamma, \gamma))' V_T(\Gamma_0, \Gamma, \gamma)^{-1}(\tfrac{1}{T}\textstyle\sum_t, g_t(\Gamma_0, \Gamma, \gamma)),$$

$$s.t. maxeig \Gamma <= 0.99,$$

$$1 \leq \gamma \leq 15,$$

$$E_t[r_{m,t+1}] - r_{f,t+1} + \tfrac{\sigma^2_{m,t}}{2} = \gamma \text{cov}(r_{m,t+1}, r_{m,t+1}) + (1-\gamma)\text{cov}(r_{m,t+1}, N_{m,DR,t+1})$$

where the vector g_t includes the $K(K+1)$ orthogonality conditions for the VAR system, plus the cross-sectional conditions for the 6 FF size/book-to-market sorted portfolios, and V_T is the continously updated variance-covariance matrix of the residuals g_t.

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Table 1: Summary statistics

Panel A presents standard deviations of the quarterly unexpected market return and its cashflow and discount-rate components on the diagonal of the matrix, and correlations of these return components below the diagonal. Panel B reports the mean and the standard deviation of cashflow (CF) beta, discount-rate (DR) beta, and CAPM beta at both the stock and fund levels in the upper panel, and the correlation matrix of these betas in the lower panel. Stock CF and DR betas are estimated based on a two-factor model using a 60-month-rolling OLS regression with at least 24 monthly observations, as specified in Equation (2), where the two factors are the cashflow and discount-rate components of the market return. The CAPM beta is estimated similarly based on a one-factor model using the market unexpected return as the factor. A fund portfolio's beta is calculated as the value-weighted average of the corresponding stock beta for all stocks held by the fund, weighted by the value of stocks held in the fund portfolio.

Panel A Corr. & std. dev.	CF news	DR news	Unexpected ret.
CF news	0.07		
DR news	0.54	0.11	
Unexpected ret.	0.08	-0.79	0.10

Panel B	Stock-level			Fund-level		
	CF beta	DR beta	CAPM beta	CF beta	DR beta	CAPM beta
Mean	1.12	-0.95	0.95	1.02	-1.00	1.00
Std. dev.	1.53	0.67	0.67	0.38	0.25	0.25
Correlation matrix	CF beta	DR beta	CAPM beta	CF beta	DR beta	CAPM beta
CF beta	1.00			1.00		
DR beta	-0.36	1.00		-0.40	1.00	
CAPM beta	0.34	-0.95	1.00	0.38	-0.97	1.00

Table 2: Quarterly 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 (5). 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 measured at the end of 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 abnormal returns earned per quarter for cashflow timing, discount-rate timing, the sum of cashflow timing and discount-rate timing, and market-unexpected-return timing, 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: Cashflow timing								
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: Discount-rate timing								
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: Sum of cashflow timing and discount-rate timing								
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: Unexpected-market-return timing								
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 3: Persistence of quarterly timing ability

Each quarter, funds are sorted into deciles according to their past 1-, 3-, or 5-year timing performance, specified in (4), separately for cashflow timing, discount-rate timing, or unexpected-market-return timing. Then, the corresponding timing measure in the next quarter is averaged across funds in each decile. The time-series average of this quarterly decile-averaged timing measure for each decile is reported with t-statistics in parenthesis. Cashflow, discount-rate, and unexpected-market-return timing measures (abnormal returns per quarter in percentage) are presented 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 measured at the end of the current quarter in excess of the average of the fund's betas over all past quarters.

Deciles	Panel A: Cashflow			Panel B: Discount-rate			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 4: Characteristics of funds sorted on past-year total timing ability

Funds are sorted into quintiles each quarter according to their past-year total timing ability, which is the sum of abnormal returns stemming from both cashflow timing and discount-rate timing. The table presents the time-series average of equally weighted fund characteristics across funds in each quintile. The last two columns report 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, expense ratio, 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), fund return volatility (the volatility of monthly fund net returns over the past 12 months), Active Share (Cremers and Petajisto, 2009), portfolio-weighted market cap of equity holdings, and portfolio-weighted B/M of holdings. Portfolio-weighted market cap (B/M) of holdings for a particular fund is defined as the average of market cap (B/M) decile numbers of all stocks held by the fund, weighted by fund portfolio weights, after we rank all CRSP-listed common stocks each quarter into deciles according to their market cap or their book-to-market equity (B/M) ratios using breakpoints of NYSE stocks.

	1(Low)	2	3	4	5(High)	5-1	t-stat
Size (millions $)	1265.96	1439.71	1447.09	1328.96	1025.95	-240.01	-2.11
Fund age (year)	17.41	18.59	18.91	19.04	17.51	0.10	0.16
Expense ratio (%)	1.28	1.19	1.17	1.19	1.28	0.00	0.12
Turnover (%)	87.78	80.22	79.20	82.97	97.72	9.94	4.57
Fund flow (%)	7.51	7.88	7.55	8.85	13.69	6.18	3.23
Flow volatility (%)	2.97	2.66	2.67	2.77	3.35	0.38	2.96
Fund return volatility (%)	5.14	4.65	4.55	4.61	5.01	-0.13	-0.46
Active share (%)	84.61	79.65	78.17	79.84	85.23	0.62	0.93
Portfolio-weighted market cap of holdings	7.92	8.39	8.54	8.45	7.83	-0.08	-0.98
Portfolio-weighted B/M of holdings	3.54	3.57	3.62	3.67	3.74	0.20	2.36

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

Funds are sorted into quintiles each quarter according to their past-year total timing ability, which is the sum of abnormal returns stemming from both cashflow (CF) timing and discount-rate (DR) timing. The table presents the time-series average of equally weighted quarterly timing performance, including CF timing, DR timing, and the sum of CF timing and DR timing, across funds in each quintile in one of the subsequent four quarters after the sorting period. Quarterly timing performance is calculated as the fund's differential beta at the beginning of a quarter with respect to a systematic factor (market cashflow news or discount-rate news) multiplied by the quarterly 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 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 errors. Panels A and B present timing performance in terms of quarterly abnormal returns in percentage without and with applying a back testing procedure of Mamaysky, Spiegel, and Zhang (2007), respectively, in selecting funds in each quintile.

Panel A: Without back testing

	CF timing				DR timing				Sum of CF timing & DR timing			
	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: With back testing

	CF timing				DR timing				Sum of CF timing & DR timing			
	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: Cashflow and discount-rate exposure for funds sorted on past-year total timing ability

Funds are sorted into quintiles each quarter according to their past-year total timing performance, which is the sum of abnormal returns stemming from cashflow (CF) timing and discount-rate (DR) timing. Each quarter, a fund's differential beta (based on its holdings) is calculated as the fund's beta measured at the end of the current quarter in excess of the average of its betas over all past quarters. Then, for each quintile, the average of differential betas across funds is computed at the beginning of the i^{th} quarter ($i = 1,2,3,4$) after the sorting quarter. Next, we run regressions of this quintile-averaged fund differential beta $\tilde{\beta}_{q,k,t+i-1}$ for quintile q ($q = 1,...,5$) at the beginning of the i^{th} quarter after the quintile sorting quarter t:

$$\tilde{\beta}_{q,k,t+i-1} = b_0 + \gamma I_{K_{t+i}>0} + \eta_{q,k,t+i-1},$$

where K_t represents either cashflow or discount-rate news in quarter t, and $I_{K_t>0}$ is a dummy variable that equals one if $K_t > 0$, and zero otherwise, and k is CF (DR) if K_t represent cashflow (discount-rate) news. Panels A and B report γ for cashflow timing and discount-rate timing, respectively, for each fund quintile and for one of the subsequent four quarters after quintile formation. t-statistics reported in parenthesis are calculated based on Newey-West standard errors. The time-series averages of equally weighted fund cashflow 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: Shifts in CF betas				Panel B: Shifts in DR betas			
	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: Other performance measures for funds sorted on past-year total timing ability

Funds are sorted into quintiles each quarter according to their past-year total timing performance, which is equal to abnormal returns from both cashflow 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 sorting quarter. Fund portfolio performance is measured in percentage using quarterly fund gross returns before expenses (compounded monthly fund net returns + 1/12 expense ratios in a calendar quarter), quarterly fund net returns after expenses, and quarterly fund portfolio DGTW-adjusted returns. The last two panels show five-factor alphas associated with fund gross returns and fund net returns, where five factors include Carhart's (1997) four factors plus Pastor and Stambaugh's (2003) liquidity factor in the quarterly frequency. t-statistics reported in parenthesis are calculated based on Newey-West standard errors.

