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Timing of Market News

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Abstract

This work examines hedge fund managers' timing skills by exploring whether they can time market news. Market news is constructed by decomposing unexpected market returns into cash-flow and discount-rate shocks. We find strong evidence of the timing of market news, especially cash-flow timing, and bootstrap analyses reveal that the timing of market cash flow and discount rate news by top-sorted timers cannot be attributed to pure luck. Out-of-sample estimates show that top cash-flow (discount-rate) timers outperform bottom timers by 3.168 to 3.768 per cent (1.80-2.436%) per annum on a risk-adjusted basis. Cash-flow news provides much more performance persistence than discount-rate news. Differentiating between the timing of and reaction to market news delivers useful results. These findings highlight the importance of market news in investment decisions.

Keywords: Market News, Cash Flow, Discount Rate, Hedge Fund, Market Timing

JEL Classification: G11, G23

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I. Introduction

This study explores whether sophisticated investors can forecast changes in market news. To answer this question, the relevant studies on this topic are reviewed, beginning with Cowles (1933). Subsequently, Treynor and Mazuy (1966) examined whether fund managers adjust their market exposure by forecasting market returns. Over several decades, numerous studies have attempted to evaluate the timing skills of fund managers with regard to the market return (e.g. Henriksson and Merton, 1981; Chen *et al.*, 2010), market volatility (e.g. Busse, 1999), and market liquidity (Cao *et al.*, 2013) of managed funds.

In this paper, we examine a new approach to evaluate hedge fund managers' market-news timing skills. Specifically, this approach decomposes unexpected market returns into a sum of discount-rate and cash-flow shocks and explores whether fund managers (as sophisticated investors) can time market news. If they can, to what extent do these timing skills have economic significance for investors? This analysis is important if the role of market news in the fund management industry is to be understood.

Cash-flow and discount-rate shocks represent an important dimension of market news. A growing literature documents their importance in describing cross-sectional return anomalies and finds that cash-flow risk plays an important role in driving stock price movements (e.g. Ang and Bekaert, 2007; Chen *et al.*, 2012). Campbell (1991) and Campbell and Vuolteenaho (2004) discover that these shocks are important state variables for asset pricing. The 2008-2009 global financial crisis (GFC) shows that stock market shocks worsen when most investors leave the market during a crisis, causing further liquidation, poor market liquidity, and higher cash-flow and discount-rate shocks. Thus, fund managers with high-level timing skills should predict market-wide shocks and naturally reduce their funds' market exposure before the shocks occur. They should identify market-news shocks as the key drivers of stock price variability and exploit their cash-flow and discount-rate information differently.

This paper is closely related to five studies. Campbell and Shiller (1988) find that changes in the price of an asset are directly related to unexpected changes in discount rates or future cash flows. Campbell (1991) uses this insight to decompose unexpected market returns into market-news shocks. Atanasov and Nitschka (2015) show that sensitivity to cash-flow shocks is further related to stock portfolio returns relative to discount-rate shocks. Galsband (2012) decomposes market returns into downside and upside market-news shocks and then focuses on downside shocks. More closely, Lan and Wermers (2016) estimate the market-news timing skills of US mutual funds by using two-factor timing models and find cash-flow (discount-rate) timing evidence of 2% (-0.8%) per annum (p.a.). However, their two-factor timing models suffer from several performance biases. First, their models ignore available public information. Ferson and Schadt (1996) and Christopherson *et al.* (1998) believe that market prices fully reflect readily available public information and show that incorporating public information (i.e. dividend yields, interest rates, and other variables) affects inferences about funds' average performance. Since most fund managers use this information to specify their portfolio strategies, ignoring such information in the timing models can cause potential biases. Ferson and Schadt (1996) note that public information makes it possible for us to (1) predict stock returns and risks across time and (2) show a strong correlation between the time-varying conditional betas and public information variables. Second, Chen and Knez (1996) and Ferson and Schadt (1996) argue that the Treynor and Mazuy (1966) timing measure, as used by Lan and Wermers (2016) and in our present study, considers the dynamics of risk exposure to public information. It is a more suited measure for examining hedge funds' performance because these funds often use dynamic trading strategies. Unlike the above literature, we examine whether sophisticated investors can time upside market-news shocks using newly developed timing models which are based on the Fung and Hsieh (2004) seven-factor model. Our cash-flow timing measure, but not our discount-rate timing measure, improves the statistical significance of the seven-factor model.[2] The conditional approach distinguishes two sources of exposure dynamics, market timing and reaction to public information, and helps us to improve the power of our pricing tests (Chen, 2007). Moreover, Chen (2007) shows that market timing is a dynamic strategy that adjusts risk exposure using market predictions and delivers call-option-like pay-offs. Chen believes that compared with mutual funds, hedge funds, who employ option-like dynamic strategies, are better able to execute market timing strategies. These reasons highlight the better features of hedge funds relative to mutual funds when evaluating market-timing ability. In practice, our work finds stronger timing evidence than Lan and Wermers (2016).

We consider hedge funds to evaluate market-news timing skills for several reasons. First, most hedge funds are managed by sophisticated managers. Second, hedge funds have been experiencing dramatic growth during the past two decades. Thus, most of the talented managers tend to work in the hedge fund industry, and naturally, it is important to understand whether a manager has enough ability to time market news. Third, hedge funds often use both dynamic strategies and time-varying market exposure (e.g. Fung and Hsieh, 2001; Patton and Ramadorai, 2013). Therefore, a combination of market-news exposure and time-varying market exposure provides a suitable platform for assessing hedge funds' timing. Finally, given the abundant evidence on hedge funds' positive performance (e.g. Jagannathan *et al.*, 2010), it is logical to want to understand whether market-news timing is a reliable source of better performance.

Following Treynor and Mazuy (1966), we examine the dynamics of funds' market exposure to market-news shocks on the basis of the relationship between funds' beta in month t and market return in month $t+1$. Two regression models are run by controlling for funds' exposure to other factors to assess how funds' beta in month t changes with market news in month $t+1$. If funds' beta changes positively with market news, this indicates

[2] The results are reported in subsection 5.2.

successful timing, implying that the fund has relatively low (high) market exposure in predicting market news and consequently cash-flow and discount-rate shocks are weak (strong). Given the growing importance of market news in risk management, our study contributes to the timing and hedge fund literature.

Market-news timing skills are evaluated at the individual fund level for 3,824 share-oriented hedge funds during the period of 1994 to 2017. We estimate monthly timing abilities for the funds with at least 36 consecutive monthly observations. To distinguish the skills from luck and to evaluate their statistical significance, a bootstrap procedure is employed. For each cross-sectional statistic of our timing coefficients, we compare actual estimates with the corresponding distribution of the statistics according to bootstrapped pseudo-funds that share the same risk exposure as actual funds but, by construction, have no timing skill. The results show strong evidence of market news timing across hedge funds and therefore top-sorted cash-flow and discount-rate timers cannot be attributed to pure luck.

Subsequently, this study examines the economic significance of timing skills by estimating the out-of-sample alphas (risk-adjusted returns) of funds at different skill levels. For each month, funds are sorted into five portfolios according to their timing coefficients, constructed from the past 36 months. We then estimate the out-of-sample alphas of the portfolios for the 3-, 6-, 9-, and 12-month holding periods. We observe that the timing skills found in our sample generate significant abnormal returns. For instance, over the 6-month holding period, the portfolio of the top-sorted cash-flow timers obtains an out-of-sample alpha of 0.495% per month (or 5.94% p.a.), while the portfolio of the bottom cash-flow timers obtains a lower out-of-sample alpha of 0.197% per month (or 2.364% p.a.). The out-of-sample alpha spread between the top and bottom cash-flow timers remains significant even 12 months after constructing the portfolios. Following Jagannathan *et al.* (2010), we find that the timing skills in our sample persist. More interestingly, these findings suggest that market-news timing adds value for fund investors.

Timing is also differentiated from reaction to market news by considering changes in the fund managers' market exposure after observing market-news shocks in the prior month. For cash-flow reactors, our tests show economic value as top-sorted cash-flow reactors deliver higher alphas than other funds in out-of-sample tests. For discount-rate reactors, poor results are returned in the alphas. These outcomes are intuitive because some market-news reactions strongly suggest managerial ability. Thus, it is important to distinguish timing from reaction to market news.