	Gross returns				Net returns				DGTW adjusted returns				Gross 5-factor alpha				Net 5-factor alpha			
	q1	q2	q3	q4	q1	q2	q3	q4	q1	q2	q3	q4	q1	q2	q3	q4	q1	q2	q3	q4
1(Low)	2.46	2.42	2.37	2.57	2.14	2.10	2.05	2.24	-0.09	-0.11	-0.12	-0.04	-0.04	-0.06	-0.10	-0.12	-0.36	-0.38	-0.42	-0.44
	(2.52)	(2.49)	(2.45)	(2.74)	(2.20)	(2.17)	(2.12)	(2.40)	(-0.59)	(-0.73)	(-0.75)	(-0.27)	(-0.22)	(-0.33)	(-0.55)	(-0.73)	(-1.97)	(-2.04)	(-2.34)	(-2.69)
2	2.52	2.60	2.51	2.58	2.22	2.30	2.21	2.28	-0.02	0.01	-0.05	-0.01	0.08	0.05	0.01	0.06	-0.22	-0.24	-0.29	-0.23
	(2.80)	(2.91)	(2.82)	(2.97)	(2.47)	(2.58)	(2.49)	(2.63)	(-0.16)	(0.07)	(-0.46)	(-0.07)	(0.65)	(0.45)	(0.07)	(0.47)	(-1.79)	(-1.99)	(-1.96)	(-1.69)
3	2.65	2.80	2.68	2.72	2.36	2.51	2.38	2.43	-0.03	0.04	0.02	0.04	0.28	0.23	0.11	0.17	-0.01	-0.06	-0.18	-0.12
	(3.05)	(3.23)	(3.09)	(3.17)	(2.72)	(2.90)	(2.76)	(2.83)	(-0.23)	(0.34)	(0.18)	(0.36)	(2.15)	(1.97)	(0.75)	(1.08)	(-0.05)	(-0.47)	(-1.26)	(-0.74)
4	2.94	2.94	2.95	2.94	2.64	2.64	2.65	2.64	0.14	0.13	0.12	0.13	0.32	0.42	0.31	0.25	0.03	0.12	0.02	-0.04
	(3.38)	(3.33)	(3.35)	(3.41)	(3.04)	(3.00)	(3.02)	(3.07)	(1.14)	(1.01)	(1.05)	(1.25)	(1.92)	(2.54)	(2.00)	(1.58)	(0.19)	(0.76)	(0.11)	(-0.24)
5(High)	3.20	3.24	3.19	3.11	2.87	2.92	2.86	2.78	0.20	0.18	0.21	0.13	0.52	0.56	0.39	0.44	0.20	0.24	0.07	0.12
	(3.49)	(3.54)	(3.47)	(3.33)	(3.14)	(3.19)	(3.12)	(2.99)	(1.36)	(1.33)	(1.63)	(1.03)	(2.11)	(2.47)	(1.89)	(1.97)	(0.82)	(1.06)	(0.33)	(0.53)
5-1	0.74	0.82	0.82	0.54	0.73	0.81	0.82	0.54	0.29	0.29	0.33	0.17	0.56	0.62	0.48	0.56	0.56	0.62	0.48	0.55
	(2.37)	(2.73)	(3.22)	(2.49)	(2.36)	(2.73)	(3.22)	(2.49)	(1.51)	(1.70)	(2.14)	(1.26)	(1.72)	(2.14)	(2.01)	(2.12)	(1.72)	(2.15)	(2.02)	(2.12)

Table 8: Monthly alphas for funds sorted on past-year total timing ability

Funds are sorted into quintiles in the most recent quarter according to their past-year total timing performance, which is equal to abnormal returns combined from both cashflow timing and discount-rate timing. Let Di, $i = 2,3,4,5$, be a dummy variable taking the value of 1 if a fund's past-year total timing performance is ranked in quintile i and taking the value of 0 otherwise. We run the following panel regression of the calendar-monthly fund net return in excess of the one-month Tbill rate, $r_{f,t+1}$:

$$r_{f,t+1} = \alpha_1 + \alpha_2 D2_{f,t} + \alpha_3 D3_{f,t} + \alpha_4 D4_{f,t} + \alpha_5 D5_{f,t} + \sum_{k=1}^{J} \lambda_k \beta_{f,k,t} + \sum_{c=1}^{C} \theta_c X_{f,c,t} + \epsilon_{f,t+1},$$

where $\beta_{f,k,t}$ is the sensitivity of fund f with respect to factor k, and $X_{f,c,t}$ is (demeaned) fund f's characteristics described in Section 5.1. For simplicity, this table reports only estimated coefficients of $\alpha_1,\ldots,\alpha_5$ in the unit of percentage per month, and p-values are included in parentheses based on heteroskedasticity-robust standard errors clustered by fund and by month. Columns (1)–(2) do not include model factors, columns (3)–(6) consider the Campbell and Vuolteenaho (2004) two-factor model, columns (7)–(8) consider the Carhart (1997) four-factor model, and columns (9)–(10) consider the five-factor model including Carhart's four factors plus Pastor and Stambaugh's (2003) liquidity factor. $\beta_{f,k,t}$ is calculated as the value-weighted stocks' sensitivity to factor k for all stocks held in fund f, except that in columns (5)–(6) it is taken as the time-series average of fund betas for each fund.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	No factor		2-factor model Time-varying betas		2-factor model Constant betas		4-factor model Time-varying betas		5-factor model Time-varying betas	
α_1	0.254	0.238	0.082	0.095	0.188	0.224	0.156	0.133	-0.002	-0.034
	(0.47)	(0.47)	(0.30)	(0.36)	(0.69)	(0.81)	(0.74)	(0.80)	(1.00)	(0.95)
α_2	0.013	0.015	-0.064	-0.062	0.018	0.018	0.003	0.006	0.013	0.014
	(0.81)	(0.79)	(0.25)	(0.29)	(0.69)	(0.71)	(0.96)	(0.91)	(0.81)	(0.79)
α_3	0.062	0.063	-0.056	-0.055	0.065	0.064	0.040	0.044	0.051	0.053
	(0.41)	(0.39)	(0.47)	(0.48)	(0.32)	(0.32)	(0.57)	(0.54)	(0.48)	(0.45)
α_4	0.158	0.157	0.015	0.011	0.159	0.157	0.140	0.141	0.149	0.149
	(0.07)	(0.06)	(0.88)	(0.91)	(0.05)	(0.05)	(0.10)	(0.09)	(0.08)	(0.08)
α_5	0.270	0.257	0.094	0.068	0.264	0.253	0.258	0.244	0.260	0.246
	(0.02)	(0.02)	(0.50)	(0.64)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
Include fund characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Table 9: The effect of industry rotation versus intra-industry allocation on timing ability

The timing performance due to industry rotation is measured as $\sum_{t=0}^{T-1}(\beta^I_{f,j,t}-\bar{\beta}^I_{f,j,t})K_{j,t+1}$, and the timing performance due to intra-industry allocation is measured as $\sum_{t=0}^{T-1}(\beta_{f,j,t}-\bar{\beta}_{f,j,t}-\beta^I_{f,j,t}+\bar{\beta}^I_{f,j,t})K_{j,t+1}$, where $K_{j,t+1}$ is the return on factor j in period $t+1$, $\beta_{f,j,t}$ ($\beta^I_{f,j,t}$) is fund f's beta (industry beta) with respect to factor j at the beginning of period $t+1$, and the fund f's target beta $\bar{\beta}_{f,j,t}$ is calculated as the average of the fund's beta over the past sample periods, and industry target beta $\bar{\beta}^I_{f,j,t}$ is calculated analogously. This table reports point estimates and t-statistics at various points in the cross-sectional distribution of these differential return timing measures. Panels Ai, Bi, and Ci, $i=1,2$, summarize quarterly abnormal returns earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Under the null hypothesis, the expected timing measures are zero. Bootstrap p-values reported in parenthesis are the probability of a higher or lower value occurring by chance and calculated based on 1000 bootstrap samples.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A1: Cashflow timing due to industry rotation								
Tim(%)	-0.22	-0.05	0.14	0.38	0.34	0.57	0.89	1.11
p-val	(0.43)	(0.87)	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.20	-0.26	0.65	1.07	1.22	1.71	2.24	2.56
p-val	(0.61)	(0.91)	(0.97)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
Panel A2: Cashflow timing due to intra-industry allocation								
Tim(%)	-0.68	-0.45	-0.17	0.15	0.08	0.39	0.89	1.27
p-val	(0.01)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-2.46	-1.82	-0.87	0.31	0.42	1.50	2.30	2.79
p-val	(0.01)	(0.04)	(0.25)	(0.08)	(0.04)	(0.00)	(0.00)	(0.00)
Panel B1: Discount-rate timing due to industry rotation								
Tim(%)	-0.49	-0.39	-0.23	-0.11	-0.08	0.04	0.14	0.20
p-val	(0.03)	(0.02)	(0.04)	(0.08)	(0.12)	(0.72)	(0.60)	(0.62)
t-stat	-2.08	-1.67	-1.04	-0.42	-0.43	0.23	0.82	1.22
p-val	(0.09)	(0.13)	(0.19)	(0.18)	(0.20)	(0.79)	(0.76)	(0.70)
Panel B2: Discount-rate timing due to intra-industry allocation								
Tim(%)	-0.73	-0.53	-0.26	-0.11	-0.08	0.07	0.26	0.38
p-val	(0.01)	(0.01)	(0.01)	(0.02)	(0.03)	(0.77)	(0.41)	(0.38)
t-stat	-2.51	-1.90	-1.17	-0.41	-0.42	0.40	1.14	1.71
p-val	(0.01)	(0.03)	(0.06)	(0.04)	(0.07)	(0.86)	(0.67)	(0.33)
Panel C1: Sum of cashflow and discount-rate timing due to industry rotation								
Tim(%)	-0.30	-0.14	0.07	0.28	0.27	0.43	0.69	0.91
p-val	(0.46)	(0.72)	(0.96)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.07	-0.46	0.22	0.66	0.68	1.22	1.80	2.08
p-val	(0.72)	(0.87)	(0.92)	(0.08)	(0.11)	(0.15)	(0.10)	(0.10)
Panel C2: Sum of cashflow and discount-rate timing due to intra-industry allocation								
Tim(%)	-0.69	-0.49	-0.22	0.04	0.02	0.28	0.64	0.93
p-val	(0.02)	(0.02)	(0.06)	(0.23)	(0.34)	(0.01)	(0.00)	(0.00)
t-stat	-2.17	-1.67	-0.93	0.07	0.09	1.06	1.78	2.23
p-val	(0.04)	(0.08)	(0.16)	(0.38)	(0.36)	(0.08)	(0.05)	(0.03)

Table 10: Quarterly timing ability across portfolio-weighted stock characteristics of holdings

All CRSP-listed common stocks are ranked into deciles each quarter according to their market cap or their book-to-market equity (B/M) ratios using breakpoints of NYSE stocks. Portfolio-weighted market cap (B/M) of holdings for a particular fund is defined as the average of market cap (B/M) decile numbers of all stocks held by the fund, weighted by fund portfolio weights. Funds are then sorted into deciles each quarter according to their portfolio-weighted market cap of holdings in Panel A or their portfolio-weighted B/M of holdings in Panel B. Next, we run panel regressions to compute the averages of next-quarter abnormal returns in each decile stemming from cash-flowing timing, discount-rate timing, and the sum of cash-flowing timing and discount-rate timing, as well as these timing returns due to industry rotation or intra-industry allocations. t-statistics reported in parentheses are calculated based on heteroskedasticity-robust standard errors clustered by fund and by date. The last two rows in each panel report the spread of timing performance between the two extreme deciles.

	Panel A: Sorted on portfolio-weighted market cap of holdings								
	Cashflow timing			Discount-rate timing			Cashflow timing + discount-rate timing		
	CF tim	Ind rotation	Intra-ind	DR tim	Ind rotation	Intra-ind	CF + DR tim	Ind rotation	Intra-ind
1(Small)	0.93	0.36	0.57	-0.22	-0.02	-0.20	0.71	0.34	0.36
	(2.58)	(2.05)	(2.10)	(-1.32)	(-0.17)	(-1.85)	(2.31)	(2.35)	(1.51)
2	0.76	0.30	0.46	-0.33	-0.08	-0.24	0.43	0.21	0.22
	(2.36)	(2.02)	(1.85)	(-1.42)	(-0.74)	(-1.57)	(1.69)	(1.62)	(1.09)
3	0.61	0.30	0.32	-0.20	-0.06	-0.15	0.41	0.24	0.17
	(2.41)	(2.14)	(1.82)	(-1.04)	(-0.56)	(-1.02)	(2.05)	(1.89)	(1.31)
4	0.53	0.32	0.21	-0.20	-0.08	-0.12	0.34	0.24	0.09
	(2.24)	(2.36)	(1.50)	(-1.16)	(-0.82)	(-0.95)	(1.86)	(1.88)	(0.94)
5	0.53	0.36	0.17	-0.21	-0.09	-0.12	0.32	0.27	0.05
	(2.38)	(2.51)	(1.49)	(-1.33)	(-0.95)	(-1.00)	(2.06)	(2.10)	(0.72)
6	0.50	0.38	0.11	-0.19	-0.13	-0.07	0.30	0.25	0.05
	(2.21)	(2.42)	(1.28)	(-1.34)	(-1.27)	(-0.75)	(1.86)	(1.84)	(0.80)
7	0.36	0.37	-0.01	-0.12	-0.10	-0.02	0.24	0.27	-0.03
	(2.11)	(2.46)	(-0.24)	(-0.97)	(-1.06)	(-0.24)	(1.76)	(1.90)	(-0.57)
8	0.36	0.39	-0.03	-0.10	-0.11	0.01	0.26	0.28	-0.02
	(1.76)	(2.28)	(-0.46)	(-0.69)	(-1.04)	(0.11)	(1.60)	(1.87)	(-0.28)
9	0.28	0.37	-0.09	-0.11	-0.11	0.00	0.17	0.26	-0.09
	(1.48)	(2.18)	(-1.35)	(-0.77)	(-1.06)	(0.04)	(1.06)	(1.78)	(-0.96)
10(Large)	0.30	0.39	-0.08	-0.21	-0.14	-0.07	0.09	0.25	-0.15
	(1.33)	(2.08)	(-1.02)	(-1.26)	(-1.29)	(-0.84)	(0.50)	(1.61)	(-1.48)
10-1	-0.62	0.03	-0.65	0.01	-0.13	0.13	-0.61	-0.10	-0.52
	(-2.04)	(0.43)	(-2.03)	(0.06)	(-1.36)	(0.97)	(-1.94)	(-1.31)	(-1.61)

	Panel B: Sorted on portfolio-weighted B/M of holdings								
	Cashflow timing			Discount-rate timing			Cashflow timing + discount-rate timing		
	CF tim	Ind rotation	Intra-ind	DR tim	Ind rotation	Intra-ind	CF + DR tim	Ind rotation	Intra-ind
1(Low)	0.36	0.34	0.02	-0.26	-0.15	-0.11	0.10	0.20	-0.10
	(1.81)	(1.87)	(0.22)	(-0.86)	(-0.91)	(-0.62)	(0.42)	(1.29)	(-0.64)
2	0.36	0.32	0.04	-0.21	-0.12	-0.09	0.15	0.20	-0.05
	(1.64)	(2.03)	(0.34)	(-0.82)	(-0.88)	(-0.55)	(0.75)	(1.37)	(-0.40)
3	0.41	0.33	0.08	-0.20	-0.11	-0.09	0.21	0.22	-0.01
	(1.68)	(2.16)	(0.63)	(-0.81)	(-0.84)	(-0.61)	(1.15)	(1.58)	(-0.11)
4	0.38	0.32	0.06	-0.19	-0.10	-0.09	0.19	0.22	-0.03
	(1.67)	(2.07)	(0.56)	(-0.92)	(-0.85)	(-0.75)	(0.97)	(1.53)	(-0.25)
5	0.48	0.32	0.16	-0.23	-0.11	-0.12	0.25	0.21	0.04
	(2.08)	(2.21)	(1.38)	(-1.46)	(-1.05)	(-1.43)	(1.46)	(1.61)	(0.46)
6	0.50	0.34	0.17	-0.17	-0.07	-0.10	0.33	0.27	0.07
	(2.27)	(2.41)	(1.56)	(-1.24)	(-0.80)	(-1.29)	(1.95)	(2.01)	(0.92)
7	0.51	0.35	0.17	-0.18	-0.06	-0.12	0.33	0.28	0.05
	(2.41)	(2.41)	(1.90)	(-1.47)	(-0.71)	(-0.93)	(1.91)	(2.06)	(0.79)
8	0.63	0.34	0.29	-0.21	-0.09	-0.12	0.42	0.26	0.17
	(2.54)	(2.42)	(2.17)	(-0.92)	(-0.97)	(-0.99)	(1.95)	(1.91)	(1.47)
9	0.69	0.34	0.29	-0.21	-0.09	-0.12	0.42	0.26	0.17
	(2.54)	(2.42)	(2.17)	(-0.92)	(-0.97)	(-0.99)	(1.95)	(1.91)	(1.47)
10(High)	0.83	0.51	0.32	-0.08	-0.04	-0.04	0.75	0.47	0.27
	(2.15)	(2.41)	(2.36)	(-0.59)	(-0.49)	(-0.41)	(2.04)	(2.45)	(1.65)
10-1	0.46	0.16	0.30	0.18	0.11	0.07	0.64	0.27	0.37
	(1.76)	(1.80)	(1.88)	(0.52)	(0.76)	(0.33)	(1.84)	(1.61)	(1.74)

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

Panel A summarizes results of the regressions of concurrent or next-quarter unexpected market return or its cashflow or discount-rate return component (in percentage) on aggregate fund net flows. Aggregate fund net flow is defined as inflow minus outflow, in aggregate, from equity fund investors as a percentage of prior quarter-end aggregate AUM. This variable is then converted to IBES quarters (see Section 6.3). t-statistics are reported in parenthesis based on Newey-West standard errors with a lag of four. Panel B presents the results of the regressions of differential cashflow beta, differential discount-rate beta, and differential unexpected-market-return beta on aggregate fund net flows. Differential beta is defined as a fund's beta measured at the end of the current quarter in excess of the average of the fund's beta in previous quarters. t-statistics reported in parentheses are calculated based on heteroskedasticity-robust standard errors clustered by fund and by quarter.