This remainder of this paper is organised as follows: Section II presents the construction of our timing measures. Section III describes the data. Section IV reports the empirical findings on timing skills and distinguishes between timing and reaction to market news. Section V presents further analyses. Finally, section VI concludes the paper with a summary of the main themes covered.

II. Methodology

2.1 Campbell-Shiller Decomposition

Changes in the price of an asset are directly related to unexpected changes in discount rates or future cash flows (Campbell and Shiller, 1988). Campbell (1991) decomposes unexpected market returns (η_t) into cash-flow and discount-rate shocks as follows:

$$\eta_t = r_{m,t} - E_{t-1}(r_{m,t}) = \eta_{cf,t} - \eta_{dr,t} \tag{1}$$

where $r_{m,t}$ is the market log return at time *t* and E_{t-1} is the expectation operator at time $t-1$. The component $\eta_{cf,t} = (E_t - E_{t-1})\sum_{j=0}^{\infty}\rho_j \Delta d_{t+j}$ (or cash-flow news) is the revision in expectations of future discounted-dividend growth rates, ρ is a constant less than one, and d is the log dividends. Analogously, the component $\eta_{dr,t} = (E_t - E_{t-1})\sum_{j=0}^{\infty}\rho_j r_{m,t+j}$ (or discount-rate news) is the revision in future expected cash flows.

We assume that the data are constructed from the first-order autoregressive rule of motion for the vector of state variables z_t with $r_{m,t}$ as the first element of an m-by-1 vector z_t and $r_{m,t} - E_{t-1}(r_{m,t})$ as the first element of an independent and identical distributed m-by-1 vector u_t:

$$z_t = a + \Gamma z_{t-1} + u_t \tag{2}$$

where Γ and a denote an m-by-m companion matrix and an m-by-1 state vector of constant parameters, respectively. It represents that discount-rate news is calculated as

$$\eta_{dr,t} = e1' \lambda u_t \tag{3}$$

where $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$ and $e1$ denote the m-by-1 vector in which the first element is one and the remaining elements are zero.

The cash-flow news is computed as

$$\eta_{cf,t} = (e1' + e1' \lambda)u_t \tag{4}$$

Since market portfolio returns contain the above two components, we define two betas for each fund by projecting returns on market news as follows:

$$\beta_m^i = \frac{Cov(r_t^i, \eta_{cf,t})}{var(\eta_t)} + \frac{Cov(r_t^i, -\eta_{dr,t})}{var(\eta_t)} = \beta_{cf}^i + \beta_{dr}^i \tag{5}$$

where β_m^i is fund *i*'s standard market beta, β_{cf}^i is the bad cash-flow component, and β_{dr}^i is the good discount-rate component (Campbell and Vuolteenaho, 2004).

Galsband (2012) decomposes η_t into downside and upside betas of market news and believes that investors care about uncertainty regarding unexpected downside market portfolio movements:

$$\beta_{cf}^{i} = \frac{cov(r_t^i, \eta_{cf,t}|\eta_t < 0)}{var(\eta_t|\eta_t < 0)} \tag{6}$$

Eq. (6) measures fund i's sensitivity to downside returns on cash-flow news. However, market timing considers the funds' upside betas, and for this reason the upside cash-flow and discount-rate betas of the market portfolio should be considered. Doing so will help to assess the co-movements between fund returns and market news.

2.2 Asset-Pricing Implication

To link fund returns to stock market news in a meaningful way, we use the basic insights of Campbell's (1993) intertemporal capital asset-pricing model (ICAPM). The intertemporal budget constraint imposes a log-linear approximation around the mean ratio of consumption to overall wealth as follows:

$$\mathrm{W_t = R_t^M(W_{t-1} - \mathbb{C}_{t-1})} \tag{7}$$

Eq. (7) implies that a change in consumption today is related to the revision of expectations about wealth today and the revision of expectations about future consumption growth:

$$\mathbb{C}_t - \mathrm{E}_{t-1}(\mathbb{C}_t) = (\mathrm{E}_t - \mathrm{E}_{t-1})\sum_{j=0}^{\infty}\rho^j r_{t+j}^M - (\mathrm{E}_t - \mathrm{E}_{t-1})\sum_{j=1}^{\infty}\rho^j \Delta\mathbb{C}_{t+j} \tag{8}$$

where $\mathbb{C}$ is the log consumption and r^M is the log return on wealth estimated from the market portfolio.

Using the Epstein and Zin (1991) and Weil (1989) functional form, we have the following:

$$\mathrm{U}_{t-1} = \left\{(1-\delta)\mathbb{C}_{t-1}^{(1-\gamma)/\theta} + \delta\left(\mathrm{E}_{t-1}\left[\mathrm{U}_t^{1-\gamma}\right]\right)^{1/\theta}\right\}^{\theta/(1-\gamma)} \tag{9}$$

where γ (δ) is the relative risk aversion coefficient (the subjective discount factor) and $\theta = (1-\gamma)/[1-(1/P)]$. Campbell (1993) formulates the utility maximisation problem using the ICAPM. He believes that an estimate of the model is correct with respect to log-normality and homoskedasticity if the intertemporal substitution elasticity P is close to 1, $\delta = \rho$, and the ratio of consumption to wealth is constant. Given these assumptions, asset i's risk premium is defined as

$$\mathrm{E}_{t-1}(r_t^i) - r_t^f + \frac{\sigma_{i,t-1}^2}{2} = \gamma \mathrm{cov}_{t-1}\left(r_t^i, r_t^M - \mathrm{E}_{t-1}(r_t^M)\right) + (1-\gamma)\mathrm{cov}_{t-1}\left(r_t^i, -\eta_{dr,t}^M\right) \tag{10}$$

where r^f (σ_i^2) is the risk-free rate (the variance) and η_{dr}^M is the same as above. $\gamma = 1$ denotes the static CAPM.

We rewrite Eq. (10) on the basis of the Treynor and Mazuy (1966) timing model, which examines the relationship between excess asset returns and excess market returns, as follows:

$$\mathrm{E}_{t-1}\left(\mathrm{r}_t^{\mathrm{i}}\right)-\mathrm{r}_t^{\mathrm{f}}+\frac{\left(\sigma_{\mathrm{i},t-1}^{+}\right)^2}{2}=\gamma\mathrm{cov}_{t-1}\left(\mathrm{r}_t^{\mathrm{i}},\max(\mathrm{r}_t^{\mathrm{M}}-\mathrm{E}_{t-1}(\mathrm{r}_t^{\mathrm{M}}),0)\right)+(1-\gamma)\mathrm{cov}_{t-1}\left(\mathrm{r}_t^{\mathrm{i}},\max\left(-\eta_{\mathrm{dr},t}^{\mathrm{M}},0\right)\right) \tag{11}$$

Following Campbell and Vuolteenaho (2004), who rewrote Eq. (10) with respect to $\mathrm{r}_t^{\mathrm{M}}-\mathrm{E}_{t-1}\mathrm{r}_t^{\mathrm{M}}=\eta_{\mathrm{cf},t}^{\mathrm{M}}-\eta_{\mathrm{dr},t}^{\mathrm{M}}$, we rewrite Eq. (11) to link excess stock returns to upside shocks of market news:

$$\mathrm{E}_{t-1}\left(\mathrm{r}_t^{\mathrm{i}}\right)-\mathrm{r}_t^{\mathrm{f}}+\frac{\left(\sigma_{\mathrm{i},t-1}^{+}\right)^2}{2}=\gamma\left(\sigma_{\mathrm{M},t-1}^{+}\right)^2\beta_{\mathrm{MCF},t-1}^{\mathrm{i}}+\left(\sigma_{\mathrm{M},t-1}^{+}\right)^2\beta_{\mathrm{MDR},t-1}^{\mathrm{i}} \tag{12}$$

where $\beta_{MCF^+}^i\equiv\frac{Cov\left(r_t^i,\eta_{cf,t}\middle|\eta_t\geq 0\right)}{Var(\eta_t|\eta_t\geq 0)}$ and $\beta_{MDR^+}^i\equiv\frac{Cov\left(r_t^i,-\eta_{dr,t}\middle|\eta_t\geq 0\right)}{Var(\eta_t|\eta_t\geq 0)}$.