	1	2	3	4	5	6
Panel A	Cashflow 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)

Panel B	Cashflow 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)

Cashflow timing vs. discount-rate timing: An examination of mutual fund market-timing skills

Separate Internet Appendix

A1 Comparison of return decomposition using our approach vs the VAR-based approach

Equation (20) in Section 7.5 of the paper shows that directly generated cashflow news based on the VAR model (18) with constraints (19) is the same as the one backed out as the unexpected return plus directly constructed discount-rate news. This feature suggests that regardless of whether cashflow news or discount-rate news is directly constructed, resulting return decomposition components are the same. This feature is important for comparing and understanding the differences between the return decomposition used in our main tests based on the three-stage growth model, which directly constructs cashflow news, and a VAR-based return decomposition appealing to Campbell, Giglio, and Polk (2013).

We first compare cashflow news generated using these two methods given the VAR-based forecasts for future cashflows as inputs, and show that given similar forecasts for future cashflows, the return decompositions using our approach and the VAR-based approach produce quite similar cashflow and discount-rate return components. Specifically, dividend growth forecasts for the next year, the year after, and the average annual growth rate over the next 3–5 years are derived from the estimated VAR model (18) as $\sum_{i=1}^{4} e2'(\Gamma^i(Z_t - \bar{Z}) + \bar{Z})$, $\sum_{i=5}^{8} e2'(\Gamma^i(Z_t - \bar{Z}) + \bar{Z})$, $1/3\sum_{i=9}^{20} e2'(\Gamma^i(Z_t - \bar{Z}) + \bar{Z})$, where $\bar{Z}$ is the unconditional mean of Z_t, and the definitions of other variables are in Section 7.5 of the paper. Because earnings forecasts are required for the three-stage growth model, we first obtain the payout ratio as realized year-end dividends divided by realized year-end earnings,[1] then calculate earnings forecasts over the next year and the year after as the corresponding dividend forecasts divided by the current payout ratio, where dividend forecasts are computed as current realized dividends multiplied by the corresponding dividend growth forecasts. Here, we assume that there is no forecasting power for the payout ratio, although the (realized) payout ratio changes over time. This assumption is consistent with little R^2 in the regression of the payout ratio. Accordingly, forecasts of the earnings growth rate over the next 3–5 years are the same as those for the dividend growth rate.

[1] Note the difference in samples: Realized aggregate earnings are the total annual earnings for firms in the IBES sample, and realized aggregate dividends are the total annual dividend payments for firms in the CRSP sample. When we derive predicted earnings from dividend forecasts and the payout ratio, the sample difference is incorporated as the sample difference is normally stable within a given year.

Figure A1 plots the two time-series of cashflow news generated using our approach and the VAR-based approach, given the VAR-based forecasts for future cashflows as inputs. Apparently, these two time-series exhibits similar dynamics. Their correlation is high, being 0.75. Back out discount-rate news as cashflow news minus the unexpected market return, and the correlation of the two time-series of discount-rate news is also high, being 0.92. The high correlations suggest that, when similar forecasts for future cashflows are used, the return decomposition used in our main tests and the VAR-based return decomposition, though implemented differently, produce quite similar references.

Next, Table A1 compares the predictive power for future realized aggregate cashflow growth using analysts' earnings forecasts vs. VAR-based dividend growth forecasts. The explanatory variables in the first three columns are $log(A1)-log(E)$, $log(A2)-log(A1)$, and LTG, respectively, where $A1$ and $A2$ are market-level earnings forecasts for the current fiscal year and the next fiscal year, respectively, E is the realized earnings in the previous year, LTG is long-term growth forecasts for the next 3–5 years. (See Appendix A in the paper for construction of these variables.) The dependent variables are the realized growth rate of aggregate earnings matching the periods of the explanatory variables. Clearly, analysts' earnings forecasts exhibit strong forecasting power for realized earnings growth over the next 5 years. The estimated slope coefficients are close to 1, except for the regression of the 3–5 year growth, in which the slope coefficient is a bit larger than 1. These results suggest that analysts' earnings forecasts, in aggregate, are a good predictor of future changes in aggregate cashflows.[2]

The last two columns of the table report predictive power for future realized aggregate dividend growth using VAR-based dividend growth forecasts. The explanatory variables are $e2'\sum_{i=1}^{4}(\Gamma^i(Z_{t-1}-\bar{Z})+\bar{Z})$ and $e2'\sum_{i=5}^{8}(\Gamma^i(Z_{t-1}-\bar{Z})+\bar{Z})$ for one- and two-year growth rates, respectively, where $e2$, Z_{t-1}, and Γ are defined in Section 7.5 in the paper. The estimated slope coefficients are close to 1. The predictive R^2 is large for one-year forecasts and small for two-year forecasts, and little for 3-5 years (untabulated results). Overall, the VAR-model

[2]Note that intercepts are significantly negative, which is consistent with analysts' optimism in their forecasts. As long as their optimism is moving slowly, it would not have a material effect on our cashflow news that is calculated as the difference of cashflow levels derived from analysts' forecasts. This is also confirmed in our robustness checks by adjusting analysts' optimism in their forecasts in Section 7.6 of the paper.

captures future cashflow dynamics, though being less powerful than analyst forecasts.

All these results combined suggest that our return decomposition, based on the three-stage growth model and analysts' earnings forecasts, is a good alternative to VAR-based decomposition. Our approach helps avoid the model-specification sensitivity issue that the VAR model faces, which has been discussed in Section 3.1 of the paper.

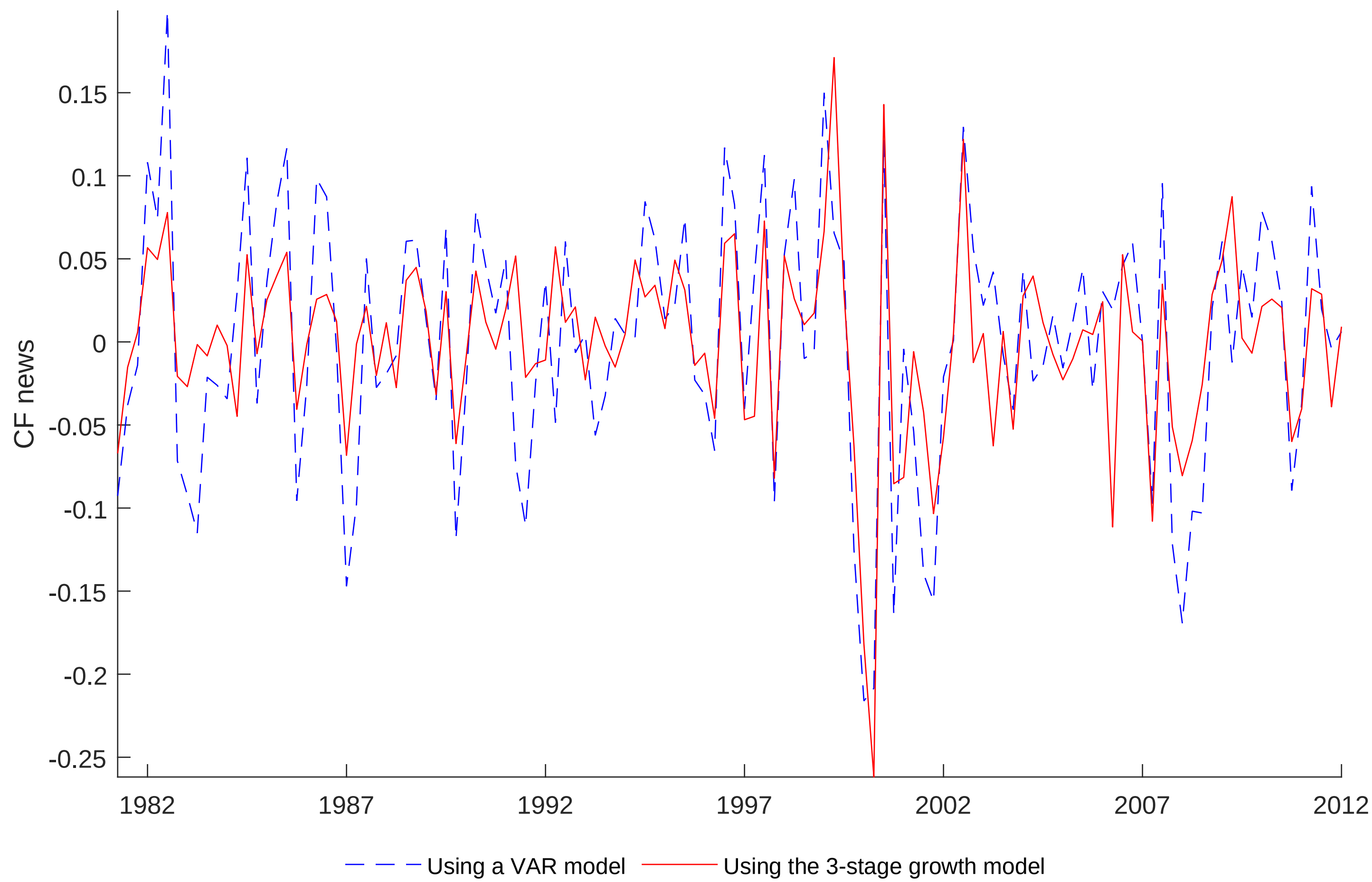

Figure A1: This figure compares quarterly cashflow news generated using the VAR model (18) in the paper vs. cashflow news generated using the 3-stage growth model described in Section 3.1, given derived VAR-based forecasts as inputs.

Table A1: Cashflow forecasting power using analysts' earnings forecasts vs. VAR-based forecasts

This table compares the forecasting power for realized earnings growth using analysts' earnings forecasts with the forecasting power for realized dividend growth using VAR-based forecasts. Point estimates are reported first, and then followed by standard errors in parentheses; the last row reports an adjusted R^2.

	1-y earnings growth	2-y earnings growth	3-5-y earnings growth	1-y dividend growth	2-y dividend growth
Intercept	-0.060	-0.128	-0.118	0.001	-0.003
	(0.006)	(0.029)	(0.026)	(0.001)	(0.003)
Forecasts	0.957	1.153	1.417	0.903	1.697
	(0.035)	(0.162)	(0.188)	(0.079)	(0.602)
Adj. R^2	0.67	0.12	0.16	0.23	0.02

A2 Tables for additional tests and robustness checks

Tables A2-A17 report the results discussed in Section 7 of our paper.

Table A2: Quarterly timing ability for initiating purchases and liquidation sales

This table reports point estimates and t-statistics at various points in the cross-sectional distribution of timing measures for a fund portfolio consisting of stocks that are first purchased (left panel) or stocks that are completely liquidated (right panel). The timing measure for a given fund with respect to a systematic factor, as specified in (5), 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 beta for initiating purchases is defined as the average beta of purchased stocks that are not held a quarter ago, weighted by the values of these stocks in the fund. A fund's beta for liquidation sales is defined as the average beta of stocks that are liquidated, weighted by the values of these stocks in the fund. A fund's differential beta is the fund's beta for initiating purchases or liquidation sales in excess of the historical average of fund beta that is value-weighted stock betas for all stocks held in the fund. Panels A, B, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Under the null hypothesis, the expected timing measures are zero. Bootstrap p-values reported in parenthesis are the probability of a higher or lower value occurring by chance and calculated based on 1000 bootstrap samples.

	Initiating purchases								Liquidation sales							
	5%	10%	25%	Mean	Median	75%	90%	95%	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing																
Tim(%)	-0.94	-0.56	-0.01	0.62	0.54	1.19	1.99	2.43	-1.63	-1.15	-0.48	0.08	0.10	0.64	1.32	1.84
p-val	(0.12)	(0.31)	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.06)	(0.23)	(0.18)	(0.00)	(0.00)	(0.00)
t-stat	-1.18	-0.80	-0.02	0.81	0.91	1.61	2.24	2.61	-1.87	-1.42	-0.73	0.11	0.17	0.94	1.55	1.93
p-val	(0.97)	(0.98)	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)	(0.23)	(0.44)	(0.39)	(0.30)	(0.24)	(0.20)	(0.17)
Panel B: Discount-rate timing																
Tim(%)	-1.65	-1.29	-0.77	-0.26	-0.27	0.13	0.51	0.81	-1.40	-1.06	-0.53	-0.14	-0.11	0.28	0.65	0.97
p-val	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.97)	(0.81)	(0.61)	(0.03)	(0.02)	(0.06)	(0.07)	(0.13)	(0.72)	(0.66)	(0.54)
t-stat	-2.46	-1.98	-1.29	-0.54	-0.51	0.22	0.94	1.32	-1.99	-1.57	-0.94	-0.21	-0.21	0.54	1.13	1.52
p-val	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.99)	(0.97)	(0.95)	(0.04)	(0.09)	(0.12)	(0.13)	(0.16)	(0.83)	(0.85)	(0.76)
Panel C: Sum of cashflow timing and discount-rate timing																
Tim(%)	-1.31	-0.85	-0.28	0.36	0.30	0.86	1.45	1.88	-1.78	-1.25	-0.57	-0.05	-0.02	0.52	1.13	1.58
p-val	(0.10)	(0.25)	(0.69)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.04)	(0.14)	(0.35)	(0.45)	(0.23)	(0.05)	(0.03)
t-stat	-1.36	-0.99	-0.36	0.38	0.43	1.09	1.69	2.07	-1.75	-1.37	-0.72	-0.03	-0.02	0.67	1.30	1.61
p-val	(0.85)	(0.87)	(0.89)	(0.08)	(0.06)	(0.08)	(0.08)	(0.06)	(0.26)	(0.31)	(0.45)	(0.42)	(0.46)	(0.56)	(0.51)	(0.56)

Table A3: Timing ability when cash positions are considered

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 (5) for the fund sample with non-missing cash positions. 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 beta is calculated based on the fund's equity and cash positions. 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 quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, the sum of cashflow timing and discount-rate timing, and market-unexpected-return timing, respectively. Bootstrap p-values are reported in parenthesis based on 1000 bootstrap samples and represent the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
				Panel A: Cashflow timing				
Tim(%)	-0.75	-0.39	0.06	0.50	0.47	0.93	1.52	1.87
p-val	(0.01)	(0.10)	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.35	-0.97	0.20	1.07	1.30	2.03	2.61	3.01
p-val	(0.69)	(0.75)	(0.99)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
				Panel B: Discount-rate timing				
Tim(%)	-0.71	-0.52	-0.30	-0.06	-0.08	0.14	0.38	0.56
p-val	(0.25)	(0.27)	(0.26)	(0.38)	(0.32)	(0.56)	(0.46)	(0.43)
t-stat	-1.94	-1.55	-0.92	-0.26	-0.28	0.41	1.02	1.44
p-val	(0.16)	(0.21)	(0.29)	(0.32)	(0.34)	(0.63)	(0.59)	(0.48)
				Panel C: Sum of cashflow timing and discount-rate timing				
Tim(%)	-0.72	-0.41	0.03	0.44	0.41	0.83	1.33	1.69
p-val	(0.24)	(0.46)	(0.94)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.25	-0.88	0.09	0.78	1.02	1.58	1.99	2.18
p-val	(0.72)	(0.75)	(0.93)	(0.04)	(0.01)	(0.03)	(0.06)	(0.09)
				Panel D: Unexpected-market-return timing				
Tim(%)	-0.50	-0.29	-0.04	0.15	0.17	0.37	0.59	0.75
p-val	(0.44)	(0.61)	(0.79)	(0.18)	(0.14)	(0.13)	(0.15)	(0.17)
t-stat	-1.12	-0.76	-0.14	0.49	0.59	1.20	1.62	1.84
p-val	(0.76)	(0.80)	(0.82)	(0.17)	(0.18)	(0.16)	(0.18)	(0.22)

Table A4: Timing ability for index funds

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 (5) for index funds. 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 beta is calculated based on the fund's equity positions. 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, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Bootstrap p-values are reported in parenthesis based on 1000 bootstrap samples and represent the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
Tim(%)	-0.49	-0.44	-0.30	0.10	0.13	0.38	0.69	0.70
pval	(0.02)	(0.00)	(0.00)	(0.04)	(0.01)	(0.00)	(0.00)	(0.00)
t-stat	-2.40	-2.11	-1.26	0.31	0.62	1.20	2.50	2.82
pval	(0.52)	(0.45)	(0.41)	(0.35)	(0.27)	(0.43)	(0.26)	(0.31)
Panel B: Discount-rate timing								
Tim(%)	-0.35	-0.29	-0.11	-0.08	-0.09	-0.02	0.06	0.12
pval	(0.12)	(0.07)	(0.26)	(0.13)	(0.11)	(0.91)	(0.83)	(0.78)
t-stat	-1.72	-1.15	-0.97	-0.53	-0.52	-0.18	0.32	0.48
pval	(0.72)	(0.73)	(0.49)	(0.28)	(0.31)	(0.87)	(0.93)	(0.99)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-0.50	-0.39	-0.34	0.02	-0.02	0.28	0.58	0.58
pval	(0.06)	(0.04)	(0.02)	(0.40)	(0.41)	(0.02)	(0.00)	(0.03)
t-stat	-1.53	-1.51	-0.94	0.09	-0.09	0.77	1.93	1.93
pval	(0.82)	(0.64)	(0.51)	(0.45)	(0.46)	(0.57)	(0.42)	(0.64)

Table A5: Informativeness of past-year timing ability in multivariate regressions

This table reports the results of pooled panel regressions and Fama-MacBeth regressions of fund timing performance on past-year timing ability ranking, while controlling for different fund characteristics. Past-year timing ability ranking is a decile ranking that is obtained by sorting funds each quarter into deciles according to their past-year total timing ability. Fund characteristics include fund size (total net assets), fund age, expense ratio, 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), fund return volatility (the volatility of monthly fund net returns over the past 12 months). The dependent variable is either next-quarter or next-year abnormal returns in percentage earned from cashflow (CF) timing, discount-rate (DR) timing, or the sum of CF timing and DR timing. t-statistics included in parenthesis are calculated based on heteroskedasticity-robust standard errors for panel regressions using two-way clusters by fund and by quarter. t-statistics for Fama-MacBeth regressions are calculated using Newey-West (1987) standard errors with a lag of 0 for quarterly timing measures or a lag of 3 for yearly timing measures.