Generally, Galsband's (2012) idea provides a guide to link asset returns to upside market-news shocks.

2.3 Market Timing Model

Our timing model is based on Treynor and Mazuy (1966). Generally, a timing model can be defined by the CAPM so that portfolio managers earn their portfolio returns:

$$r_{p,t+1}=\alpha_p+\beta_{p,t}MKT_{t+1}+u_{p,t+1},\qquad t=0,\dots,T-1, \tag{13}$$

where $r_{p,t+1}$ is the returns in excess of portfolio p's risk-free return in month $t+1$ and MKT_{t+1} is the excess market return. Eq. (13) shows changes in the market beta across time. $\beta_{p,t}$ denotes the skill of a manager in month t to forecast his or her market condition in month $t+1$. Various timing models differ in terms of the market conditions they focus on.

The existing timing models, namely, Admati *et al.* (1986) and Ferson and Schadt (1996), estimate a portfolio manager's market beta as a linear function of his or her prediction on market condition. The models are justified from a Taylor expansion by ignoring higher-order terms (Shanken, 1990):

$$\beta_{p,t}=\beta_p+\gamma_p E(market\ \ condition_{t+1}|N_t), \tag{14}$$

where N_t is the set of news available to a manager in time t and γ is the essence of a manager's timing skill (i.e. how the market beta changes with the forecast of market condition). Although prior studies examine market-timing volatility and liquidity, we examine a new aspect of timing skill (i.e. the skill to time market news) by rewriting Eq. (14) as follows:

$$\beta_{p,t}=\beta_p+\gamma_p^{cf}\left(\eta_{cf,t+1}-\bar{\eta}_{cf}\right) \tag{15}$$

$$\beta_{p,t}=\beta_p+\gamma_p^{dr}\left(\eta_{dr,t+1}-\bar{\eta}_{dr}\right) \tag{16}$$

where $\left(\eta_{cf,t+1}-\bar{\eta}_{cf}\right)$ and $\left(\eta_{dr,t+1}-\bar{\eta}_{dr}\right)$ denote the predictions of a manager (i.e. timing signals) regarding cash-flow and discount-rate news, respectively; and $\eta_{cf,t+1}$ $(\eta_{dr,t+1})$ is the measure of cash-flow (discount-rate) news in month $t+1$. Following Ferson and Schadt (1996) and Busse (1999), we de-mean a manager's signal by subtracting $\bar{\eta}_{cf}$ and $\bar{\eta}_{dr}$ for simpler interpretation. β_p is portfolio p's average beta. Generally, our inferences about market-news timing skills are unaffected with or without de-meaning the market-news signals $\bar{\eta}_{cf}$ and $\bar{\eta}_{dr}$.

We run the market-news timing models by replacing Eqs. (15) and (16) with Eq. (13):

$$r_{p,t+1} = \alpha_p^{cf} + \beta_p MKT_{t+1} + \gamma_p^{cf} MKT_{t+1}\left(\eta_{cf,t+1} - \bar{\eta}_{cf}\right) + \varepsilon_{p,t+1}^{cf} \tag{17}$$

$$r_{p,t+1} = \alpha_p^{dr} + \beta_p MKT_{t+1} + \gamma_p^{dr} MKT_{t+1}\left(\eta_{dr,t+1} - \bar{\eta}_{dr}\right) + \varepsilon_{p,t+1}^{dr} \tag{18}$$

Eqs. (17) and (18) are parallel to the existing models of market return timing [$\beta_{p,t} = \beta_p + \gamma_p(MKT_{t+1} + v_{t+1})$], market volatility timing [$\beta_{p,t} = \beta_p + \gamma_p(VOL_{t+1} - \overline{VOL} + v_{t+1})$], and market liquidity timing [$\beta_{p,t} = \beta_p + \gamma_p\left(L_{m,t+1} - \bar{L}_m + v_{t+1}\right)$], except that here we consider market news as the market condition. Note that we ignore the forecasting noise v_{t+1} in our timing measures since the error component u_t has been already applied in Eqs. (3) and (4) to construct η_{dr} and η_{cf}. A positive timing coefficient γ implies that the portfolio has a high market beta during good market conditions resulting from either a good cash flow or a good discount rate. A negative timing coefficient γ suggests that the portfolio has a low market beta during bad market conditions resulting from either a bad cash flow or a bad discount rate.

Hedge funds often pursue dynamic trading strategies (Fung and Hsieh, 2001; Cao *et al.*, 2013) and use derivatives (Chen, 2011), so traditional risk factors based on linear pay-offs do not seem to be suited to examining their performance. We therefore test market-news timing ability using Fung and Hsieh's (2004) seven-factor model as our basic model. These seven factors contain both option-like variables and linear variables, and they accurately explain the variations in hedge fund returns. They contain the monthly changes in the 10-year Treasury yields, the difference in monthly changes in yields between the 10-year Treasury and the Moody's Baa bonds, and the factors of size, stock market return, currency, bond, and commodity. Of all these factors, stock market exposure plays a key role in share-oriented hedge funds. We therefore test market-news timing skill by examining changes in stock market exposure and leave it to future studies to estimate potential changes in the exposure of other markets. Our basic timing models have the following forms:

$$r_{p,t+1} = \alpha_p^{cf} + \beta_p MKT_{t+1} + \gamma_p^{cf} MKT_{t+1}\left(\eta_{cf,t+1} - \bar{\eta}_{cf}\right) + \textstyle\sum_{j=1}^{J} \beta_j I_{j,t+1} + \varepsilon_{p,t+1}^{cf} \tag{19}$$

$$r_{p,t+1} = \alpha_p^{dr} + \beta_p MKT_{t+1} + \gamma_p^{dr} MKT_{t+1}\left(\eta_{dr,t+1} - \bar{\eta}_{dr}\right) + \textstyle\sum_{j=1}^{J} \beta_j I_{j,t+1} + \varepsilon_{p,t+1}^{dr} \tag{20}$$

where I is the indices beside the stock market index ($J = 6$), γ^{cf} measures the timing skills of cash-flow news, and γ^{dr} measures the timing skills of discount-rate news.

III. Data

3.1 The VAR State Variables

Campbell and Vuolteenaho (2004) decompose the CAPM beta into two market-news components reflecting information about discount rates and future cash flows. Chen and Zhao (2009) find that both the sample period and the choice of state variables affect Campbell and Vuolteenaho's (2004) findings. To address their criticisms, we widely examine the sensitivity of our findings to a variety of different state variables in a VAR model. All variables are defined in Part B of the Appendix.

Table 1 reports the benchmark features of our first-order VAR model for the period 1994 to 2017. The model is run monthly using ordinary least squares (OLS) by defining $\rho = 0.95^{1/12}$. Our findings do not change qualitatively when we use other possible values of the linearisation parameters. Each row is related to a dependent variable stated in the header of the row. Table 1 also reports the stock market returns' forecasting equation when return lags, TYs, VSs, and PEs are used as regressors. The four state variables report some forecasting potentials. Momentum is strongly pronounced for monthly returns. The VS coefficient negatively predicts stock market returns, with a t-statistic of -2.08. The TY coefficient is positive but not significant. A higher PE ratio is related to lower returns, as reported in Campbell and Shiller (1988), Campbell and Vuolteenaho (2004), and Campbell *et al.* (2013). The latter rows report the forecasting power of our VAR model for other state variables. Generally, the R^2s are high and the autoregressive coefficients of all state variables are very close to unity. Changes in expected returns are almost irrelevant to changes in cash flows, with a correlation coefficient of 0.08.[3]