	1-q CF timing		1-q DR timing		1-q CF+DR timing		1-y CF timing		1-y DR timing		1-y CF+DR timing	
	OLS	Fama-MacBeth	OLS	Fama-MacBeth	OLS	Fama-MacBeth	OLS	Fama-MacBeth	OLS	Fama-MacBeth	OLS	Fama-MacBeth
Past-year timing ability ranking	0.200	0.159	-0.044	-0.046	0.156	0.113	0.493	0.398	-0.226	-0.201	0.267	0.197
	(5.28)	(5.45)	(-0.96)	(-1.51)	(3.95)	(3.68)	(6.05)	(4.37)	(-1.80)	(-1.85)	(2.64)	(1.81)
Fund size	-0.014	0.005	0.016	0.002	0.002	0.008	-0.078	-0.002	-0.073	-0.000	-0.150	-0.002
	(-0.58)	(0.73)	(0.61)	(0.29)	(0.05)	(0.74)	(-1.41)	(-0.20)	(-1.63)	(-0.12)	(-2.34)	(-0.11)
Fund age	-0.001	-0.000	0.002	0.001	0.001	0.000	-0.003	0.001	0.017	0.007	0.014	0.007
	(-0.50)	(-0.39)	(0.62)	(0.42)	(0.39)	(0.11)	(-0.56)	(0.09)	(2.42)	(1.69)	(1.98)	(1.60)
Expense Ratio	-15.639	1.196	17.308	1.473	1.669	2.669	-68.212	-0.496	48.436	10.817	-19.775	10.321
	(-1.41)	(0.42)	(2.31)	(0.43)	(0.12)	(0.67)	(-3.22)	(-0.37)	(2.44)	(0.70)	(-0.87)	(1.08)
Fund Turnover Ratio	0.127	0.099	-0.056	-0.048	0.072	0.051	0.445	0.419	-0.327	-0.252	0.118	0.168
	(2.48)	(3.03)	(-1.55)	(-1.77)	(1.57)	(1.95)	(3.12)	(3.05)	(-3.18)	(-2.44)	(0.97)	(1.85)
Fund flow	-0.012	-0.044	-0.004	-0.000	-0.017	-0.045	-0.178	-0.254	-0.040	-0.056	-0.218	-0.310
	(-0.36)	(-2.14)	(-0.21)	(-0.01)	(-0.38)	(-1.59)	(-1.46)	(-2.06)	(-0.72)	(-0.67)	(-1.56)	(-2.31)
Flow volatility	-0.252	0.058	1.066	0.921	0.814	0.978	-0.394	0.830	2.700	2.797	2.305	3.627
	(-0.47)	(0.16)	(1.50)	(1.99)	(1.11)	(2.06)	(-0.21)	(0.72)	(1.68)	(2.26)	(1.22)	(2.77)
Fund ret volatility	1.793	-0.634	-14.680	-0.518	-12.887	-1.152	18.425	2.577	-16.912	-14.209	1.513	-11.632
	(0.31)	(-0.24)	(-1.70)	(-0.19)	(-1.01)	(-0.34)	(1.07)	(0.34)	(-1.09)	(-1.12)	(0.05)	(-0.71)

Table A6: Timing ability based on the Gordon model

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 (5). Market cashflow news and discount-rate news are constructed based on the Gordon growth model according to (17). Panels A, B, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
Tim(%)	-0.49	-0.29	-0.08	0.32	0.15	0.52	1.16	1.67
pval	(0.20)	(0.31)	(0.65)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-2.46	-1.75	-0.53	0.68	0.82	1.95	2.82	3.29
pval	(0.01)	(0.07)	(0.67)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Panel B: Discount-rate timing								
Tim(%)	-0.59	-0.43	-0.24	-0.12	-0.09	0.03	0.16	0.25
pval	(0.15)	(0.17)	(0.16)	(0.10)	(0.15)	(0.91)	(0.93)	(0.94)
t-stat	-1.76	-1.49	-0.98	-0.41	-0.43	0.16	0.69	0.98
pval	(0.28)	(0.26)	(0.22)	(0.14)	(0.16)	(0.91)	(0.95)	(0.96)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-0.63	-0.43	-0.16	0.20	0.09	0.41	0.97	1.46
pval	(0.26)	(0.32)	(0.52)	(0.03)	(0.15)	(0.03)	(0.00)	(0.00)
t-stat	-2.03	-1.57	-0.67	0.28	0.33	1.25	2.01	2.51
pval	(0.13)	(0.19)	(0.49)	(0.18)	(0.18)	(0.05)	(0.02)	(0.01)

Table A7: Timing ability based on the first-stage of the three-stage earnings growth model

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 (5). Panels A, B, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Market cashflow news is calculated as $E_{t+1}\sum_{j=0}^{5}\rho^j\theta_{t,1+j} - E_t\sum_{j=0}^{5}\rho^j\theta_{t,1+j}$ based on the first-stage forecasts of the three-stage earnings growth model. The discount-rate component is backed out as the difference between the cashflow component and the unexpected market return. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
Tim(%)	-0.66	-0.40	-0.09	0.41	0.24	0.75	1.54	2.01
pval	(0.07)	(0.17)	(0.65)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
t-stat	-1.94	-1.33	-0.25	0.42	0.60	1.25	1.83	2.24
pval	(0.14)	(0.35)	(0.78)	(0.18)	(0.13)	(0.13)	(0.11)	(0.07)
Panel B: Discount-rate timing								
Tim(%)	-0.76	-0.58	-0.28	-0.11	-0.07	0.11	0.29	0.42
pval	(0.02)	(0.02)	(0.06)	(0.10)	(0.19)	(0.60)	(0.51)	(0.50)
t-stat	-2.57	-2.07	-1.11	-0.35	-0.28	0.51	1.18	1.63
pval	(0.01)	(0.02)	(0.11)	(0.15)	(0.24)	(0.66)	(0.53)	(0.41)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-0.74	-0.46	-0.11	0.30	0.24	0.65	1.22	1.63
pval	(0.21)	(0.37)	(0.73)	(0.02)	(0.03)	(0.00)	(0.00)	(0.00)
t-stat	-1.60	-1.09	-0.25	0.33	0.46	0.99	1.49	1.88
pval	(0.41)	(0.59)	(0.82)	(0.21)	(0.15)	(0.23)	(0.28)	(0.23)

Table A8: Timing ability using Campbell, Giglio, and Polk's (2013) state variables

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 (5). The market cashflow and discount-rate return components are constructed from the VAR model (18) in the paper, which is estimated using continuously updated GMM that accounts for time-series and cross-sectional (FF 6 portfolios) return patterns according to the ICAPM model, as suggested by Campbell, Giglio, and Polk (2013). The state variables in the VAR model include market excess returns, dividend growth, the dividend yield, term spread, default spread, and value premium of small stocks. Panels A, B, and C summarize the abnormal returns in percentage earned per quarter for cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
	5%	10%	25%	Mean	Median	75%	90%	95%
Tim(%)	-0.23	-0.02	0.22	0.49	0.45	0.74	1.05	1.30
pval	(0.97)	(0.99)	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
t-stat	-0.56	-0.07	0.66	1.19	1.29	1.83	2.30	2.57
pval	(0.98)	(0.99)	(0.99)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Panel B: Discount-rate timing								
Tim(%)	-2.11	-1.58	-0.85	-0.24	-0.19	0.41	1.02	1.55
pval	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.02)	(0.00)	(0.00)
t-stat	-4.21	-3.52	-2.21	-0.49	-0.67	1.27	2.55	3.45
pval	(0.00)	(0.00)	(0.00)	(0.18)	(0.15)	(0.16)	(0.11)	(0.10)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-1.54	-1.10	-0.34	0.25	0.24	0.81	1.56	2.27
pval	(0.02)	(0.03)	(0.35)	(0.09)	(0.08)	(0.00)	(0.00)	(0.00)
t-stat	-2.57	-1.85	-0.69	0.39	0.50	1.51	2.39	3.11
pval	(0.01)	(0.07)	(0.46)	(0.18)	(0.13)	(0.03)	(0.01)	(0.00)

Table A9: Timing ability using the dividend yield as a predictor

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 (5). A restricted VAR model, in which dividend growth, the market excess return, and the log dividend-price ratio are state variables and the lagged log dividend-price ratio is the sole predictor, is estimated using the sample from Jan. 1927 to Dec. 2011. Then, the market discount-rate return component is constructed directly from the estimated VAR model, and the market cashflow return component is calculated as the unexpected market return plus the discount-rate component. Panels A, B, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
Tim(%)	-0.79	-0.56	-0.22	0.47	0.11	0.81	1.92	2.92
pval	(0.80)	(0.74)	(0.67)	(0.06)	(0.29)	(0.08)	(0.03)	(0.02)
t-stat	-1.75	-1.34	-0.58	0.25	0.27	1.19	1.79	2.05
pval	(0.28)	(0.36)	(0.57)	(0.26)	(0.28)	(0.11)	(0.11)	(0.12)
Panel B: Discount-rate timing								
Tim(%)	-1.58	-1.09	-0.48	-0.20	-0.06	0.21	0.48	0.71
pval	(0.23)	(0.20)	(0.19)	(0.14)	(0.31)	(0.79)	(0.91)	(0.94)
t-stat	-1.89	-1.52	-0.85	-0.13	-0.16	0.58	1.33	1.72
pval	(0.17)	(0.21)	(0.33)	(0.31)	(0.29)	(0.68)	(0.43)	(0.34)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-0.83	-0.57	-0.23	0.27	0.07	0.51	1.34	2.06
pval	(0.79)	(0.74)	(0.66)	(0.11)	(0.36)	(0.22)	(0.07)	(0.05)
t-stat	-1.83	-1.33	-0.60	0.21	0.19	1.06	1.77	2.25
pval	(0.21)	(0.38)	(0.56)	(0.29)	(0.32)	(0.17)	(0.09)	(0.04)