Table 1 VAR Parameter Estimates

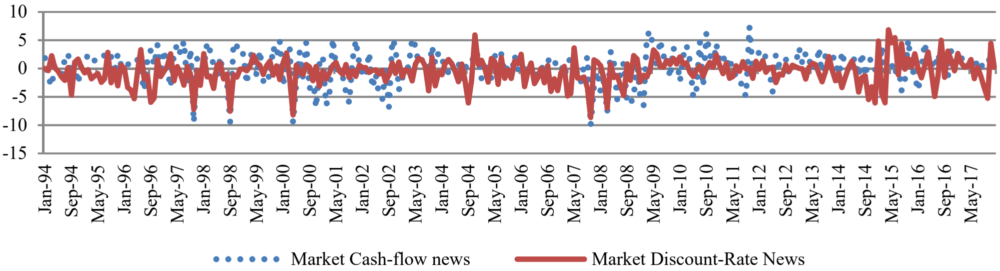
VAR Parameters	Constant	$r_{m,t}$	TY_t	PE_t	VS_t	$R^2\%$
$r_{m,t+1}$	0.08	0.14	0.06	-0.04	-0.05	2.12
	(1.98)*	(2.19)**	(1.55)	(-2.02)**	(-2.08)**	
TY_{t+1}	0.05	-0.44	0.92	-0.14	0.26	85.01
	(0.25)	(-1.28)	(44.20)***	(-1.77)*	(2.16)**	
PE_{t+1}	0.06	0.51	-0.05	0.96	-0.05	96.12
	(2.41)***	(12.79)***	(-1.56)	(172.26)***	(-0.36)	
VS_{t+1}	0.10	-0.09	-0.06	0.05	0.90	87.53
	(2.43)***	(-0.83)	(-1.62)	(0.62)	(48.50)***	

Note: This table reports the *OLS* parameter estimates of our first-order *VAR* model, consisting of a constant, market return (r_m), term yield spread (TY), price-earnings ratio (PE), and small-stock value spread (VS). The *OLS* t-statistics are reported in parentheses. Each row is related to a dependent variable. Columns 2 through 6 represent coefficients of the explanatory variables, and the past column reports the adjusted R^2s. *, **, and *** report statistical significance at the confidence levels of 90%, 95%, and 99%, respectively. The sample period for the dependent variables spans the monthly data for the period 1994 to 2017.

[3] Detailed results of the correlation test are available on request.

Fig. 1 shows the monthly time series of market news (shocks), as defined in Eqs. (3) and (4). The decomposition of these two shocks is obviously seen over the sample period. Changes in cash-flow shocks are higher in magnitude than changes in discount-rate shocks. Substantial downside spikes in market news happened around time of the Asian Financial Crisis (October 1997), the LTCM turmoil (September 1998), the Internet bubble burst (April 2000), the GFC (October 2007), and the Bear Sterns bankruptcy (March 2008), strongly suggesting that these measures highlight the well-known market shocks very well.

Figure 1 Monthly Time Series of Market News



Note: This figure shows the monthly time series of market discount-rate (solid line) and cash-flow (dotted line) news, as defined in Eqs. (3) and (4). The sample period covers 1994 to 2017.

3.2 Hedge Fund Sample

We collect our hedge fund data from the Lipper TASS database. Although the database includes returns dating back to November 1977, it does not consider dead funds until 1994, and the data from earlier periods suffer survivorship bias. Thus, for this study, we consider a sample period from January 1994 onward. Furthermore, we use only funds that have monthly net-of-fee returns with average assets under management (AUM) of at least \$10 million.[4] Following Fung and Hsieh (1997, 2000) and Aggarwal and Jorion (2010), we clean the hedge fund data by the survivorship, backfill, and master-feeder duplicates biases (see Part A of the Appendix).

TASS sorts hedge funds into 10 strategies: convertible arbitrage, emerging markets, dedicated short bias, equity market neutral, fixed income arbitrage, event-driven, global macro, managed futures, multi-strategy, and long-short equity. Fund of Funds (FoFs) is a separate strategy. Since most funds are traded on the stock market, we consider share-oriented strategies by dropping managed futures and fixed income arbitrage. We also eliminate the dedicated short bias strategy from our sample due to its inadequate funds. Our final sample contains 3,568 share-oriented funds (1,122 FoFs and 2,446 hedge funds) during the period 1994 to 2017. The sample also includes 1,209 live funds and 2,359 dead funds. To obtain meaningful results, we require at least 36 monthly returns for each fund.

[4] For the robustness check, we use other AUM filters (i.e. at least \$5 million or \$20 million) and obtain unchanged results.

Panel A of Table 2 reports the monthly returns on the funds. It shows that the average monthly return of all funds is 0.92%, with a standard deviation of 0.70%. The average monthly return on hedge funds (1.12%) is higher than that on FoFs (0.64%). Fung and Hsieh (2000) provide two reasons for this spread in average returns. First, investors pay higher management fees and operating expenses in FoFs than they do in hedge funds. Second, FoFs often hold some cash to cover potential redemptions. In contrast, Fung and Hsieh (2000) find that FoFs have lower backfill and survivorship biases than hedge funds. Panel A also shows that emerging markets earn the highest average monthly return (1.42%) and equity market neutral has the lowest return (0.71%). Among the strategies, emerging markets has the highest return volatility (0.95%) and equity market neutral has the lowest volatility (0.43%).

3.3 Market News and Factor Data

Panel B of Table 2 reports the summary statistics of the cash-flow (η_{cf}) and discount-rate (η_{dr}) components. The parameters of these two components are firstly estimated by our VAR model, and then the components are calculated by Eqs. (3) and (4). The time series means (medians) of η_{cf} and η_{dr} are 0.77% (0.82%) and 0.17% (0.23%), respectively, indicating a higher magnitude in η_{cf}s. η_{cf} (η_{dr}) has a standard deviation of 1.54% (2.40%) per month, indicating remarkable market-news variation across time. The panel also reports the descriptive statistics for Fung and Hsieh's (2004) factors.[5] The average excess market return (MKT) is 0.50% per month, with the standard deviation being 1.79%. The lowest MKT (-17.15%) happens in October 2008, while the highest MKT (11.34%) occurs in October 2011. The correlations between MKT and the η_{cf} and η_{dr} components are 0.19 and 0.27, respectively.

Table 2 Descriptive Statistics of the Data

Variables	N	Mean	Median	Standard Deviation	25%	75%
Panel A: Average hedge fund returns						
All Funds	3568	0.92	0.83	0.70	0.35	1.13
Hedge funds	2417	1.12	1.04	0.78	0.52	1.38
Fund of Funds	1151	0.64	0.60	0.44	0.23	0.77
Emerging market	291	1.42	1.34	0.95	0.64	1.78
Convertible arbitrage	84	0.94	0.91	0.48	0.41	1.12
Equity market neutral	185	0.71	0.66	0.43	0.17	1.07
Global macro	121	1.11	1.07	0.87	0.47	1.42
Long-short equity	1466	1.23	1.15	0.70	0.54	1.54
Even-driven	361	1.13	1.09	0.70	0.52	1.32
Multi-strategy	256	0.95	0.88	0.72	0.22	1.23

[5] The currency, bond, and commodity trend factors are collected from http://faculty.fuqua.duke.edu/_dah7/DataLibrary/TF-FAC.xls. Other factors are available in the Federal Reserve Bank databases and from the Center for Research in Security Prices.

Panel B: Timing measures and factor data					
η_{cf}	0.77	0.82	1.54	-1.22	1.32
η_{dr}	0.17	0.23	2.40	-2.07	1.19
MKT	0.50	0.55	1.79	-1.19	2.62
SMB	0.33	-0.03	3.88	-1.98	2.50
CY	0.13	0.13	0.42	-1.86	0.30
CBY	0.14	0.14	0.36	0.05	0.22
BTF	-1.24	-4.68	14.87	-11.18	4.06
ETF	0.33	-4.16	19.96	-13.24	9.42
CTF	-0.17	-2.75	14.09	-9.48	6.13

Note: This table reports the descriptive statistics of the data. Panel A reports the average monthly returns on all funds, FoFs, hedge funds, and funds in each strategy in % per month. *N* denotes the number of funds over the sample period. Panel B reports the cash-flow and discount-rate measures, and the Fung and Hsieh (2004) factors MKT, SMB, CY, CBY, BTF, ETF, and CTF are the excess market return, the firm's size, the monthly changes in the 10-year Treasury constant maturity yield, the monthly changes in the Moody's Baa yield less the 10-year Treasury constant maturity yield, the bond trend factor, the exchange trend factor, and the commodity trend factor, respectively. η_{dr} represents the discount-rate news components computed by Eq. (3), and η_{cf} denotes the cash-flow news components computed by Eq. (4). The sample period spans the monthly data of the period 1994 to 2017.

IV. Empirical Findings

In this section, we first present the cross-sectional t-statistic distribution of market-news timing coefficients across funds. Then, we conduct a bootstrap analysis to estimate the statistical significance of the timing abilities in our sample funds. We find that (1) cash-flow timing skills are related to significant risk-adjusted returns in out-of-sample estimates, (2) these skills persist over time, and (3) it is very important to distinguish the cash-flow timing skill from the discount-rate timing skill for generating investment value.

4.1 Cross-Sectional T-Statistic Distribution of Market-News Timing

We estimate market-news timing skills using Eqs. (19) and (20) for individual funds. Table 3 reports the cross-sectional t-statistic distribution of market-news timing coefficients. It reports the percentage of t-statistics greater than the determined cut-off values. For instance, 21.18% of the funds show t-statistics exceeding 1.30. For the full sample, the left tails are thinner than the right tails. FoFs have a lower proportion of t-statistics exceeding the determined cut-off values than hedge funds, and 15.72% of the funds show t-statistics less than -1.30, indicating negative timing evidence in some funds.

Under the normality hypothesis, significant values of the t-statistic distribution indicate timing abilities. However, conventional inference might be misleading if we infer the hedge funds' cross-sectional test statistics. There are three reasons for this misleading inference. First, hedge fund returns often do not follow a normal distribution due to their dynamic trading strategies. Second, if we assess managerial skill for a great number of hedge funds, it will cause multiple comparison problems. Thus, some funds will have significant t-statistics even if none of them have correct timing skill. Third, if there are correlations between fund returns within a strategy, the timing measures cannot be independent across funds. These reasons motivate us to use a bootstrap analysis to examine the significance of our timing coefficients. A bootstrap analysis allows us to understand whether our estimated timing coefficients reflect correct managerial ability or pure luck.

Table 3 Cross-sectional t-statistic Distribution of Market-News Timing Coefficients

	Percentage of the funds					
Strategies	$t \leq -3.20$	$t \leq -2.10$	$t \leq -1.30$	$t \geq 1.30$	$t \geq 2.10$	$t \geq 3.20$
All Funds	5.39	7.85	15.72	21.18	10.43	6.61
Hedge funds	5.92	8.29	15.74	23.85	11.54	7.48
Fund of Funds	4.65	7.24	15.68	17.49	8.89	5.42
Emerging market	9.65	14.33	26.07	17.88	8.47	5.24
Convertible arbitrage	9.43	11.51	25.58	14.36	4.50	1.68
Equity market neutral	7.69	9.33	16.42	19.40	9.36	5.17
Global macro	4.92	5.46	11.65	25.83	8.88	4.93
Long-short equity	4.94	6.68	12.88	25.49	12.93	8.63
Even-driven	4.66	7.32	11.71	29.66	13.97	9.31
Multi-strategy	4.53	8.74	19.47	20.49	10.40	7.14

Note: This table reports the t-statistic distribution of market-news timing coefficients by running the following timing models for each fund:

$$r_{p,t+1} = \alpha_p^{cf} + \beta_{p,1}MKT_{t+1} + \gamma_p^{cf}MKT_{t+1}(\eta_{cf,t+1} - \bar{\eta}_{cf}) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}CY_{t+1} + \beta_{p,4}CBY_{t+1} + \beta_{p,5}BTF_{t+1} + \beta_{p,6}ETF_{t+1} + \beta_{p,7}CTF_{t+1} + \varepsilon_{p,t+1}^{cf}$$

$$r_{p,t+1} = \alpha_p^{dr} + \beta_{p,1}MKT_{t+1} + \gamma_p^{dr}MKT_{t+1}(\eta_{dr,t+1} - \bar{\eta}_{dr}) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}CY_{t+1} + \beta_{p,4}CBY_{t+1} + \beta_{p,5}BTF_{t+1} + \beta_{p,6}ETF_{t+1} + \beta_{p,7}CTF_{t+1} + \varepsilon_{p,t+1}^{dr}$$

where $r_{p,t+1}$ denotes the excess return on each fund in month $t+1$. MKT, SMB, CY, CBY, BTF, ETF, and CTF are defined as in Table 2. η_{dr} and η_{cf} denote the discount-rate and cash-flow news computed by Eqs. (3) and (4), respectively. $\bar{\eta}_{dr}$ ($\bar{\eta}_{cf}$) is the mean level of discount-rate (cash-flow) news. γ denotes the timing skill. The t-statistics are heteroskedasticity consistent. The table shows the percentage of hedge funds with timing coefficient *t*-statistics greater than the determined values. The sample period spans the monthly data of the period 1994 to 2017.

4.2 Bootstrap Analysis

Following Patton (2009) and Fama and French (2010), we conduct a bootstrap analysis to estimate the statistical significance of market-news timing coefficients for individual funds. We perform one bootstrap analysis that preserves simultaneously (1) the autocorrelation of fund residuals, (2) the correlation of fund residuals across funds, and (3) the correlation between factors and fund residuals (Patton, 2009). These serve to help construct hypothetical funds that obtain factor loadings identical to actual funds without timing skill. Then, we examine if the estimated t-statistics of the actual funds' timing coefficients have significant spreads compared with the bootstrapped distributions without timing skill. Our bootstrap analysis consists of five steps. First, we estimate market timing models for fund p as follows:

$$r_{p,t+1} = \alpha_p^{cf} + \beta_p MKT_{t+1} + \gamma_p^{cf} MKT_{t+1}(\eta_{cf,t+1} - \bar{\eta}_{cf}) + \sum_{j=1}^{J} \beta_j I_{j,t+1} + \varepsilon_{p,t+1}^{cf} \quad (21)$$

$$r_{p,t+1} = \alpha_p^{dr} + \beta_p MKT_{t+1} + \gamma_p^{dr} MKT_{t+1}(\eta_{dr,t+1} - \bar{\eta}_{dr}) + \sum_{j=1}^{J} \beta_j I_{j,t+1} + \varepsilon_{p,t+1}^{dr} \quad (22)$$

We then save the estimated coefficients ($\hat{\alpha}_p, \hat{\beta}_p, \hat{\gamma}_p, \ldots$) and the time series of residuals ($\hat{\varepsilon}_{p,t+1}, t_0, \ldots, T_p - 1$), where T_p is the number of fund p's monthly observations. Second, we resample the estimated residuals and construct the time series of the randomly resampled residual $\hat{\varepsilon}_{p,t+1}^k$, where k is the bootstrap iteration index $k = 1,2,\ldots,K$. We then construct monthly excess returns of a pseudo-fund without timing ability (i.e. $\gamma_p = 0$ or $t_\gamma = 0$) where the timing terms' coefficients equal zero.

$$r_{p,t+1}^k = \hat{\alpha}_p + \hat{\beta}_p MKT_{t+1} + \sum_{j=1}^{J} \hat{\beta}_j I_{j,t+1} + \hat{\varepsilon}_{p,t+1}^k \quad (23)$$

Third, we estimate Eqs. (21) and (22) using the pseudo-fund returns resulting from step 2 and save the estimated timing coefficients and their relevant t-statistics. Since the pseudo-fund has $\gamma = 0$, non-zero timing coefficients and t-statistics are resulted from the sampling variation. Fourth, we conduct steps 1 to 3 across the sample funds and generate the cross-sectional statistics (i.e. the top 10th percentile) of the timing coefficient estimates and their relevant t-statistics across all funds in our sample. Finally, we iterate steps 1 to 4 for *K* iterations to construct the empirical distributions (i.e. the top 10th percentile) of the cross-sectional statistics of the pseudo-fund t-statistics. We set the number of bootstrap simulations *K* to 10,000. For the cross-sectional statistics, we compute the p-value of the pseudo-fund t-statistics as frequency of bootstrapped cross-sectional statistical values (i.e. the top 10th percentile) for the funds from *K* simulations exceeding the actual cross-sectional statistical values.