Table A10: Timing ability using the break-adjusted dividend yield as a predictor

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 (5). The market discount-rate return component is constructed directly from return forecasts using the log dividend yield with adjustment of structural breaks in its mean, as in Lettau and van Nieuwerburgh (2008). The market cashflow return component is then constructed as the unexpected market return plus the discount-rate component. Panels A, B, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
Tim(%)	-0.77	-0.50	-0.14	0.48	0.23	0.83	1.83	2.57
pval	(0.48)	(0.49)	(0.66)	(0.01)	(0.01)	(0.02)	(0.03)	(0.04)
t-stat	-1.80	-1.27	-0.47	0.55	0.71	1.50	2.30	2.70
pval	(0.21)	(0.43)	(0.73)	(0.06)	(0.05)	(0.04)	(0.01)	(0.01)
Panel B: Discount-rate timing								
Tim(%)	-0.76	-0.47	-0.16	-0.02	-0.03	0.23	0.49	0.69
pval	(0.42)	(0.53)	(0.69)	(0.44)	(0.34)	(0.39)	(0.43)	(0.48)
t-stat	-1.48	-1.10	-0.52	0.11	0.11	0.75	1.34	1.71
pval	(0.60)	(0.70)	(0.73)	(0.33)	(0.35)	(0.42)	(0.37)	(0.33)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-0.99	-0.62	-0.19	0.46	0.24	0.93	1.91	2.78
pval	(0.54)	(0.61)	(0.76)	(0.02)	(0.06)	(0.03)	(0.05)	(0.06)
t-stat	-1.58	-1.12	-0.42	0.47	0.55	1.36	1.94	2.29
pval	(0.45)	(0.64)	(0.80)	(0.11)	(0.11)	(0.04)	(0.05)	(0.05)

Table A11: Timing ability using earnings as the cashflow 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 (5). The market cashflow return component is constructed based on quarterly earnings growth forecasts using lagged log earnings-price ratios, and the market discount-rate return component is constructed as the difference between the cashflow component and unexpected market return. Panels A, B, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A:Cashflow timing								
Tim(%)	-0.62	-0.33	-0.02	0.31	0.25	0.61	1.09	1.50
pval	(0.40)	(0.64)	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.66	-1.08	-0.07	0.61	0.80	1.45	1.99	2.29
pval	(0.40)	(0.77)	(1.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.02)
Panel B: Discount-rate timing								
Tim(%)	-0.66	-0.43	-0.18	-0.03	-0.02	0.14	0.35	0.51
pval	(0.06)	(0.07)	(0.19)	(0.25)	(0.32)	(0.42)	(0.30)	(0.25)
t-stat	-1.80	-1.43	-0.74	-0.06	-0.09	0.60	1.35	1.75
pval	(0.25)	(0.30)	(0.48)	(0.43)	(0.39)	(0.62)	(0.38)	(0.26)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-0.59	-0.32	-0.03	0.28	0.23	0.55	0.96	1.34
pval	(0.71)	(0.89)	(0.99)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
t-stat	-1.39	-0.89	-0.10	0.55	0.68	1.28	1.80	2.11
pval	(0.78)	(0.94)	(0.99)	(0.01)	(0.00)	(0.02)	(0.03)	(0.05)

Table A12: Timing ability based on external-financing-adjusted earnings forecasts

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 (5). Panels A, B, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. We first rank all firms each year according to the amount of their net external financing (equity and debt issuance) and calculate the percentile ranking, $Rank_i^{EF}$, for each firm i. Then, analysts' earnings forecasts are adjusted as

$$EPS_i = Rank_i^{EF} \times LOWEPS_i + (1 - Rank_i^{EF}) \times HIGHEPS_i$$

before constructing market cashflow news as in the main test of the paper, where $LOWEPS_i$ is the lowest forecasts and $HIGHEPS_i$ is the highest forecast. The discount-rate return component is backed out as the difference between the cashflow component and the unexpected market return. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
Tim(%)	-0.57	-0.27	0.10	0.54	0.49	0.92	1.53	1.88
pval	(0.15)	(0.53)	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.61	-0.81	0.37	1.12	1.35	2.10	2.69	3.06
pval	(0.41)	(0.80)	(0.98)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: Discount-rate timing								
Tim(%)	-0.96	-0.71	-0.39	-0.16	-0.11	0.09	0.30	0.49
pval	(0.01)	(0.01)	(0.02)	(0.04)	(0.09)	(0.77)	(0.58)	(0.41)
t-stat	-2.38	-1.87	-1.14	-0.42	-0.38	0.30	0.99	1.45
pval	(0.01)	(0.04)	(0.11)	(0.10)	(0.17)	(0.84)	(0.74)	(0.59)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-0.66	-0.40	0.03	0.38	0.38	0.75	1.13	1.49
pval	(0.26)	(0.47)	(0.95)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.45	-0.82	0.07	0.76	0.81	1.57	2.25	2.73
pval	(0.53)	(0.81)	(0.94)	(0.03)	(0.03)	(0.02)	(0.01)	(0.00)

Table A13: Timing ability based on forecasting-error-adjusted earnings forecasts

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 (5). Panels A, B, and C summarize quarterly abnormal returns in percentage earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Each IBES-month we rank all firms according to their consensus earnings forecast errors and calculate the percentile ranking, $Rank_i^{FE}$, for each firm i. The forecast error is defined as earnings forecast minus the actual, then divided by the price at the beginning of the fiscal year. Then, analysts' earnings forecasts are adjusted as

$$EPS_i = Rank_i^{FE} \times LOWEPS_i + (1 - Rank_i^{FE}) \times HIGHEPS_i$$

before constructing market cashflow news, as described in the main test of the paper, where $LOWEPS_i$ is the lowest forecasts and $HIGHEPS_i$ is the highest forecast. The discount-rate return component is backed out as the difference between the cashflow component and the unexpected market return. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
Tim(%)	-0.66	-0.37	0.01	0.46	0.38	0.82	1.47	1.91
pval	(0.08)	(0.26)	(0.93)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.94	-1.19	0.05	0.84	1.09	1.84	2.37	2.76
pval	(0.17)	(0.49)	(0.92)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Panel B: Discount-rate timing								
Tim(%)	-0.96	-0.70	-0.40	-0.18	-0.13	0.08	0.27	0.43
pval	(0.01)	(0.02)	(0.02)	(0.05)	(0.08)	(0.81)	(0.70)	(0.57)
t-stat	-2.41	-1.90	-1.17	-0.47	-0.43	0.27	0.95	1.37
pval	(0.02)	(0.04)	(0.09)	(0.08)	(0.13)	(0.86)	(0.78)	(0.68)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-0.79	-0.49	-0.09	0.28	0.26	0.62	1.07	1.44
pval	(0.13)	(0.27)	(0.72)	(0.03)	(0.03)	(0.01)	(0.00)	(0.00)
t-stat	-1.61	-1.05	-0.23	0.47	0.57	1.23	1.84	2.19
pval	(0.38)	(0.60)	(0.79)	(0.16)	(0.13)	(0.13)	(0.10)	(0.09)

Table A14: Quarterly 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 cashflow 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 upper, middle, and lower panels summarize the abnormal returns earned per quarter from cashflow (CF) timing, discount-rate (DR) timing, and the sum of cashflow timing and discount-rate timing, respectively. Under the null hypothesis, the expected timing measures are zero. Bootstrap p-values reported in parenthesis are the probability of a higher or lower value occurring by chance and calculated based on 1000 bootstrap samples.

	Recession								Expansion							
CF timing	5%	10%	25%	Mean	Median	75%	90%	95%	5%	10%	25%	Mean	Median	75%	90%	95%
Tim(%)	-3.38	-1.95	-0.07	1.62	1.35	3.31	5.50	6.88	-0.49	-0.28	-0.02	0.36	0.24	0.62	1.17	1.62
p-val	(0.00)	(0.00)	(0.90)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.44)	(0.56)	(0.94)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-2.35	-1.68	-0.08	1.20	1.26	2.13	2.87	3.35	-2.43	-1.49	-0.10	1.03	1.13	2.37	3.57	4.29
p-val	(0.20)	(0.31)	(0.97)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.27)	(0.94)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
DR timing	5%	10%	25%	Mean	Median	75%	90%	95%	5%	10%	25%	Mean	Median	75%	90%	95%
Tim(%)	-4.56	-3.19	-1.76	-0.77	-0.54	0.53	1.45	2.18	-1.12	-0.83	-0.49	-0.31	-0.26	-0.06	0.11	0.27
p-val	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.32)	(0.14)	(0.10)	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)	(0.99)	(0.99)	(0.99)
t-stat	-1.88	-1.71	-1.33	-0.74	-0.67	0.74	1.34	1.68	-2.34	-2.09	-1.65	-0.88	-1.04	-0.30	0.53	1.07
p-val	(0.29)	(0.23)	(0.15)	(0.12)	(0.16)	(0.46)	(0.44)	(0.40)	(0.05)	(0.03)	(0.02)	(0.02)	(0.01)	(0.99)	(0.98)	(0.93)
CF & DR timing	5%	10%	25%	Mean	Median	75%	90%	95%	5%	10%	25%	Mean	Median	75%	90%	95%
Tim(%)	-4.22	-2.52	-0.75	0.85	0.91	2.40	4.32	5.77	-0.80	-0.53	-0.22	0.05	0.01	0.26	0.66	0.97
p-val	(0.00)	(0.01)	(0.18)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.29)	(0.34)	(0.43)	(0.36)	(0.46)	(0.34)	(0.14)	(0.10)
t-stat	-2.31	-1.55	-0.48	0.42	0.70	1.51	1.99	2.37	-2.24	-1.61	-0.86	0.20	0.05	0.97	1.78	2.37
p-val	(0.23)	(0.38)	(0.68)	(0.22)	(0.09)	(0.06)	(0.11)	(0.15)	(0.07)	(0.19)	(0.30)	(0.31)	(0.46)	(0.23)	(0.10)	(0.05)

Table A15: Treynor-Mazuy and Henriksson-Merton timing measures

Following the spirit of Treynor and Mazuy (1966) and Henriksson and Merton (1981), we use holdings-based fund betas to test whether there exists positive performance for cashflow timing, discount-rate timing, or unexpected-market-return timing. We run the following regressions:

$$\text{Treynor and Mazuy: } \beta_{f,j,t-1} = \beta + \gamma K_{j,t} + \eta_{f,t},$$

$$\text{Henriksson and Merton: } \beta_{f,j,t-1} = \beta + \gamma I_{K_{j,t}} + \eta_{f,t},$$

where $\beta_{f,j,t-1}$ is fund f's sensitivity to factor j at the beginning of quarter t, factor j can be the unexpected market return or its cashflow or discount-rate component, $K_{j,t}$ is the quarter-t return on factor j, and $I_{K_{j,t}}$ is a dummy variable taking the value of 1 if $K_{j,t} > 0$ and 0 otherwise. This table reports the cross-sectional statistics of the slope coefficient γ and the associated t-statistics. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	Treynor-Mazuy timing measure							
	5%	10%	25%	Mean	Median	75%	90%	95%
	Cashflow timing							
Tim	-1.43 (0.76)	-0.63 (0.93)	0.17 (0.01)	0.64 (0.05)	0.69 (0.02)	1.22 (0.06)	1.84 (0.14)	2.47 (0.15)
t-stat	-1.92 (0.33)	-0.99 (0.77)	0.33 (0.00)	1.55 (0.00)	1.64 (0.00)	2.69 (0.00)	3.94 (0.00)	4.94 (0.00)
	Discount-rate timing							
Tim	-0.50 (0.27)	-0.39 (0.20)	-0.24 (0.13)	-0.09 (0.14)	-0.09 (0.10)	0.04 (0.88)	0.20 (0.79)	0.35 (0.68)
t-stat	-3.06 (0.01)	-2.45 (0.01)	-1.50 (0.04)	-0.67 (0.05)	-0.59 (0.06)	0.25 (0.86)	1.01 (0.77)	1.58 (0.62)
	Unexpected-market-return timing							
Tim	-0.67 (0.07)	-0.51 (0.06)	-0.29 (0.06)	-0.10 (0.14)	-0.08 (0.14)	0.11 (0.65)	0.30 (0.50)	0.45 (0.45)
t-stat	-3.35 (0.00)	-2.40 (0.02)	-1.36 (0.06)	-0.50 (0.10)	-0.43 (0.14)	0.51 (0.67)	1.36 (0.47)	1.92 (0.35)
	Henriksson-Merton timing measure							
	5%	10%	25%	Mean	Median	75%	90%	95%
	Cashflow timing							
Tim(%)	-0.14 (0.69)	-0.06 (0.92)	0.03 (0.00)	0.12 (0.00)	0.12 (0.00)	0.21 (0.00)	0.31 (0.00)	0.39 (0.00)
t-stat	-1.32 (0.71)	-0.70 (0.90)	0.41 (0.00)	1.40 (0.00)	1.51 (0.00)	2.48 (0.00)	3.28 (0.00)	3.79 (0.00)
	Discount-rate timing							
Tim(%)	-0.14 (0.01)	-0.11 (0.02)	-0.05 (0.05)	-0.01 (0.21)	-0.01 (0.27)	0.03 (0.49)	0.07 (0.30)	0.10 (0.27)
t-stat	-2.77 (0.01)	-2.13 (0.02)	-1.19 (0.08)	-0.30 (0.20)	-0.22 (0.28)	0.63 (0.51)	1.47 (0.27)	1.94 (0.19)
	Unexpected-market-return timing							
Tim(%)	-0.11 (0.09)	-0.09 (0.09)	-0.04 (0.17)	-0.01 (0.30)	-0.01 (0.34)	0.03 (0.43)	0.06 (0.34)	0.09 (0.28)
t-stat	-2.32 (0.05)	-1.80 (0.09)	-0.97 (0.19)	-0.17 (0.31)	-0.15 (0.34)	0.64 (0.50)	1.49 (0.26)	1.95 (0.19)

Table A16: Timing ability based on a manipulation-proof performance measure

This table reports point estimates and t-statistics at various points in the cross-sectional distribution of the manipulation-proof performance measure proposed by Ingersoll et al. (2007) and specified in (27) for fund timing performance. Panels A, B, and C summarize this measure in terms of annualized certainty equivalent abnormal returns earned from cashflow timing, discount-rate timing, and the sum of cashflow timing and discount-rate timing, respectively. Bootstrap p-value is reported in parenthesis based on 1000 bootstrap samples, and represents the probability of a higher (lower) value occurring by chance.

	5%	10%	25%	Mean	Median	75%	90%	95%
Panel A: Cashflow timing								
Tim(%)	-2.77	-1.55	0.05	1.49	1.37	2.94	5.25	6.50
pval	(0.07)	(0.27)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
t-stat	-1.72	-1.13	0.04	0.89	1.07	1.87	2.55	2.98
pval	(0.38)	(0.68)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: Discount-rate timing								
Tim(%)	-4.83	-3.75	-2.23	-1.26	-0.96	-0.03	0.74	1.33
pval	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.07)	(0.79)	(0.67)
t-stat	-2.56	-2.06	-1.38	-0.70	-0.71	-0.02	0.71	1.21
pval	(0.01)	(0.02)	(0.05)	(0.04)	(0.07)	(0.07)	(0.85)	(0.73)
Panel C: Sum of cashflow timing and discount-rate timing								
Tim(%)	-3.75	-2.54	-0.75	0.43	0.68	1.84	3.28	4.46
pval	(0.13)	(0.20)	(0.66)	(0.07)	(0.03)	(0.00)	(0.00)	(0.00)
t-stat	-1.59	-1.13	-0.39	0.31	0.36	1.01	1.69	2.11
pval	(0.53)	(0.69)	(0.85)	(0.12)	(0.09)	(0.12)	(0.10)	(0.08)

Table A17: Test whether timing ability and stock-selection ability are negatively related

Funds are sorted into quintiles each quarter according to their past-year total timing ability. We then run the following regressions of next-quarter fund net returns, similar to Jagannathan and Korajczyk (1986):

$$r_{f,t} = \alpha + \beta r_{m,t} + \gamma w_{m,t} + e_{f,t},$$

where $r_{f,t}$ and $r_{m,t}$ are the time-t fund return and market return, respectively, $w_{m,t} = r^2_{m,t}$ in the Treynor-Mazuy (TM) model, or $w_{m,t} = \max(\mathrm{r_{m,t}}, 0)$ in the Henriksson-Merton (HM) model. Estimated coefficients α, β, and γ are reported for each fund quintile, with Newey-West standard errors included in parentheses.

	Henriksson-Merton			Treynor-Mazuy		
	α	β	γ	α	β	γ
1(Low)	-0.007	1.045	0.030	-0.006	1.061	0.043
	(0.003)	(0.044)	(0.073)	(0.003)	(0.023)	(0.176)
2	-0.003	0.984	0.011	-0.003	0.989	-0.055
	(0.002)	(0.027)	(0.045)	(0.002)	(0.015)	(0.109)
3	-0.001	0.954	0.000	0.000	0.953	-0.085
	(0.002)	(0.030)	(0.049)	(0.002)	(0.016)	(0.119)
4	0.001	0.937	0.030	0.002	0.952	0.005
	(0.003)	(0.034)	(0.056)	(0.002)	(0.018)	(0.137)
5(High)	-0.001	0.919	0.129	0.002	0.987	0.241
	(0.004)	(0.050)	(0.083)	(0.003)	(0.027)	(0.201)