Using the above bootstrap analysis, we answer the key question as to whether positive (or negative) timing skill can be the result of pure luck. We thus compare the actual estimates with the corresponding distribution of the bootstrapped pseudo-fund estimates for each cross-sectional statistic of the market-timing coefficients (or its relevant t-statistics) and examine whether the coefficients can be explained by the random sampling variation. Note that we perform our bootstrap analysis for the timing coefficient t-statistics (i.e. t_γ) since they are important statistics with effective sampling properties in the analysis.

Table 4 reports the p-values of the market-news timing coefficient t-statistics at different percentiles of the bootstrap analysis. The $\hat{\gamma}^{cf}$ and $\hat{\gamma}^{dr}$ *t*-statistics are those concerning market-news timing coefficients across individual funds, and the percentiles of 1%, 5%, and 10% are the empirical p-values of 1%, 5%, and 10% resulting from the bootstrap simulations. The bottom (top) *t*-statistic is the negative (positive) timing coefficients estimated from individual funds. For example, the bottom 1% *t*-statistics for $\hat{\gamma}^{cf}$ represent the negative cash-flow timing coefficients, with the statistical significance being 99%. All percentiles of 1% to 10% in Panel A reveal that the top-sorted cash-flow timing funds are unlikely to be attributed to random chance. For example, for the all-fund sample, the $t_{\hat{\gamma}^{cf}}$s of the top-sorted 1%, 5%, and 10% cash-flow timing funds are significant, with magnitudes of 4.06, 3.04, and 2.85, respectively. The same results are provided for the hedge fund and FoFs samples.

We also conduct the above bootstrap analyses for both timing coefficients within each strategy. For the cash-flow timing coefficients, we find low p-values for the top-sorted t-statistics of emerging market, equity market neutral, event-driven, and global macro, implying that the top-sorted timing coefficients are not estimated by random chance. For the discount-rate timing coefficients, we find the same results but with less significance. The cash-flow and discount-rate timing coefficients of the top-sorted funds in the convertible arbitrage, long-short equity, and multi-strategy strategies cannot be distinguished from luck. Note that the negative timing coefficients of hedge funds cannot be attributed to random chance, except for FoFs. For instance, the p-values of the bottom-sorted $\hat{\gamma}^{cf}$ s for the cash-flow timing coefficients are all close to zero in the all-fund and hedge-fund samples.

Further, convertible arbitrage funds often buy convertible bonds and sell the underlying stocks. These funds, however, may still take bets on changes in either credit risk or market cash-flow shocks when making entry and exit decisions in the convertible-bond market, which shows timing ability. For example, Panel A of Table 4 shows that convertible arbitrage has a timing coefficient of 4.72 for the top 1% cash-flow timing funds, implying that if a manager predicts an excess return of 1% in the high yield bond market in the next month, he or she will increase the portfolio exposure by about 4% according to Eq. (21). This shows the economic significance of timing ability. Moreover, event-driven funds show negative timing ability. This outcome is consistent with Mitchell and Pulvino (2001), who find negative timing evidence in merger arbitrage funds, meaning that the funds obtain higher risk exposure during down markets than during up markets because merger and acquisition deals in the funds are more likely to fail during down markets. Thus, negative timing evidence in funds is more likely to be a feature of their investment style rather than an indicator of their poor timing ability. Emerging market funds also present negative timing evidence due to low liquidity and short sale constraints in most emerging markets. The above results are consistent with Chen (2007).

Overall, we have determined that top-sorted fund managers can time market news and that negative timing coefficients cannot be attributed to randomness. We now proceed to explore whether market-news timing reflects correct managerial skills.

4.3 Economic Significance of Market-News Timing

We examine here whether timing skills persist over time and add economic value for investors. If so, they should indicate valuable managerial skills. To assess the practical significance of our timing measures, we investigate their investment value by choosing top-sorted cash-flow and discount-rate timers.

Table 4 Bootstrap Analysis of Market Timing

Classes of Funds	Bottom t-statistics for $\hat{\gamma}^{cf}$ 1%	5%	10%	Top t-statistics for $\hat{\gamma}^{cf}$ 10%	5%	1%
Panel A: Market cash-flow news						
All Funds	-4.27	-2.34	-2.10	2.85	3.04	4.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Hedge funds	-3.83	-3.04	-2.28	2.88	3.20	4.32
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Fund of Funds	-3.70	-1.52	-0.99	2.09	2.40	3.02
	(0.00)	(0.32)	(0.44)	(0.00)	(0.00)	(0.00)
Emerging market	-4.14	-3.07	-2.33	0.26	0.60	1.08
	(0.00)	(0.00)	(0.00)	(0.94)	(0.85)	(0.62)
Convertible arbitrage	-5.10	-3.99	-2.44	3.00	3.60	4.72
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Equity market neutral	-4.37	-3.67	-1.77	0.74	1.12	2.11
	(0.00)	(0.00)	(0.16)	(0.97)	(0.60)	(0.02)
Global macro	-1.70	-1.24	-0.72	0.44	0.93	2.01
	(0.05)	(0.42)	(0.92)	(0.92)	(1.00)	(0.05)
Long-short equity	-3.42	-2.87	-1.86	2.80	3.08	4.61
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)
Even-driven	-3.72	-0.89	-1.08	1.30	1.85	3.14
	(0.00)	(0.99)	(0.96)	(1.00)	(0.80)	(0.00)
Multi-strategy	-3.39	-2.45	-2.11	2.76	3.12	3.73
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B: Market discount-rate news						
Classes of Funds	Bottom t-statistics for $\hat{\gamma}^{dr}$			Top t-statistics for $\hat{\gamma}^{dr}$		
All Funds	-3.11	-1.85	-1.28	0.54	1.16	2.68
	(0.00)	(0.04)	(0.46)	(1.00)	(0.96)	(0.00)
Hedge funds	-3.29	-1.94	-1.43	0.70	1.24	2.91
	(0.00)	(0.01)	(0.47)	(1.00)	(0.94)	(0.00)
Fund of Funds	-2.93	-0.82	-0.34	0.32	0.97	2.12
	(0.00)	(1.00)	(1.00)	(1.00)	(1.00)	(0.00)
Emerging market	-3.07	-1.32	-0.76	0.59	0.91	1.45
	(0.00)	(0.72)	(1.00)	(1.00)	(0.93)	(0.66)
Convertible arbitrage	-3.19	-2.80	-1.76	0.81	1.48	2.60
	(0.00)	(0.00)	(0.06)	(1.00)	(0.90)	(0.00)
Equity market neutral	-3.18	-2.38	-1.33	0.53	0.94	1.59
	(0.00)	(0.00)	(0.96)	(1.00)	(0.87)	(0.42)
Global macro	-1.65	-0.24	-0.04	0.27	0.80	1.78
	(0.10)	(1.00)	(1.00)	(1.00)	(0.83)	(0.07)
Long-short equity	-2.84	-1.70	-1.07	0.72	1.26	2.60
	(0.00)	(0.06)	(0.61)	(1.00)	(1.00)	(0.00)
Even-driven	-2.99	-1.76	-0.98	0.83	1.01	1.16
	(0.00)	(0.06)	(1.00)	(1.00)	(1.00)	(0.96)
Multi-strategy	-2.63	-1.90	-1.34	0.59	1.19	1.99
	(0.00)	(0.09)	(0.19)	(1.00)	(1.00)	(0.02)

Note: This table reports the results of the bootstrap analyses of market-news timing. We run the following timing models for each fund:

$$r_{p,t+1} = \alpha_p^{cf} + \beta_{p,1}MKT_{t+1} + \gamma_p^{cf}MKT_{t+1}(\eta_{cf,t+1} - \bar{\eta}_{cf}) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}CY_{t+1} + \beta_{p,4}CBY_{t+1} + \beta_{p,5}BTF_{t+1} + \beta_{p,6}ETF_{t+1} + \beta_{p,7}CTF_{t+1} + \varepsilon_{p,t+1}^{cf}$$

$$r_{p,t+1} = \alpha_p^{dr} + \beta_{p,1}MKT_{t+1} + \gamma_p^{dr}MKT_{t+1}(\eta_{dr,t+1} - \bar{\eta}_{dr}) + \beta_{p,2}SMB_{t+1} + \beta_{p,3}CY_{t+1} + \beta_{p,4}CBY_{t+1} + \beta_{p,5}BTF_{t+1} + \beta_{p,6}ETF_{t+1} + \beta_{p,7}CTF_{t+1} + \varepsilon_{p,t+1}^{dr}$$

where $r_{p,t+1}$ is fund p's excess return in month $t+1$. MKT, SMB, CY, CBY, BTF, ETF, and CTF are defined as in Table 2. η_{dr} (η_{cf}) is the discount-rate (cash-flow) news computed by Eq. (3) (Eq. (4)). $\bar{\eta}_{dr}$ ($\bar{\eta}_{cf}$) is the mean level of discount-rate (cash-flow) news. γ denotes the timing skill. Bottom and top *t*-statistics for $\hat{\gamma}^{cf}$ and $\hat{\gamma}^{dr}$ represent the sorted t-statistics of market-news timing coefficients across individual funds. The empirical p-values of 1%, 5%, and 10% are derived from the bootstrap simulations, while the number of resampling repetitions is 10,000.

For each month, we estimate the timing coefficients of each fund using the past 36-month estimation period. We then construct five portfolios on the basis of these coefficients. We hold these portfolios for the 3-, 6-, 9-, or 12-month holding periods, and this process is iterated. This generates four separate time series of returns for each holding period and for each of the five portfolios in different levels of timing skills. Once a fund disappears during the holding period, fund returns are involved in computing portfolio returns till their disappearance, and the portfolio is rebalanced. Then, we run the seven-factor model for each timing coefficient and each alpha of the portfolio. Since these investment strategies are mostly related to an FoF manager, we use them for two samples of all funds (i.e. FoFs) and hedge funds.

Panels A and B of Table 5 report striking findings on the economic values of market-news timing skills. For the cash-flow-timing timers, portfolios 1 through 3 for all funds and portfolios 1 through 4 for hedge funds deliver significant alphas over the post-ranking periods. For example, the portfolio alpha of the 12-month holding period is 0.412% per month, with the t-statistic being 2.49 for all funds. The top cash-flow timing funds also show larger significant out-of-sample alphas than other funds. For example, there is a range of between 0.26% to 0.31% per month across the holding periods for the spread in alphas between the top and bottom timing funds (P1-5), which remains significant even one year after the ranking period. The top cash-flow timing funds economically and statistically outperform the bottom timing funds by 3.168 to 3.768 per cent p.a. on a risk-adjusted basis. The top cash-flow timing funds economically and statistically outperform the bottom timing funds on a risk-adjusted basis. We find the same results on hedge funds in which top-sorted cash-flow timing portfolios obtain higher average alphas than other portfolios. Although hedge funds without cash-flow timing skill can still obtain alphas using other sources, top cash-flow timers resist by earning an annualised alpha of 5.388%, implying that cash-flow timing indicates managerial ability.

Panel B reports the same results as above for discount-rate-timing timers, except that the alphas show less significance than the cash-flow timers' alphas. Specifically, the top discount-rate timing funds outperform the bottom timing funds by 1.80 to 2.436 per cent p.a. on a risk-adjusted basis, while their magnitudes are economically and statistically lower than the cash-flow timing funds. Moreover, hedge funds' discount-rate timing obtains higher alphas than other portfolios. Even though hedge funds without discount-rate timing skill can still obtain alphas using other sources, top discount-rate timers resist by earning an annualised alpha of 2.388%, implying that discount-rate timing can reflect managerial ability, but the timing power is lower than cash-flow timing. There are two reasons that can explain the higher cash-flow timing. First, Atanasov and Nitschka (2015) find that sensitivities to cash-flow shocks are more significantly related to stock returns relative to discount-rate shocks. Specifically, the ICAPM explains that the price of cash-flow risk is calculated by $\gamma\sigma_M^2$, and the price of discount-rate risk is calculated by σ_M^2, where γ is the relative risk aversion coefficient and σ_M^2 is the variance of unexpected returns on the market portfolio. A higher cash-flow risk than discount-rate risk stems from the additional γ used in generating cash-flow risk. Second, they believe that asset pricing models formulated on common sources of systematic risk are often reflected in the cash-flow news component.

Table 5 Economic Value of Market-News Timing: Out-of-Sample Alphas

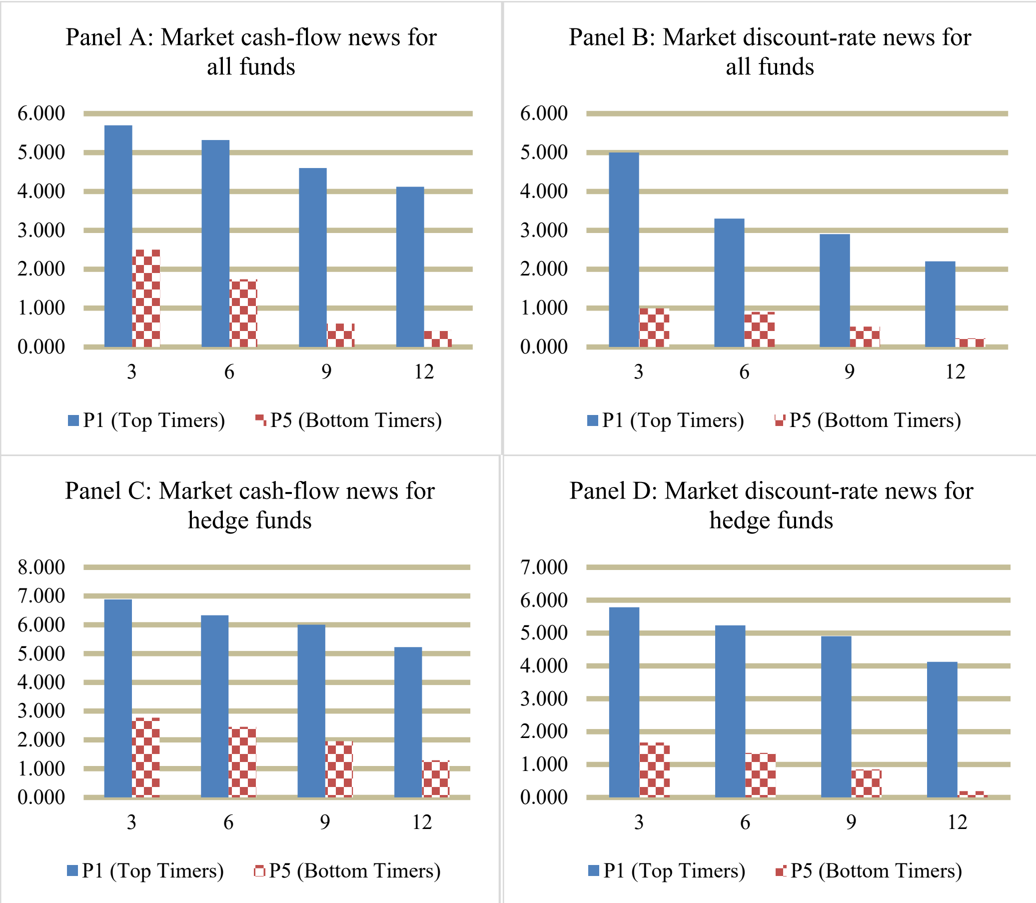
Portfolios	All Funds				Hedge Funds			
	k = 3	k = 6	k = 9	k = 12	k = 3	k = 6	k = 9	k = 12
Panel A: Market cash-flow timing								
P1 (Top timers)	0.499	0.473	0.436	0.412	0.516	0.495	0.479	0.449
	(3.10)	(2.95)	(2.74)	(2.49)	(3.30)	(3.11)	(2.92)	(2.84)
P2	0.336	0.312	0.282	0.254	0.374	0.344	0.301	0.284
	(2.77)	(3.59)	(3.33)	(2.08)	(3.00)	(2.86)	(2.68)	(2.51)
P3	0.230	0.214	0.190	0.174	0.292	0.271	0.245	0.226
	(2.00)	(1.90)	(1.77)	(1.70)	(2.55)	(2.38)	(2.25)	(2.06)
P4	0.192	0.177	0.166	0.161	0.237	0.225	0.212	0.202
	(1.80)	(1.60)	(1.49)	(1.38)	(2.18)	(2.06)	(1.95)	(1.84)
P5 (Bottom timers)	0.185	0.173	0.165	0.148	0.217	0.197	0.190	0.170
	(1.14)	(0.84)	(0.73)	(0.59)	(1.42)	(1.33)	(1.15)	(1.04)
P1-5	0.314	0.30	0.271	0.264	0.299	0.298	0.289	0.279
	(2.90)	(2.72)	(2.52)	(2.45)	(2.67)	(2.66)	(2.58)	(2.50)
Panel B: Market discount-rate timing								
P1 (Top timers)	0.226	0.195	0.174	0.157	0.248	0.227	0.214	0.199
	(2.12)	(1.90)	(1.68)	(1.49)	(2.31)	(2.13)	(1.98)	(1.88)
P2	0.143	0.13	0.105	0.099	0.193	0.174	0.162	0.13
	(1.18)	(1.09)	(0.89)	(0.73)	(1.75)	(1.52)	(1.33)	(1.09)
P3	0.053	0.041	0.028	0.016	0.093	0.084	0.073	0.06
	(0.39)	(0.32)	(0.21)	(0.08)	(0.74)	(0.61)	(0.52)	(0.38)
P4	0.047	0.031	0.014	0.004	0.057	0.041	0.028	0.019
	(0.35)	(0.21)	(0.04)	(0.002)	(0.39)	(0.31)	(0.25)	(0.17)
P5 (Bottom timers)	0.040	0.025	0.016	0.007	0.045	0.032	0.022	0.011
	(0.26)	(0.22)	(0.15)	(0.10)	(0.30)	(0.25)	(0.20)	(0.16)
P1-5	0.186	0.17	0.158	0.150	0.203	0.195	0.192	0.188
	(1.47)	(1.38)	(1.30)	(1.24)	(1.58)	(1.49)	(1.46)	(1.42)

Note: This table reports the out-of-sample alphas of the portfolios at different levels of market-news timing skills. For each month, we form five portfolios on the basis of the funds' market-news timing coefficients estimated from the past 36 months (i.e. ranking period) and then hold these portfolios for different periods of K months. We repeat the above sorting exercise for the funds' discount-rate timing coefficients. Panels A and B represent the out-of-sample alphas (in % per month) of the seven-factor models generated from the post-ranking returns for the cash-flow and discount-rate timing coefficients, respectively. T-statistics are estimated by autocorrelation-consistent standard errors and Newey and West heteroskedasticity with two lags in parentheses.

The economic significance of our timing skills can be further observed in Fig. 2 and Fig.

3. Fig. 2 shows the out-of-sample alphas of the top versus bottom timing portfolios for various holding periods. It plots that the top timing funds earn higher average alphas than bottom funds over the post-ranking periods. Fig. 3 plots the cumulative returns of the portfolios of the top and bottom timing funds over the 12-month holding period. It shows two things: (1) that returns in cash-flow news are higher than discount-rate news and (2) substantial downside spikes occur during the financial crisis periods, as plotted in Fig. 1.

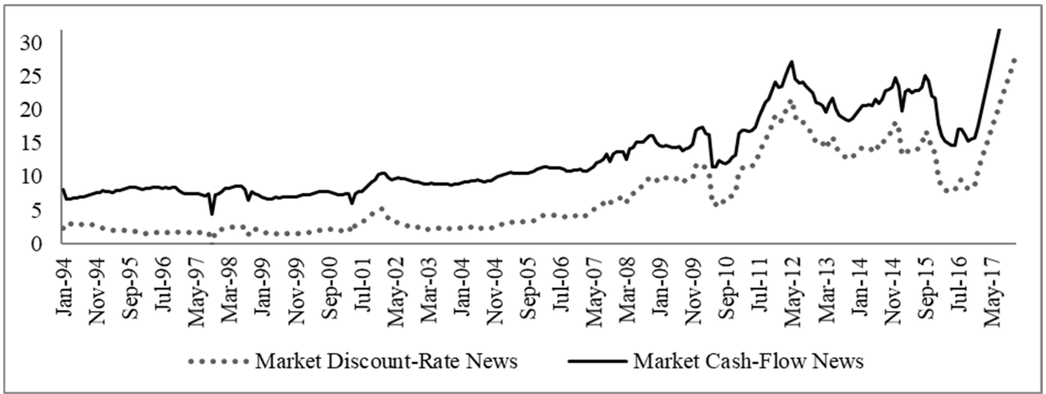
Figure 2 Out-of-Sample Alphas of the Top vs. Bottom Timing Fund Portfolios



Note: This figure shows the out-of-sample alphas of the portfolios of top vs. bottom timing funds over the 3-, 6-, 9-, and 12-month holding periods. For each month, we construct the portfolios according to the funds' market cash-flow and discount-rate timing coefficients resulting from the past 36 months. Panels A and B report the results for all funds (i.e. hedge funds and FoFs), while panels C and D report the results for hedge funds.

We also examine the persistence of timing skills in our sample funds using the portfolio returns of the post-ranking periods. Specifically, after constructing five portfolios on the basis of each of the past market coefficients, we run Eqs. (21) and (22) and estimate fund managers' subsequent timing skills. There is significant evidence of persistence in both timing skills. For instance, Panel A of Table 5 reports that the portfolio of top (bottom) cash-flow timers in the past 36 months obtains an out-of-sample timing coefficient of 0.449 (0.170), with a t-statistic of 2.84 (1.04) over the 12-month holding period. When running Eq. (21) into the time series of spread in returns between the top and bottom cash-flow timing funds, we find a timing coefficient of 0.279, with a t-statistic of 2.50, over the 12-month holding period. However, the discount-rate timing evidence is economically and statistically poorer than the cash-flow timing evidence.

Figure 3 Cumulative Returns on Hedge Funds for the Top vs. Bottom Cash-Flow and Discount-Rate Timing



Note: This figure shows the cumulative returns on the portfolios of hedge funds' top vs. bottom cash-flow and discount-rate timing over the 12-month holding period. For each month, we construct the portfolios on the basis of the hedge funds' cash-flow and discount-rate timing coefficients resulting from the past 36 months.

Overall, we find strong and reliable evidence that the timing skills of our sample funds, especially cash-flow timing skills, add economic value for investors, confirming that the timing of cash-flow news shows managerial ability and can be an important source for the hedge fund alphas. Using out-of-sample tests, these abilities persist over time and are consistent with Jagannathan *et al.* (2010).

4.4 Timing and Reaction to Market News

Following the literature, we use a basic analysis to examine whether fund managers can predict the levels of market conditions (i.e. market news). If market news is strongly correlated, their values in month $t+1$ include information from previous months. A fund manager should therefore adjust his or her market exposure on the basis of the lagged market-news values. Ferson and Schadt (1996) explain that the lagged market conditions contain public information and that an adjustment in fund betas resulting from public information cannot reflect correct timing ability.

If fund managers use market news observed in month t to infer a predictable component of market news and adjust their fund betas accordingly, they do not have timing ability but rather are simply reacting to past market news. This presents an important spread between timing and reaction to market news: market-news reactors adjust their fund betas according to market news observed in month t, and market-news timers control market exposure by their prediction of market news in month $t+1$. To separate timing skill from market-news reaction, we use the following models by involving both timing terms and reaction terms of market news:

$$r_{p,t+1} = \alpha_p^{cf} + \beta_p MKT_{t+1} + \gamma_p^{cf} MKT_{t+1}\tilde{\eta}_{cf,t+1} + \varphi_p^{cf} MKT_{t+1}\left(\eta_{cf,t} - \bar{\eta}_{cf}\right) + \sum_{j=1}^{J} \beta_j I_{j,t+1} + \varepsilon_{p,t+1}^{cf} \tag{24}$$

$$r_{p,t+1} = \alpha_p^{dr} + \beta_p MKT_{t+1} + \gamma_p^{dr} MKT_{t+1}\tilde{\eta}_{dr,t+1} + \varphi_p^{dr} MKT_{t+1}\left(\eta_{dr,t} - \bar{\eta}_{dr}\right) + \sum_{j=1}^{J} \beta_j I_{j,t+1} + \varepsilon_{p,t+1}^{dr} \tag{25}$$

where $\eta_{cf,t}$ ($\eta_{dr,t}$) is the lagged one-month cash-flow (discount-rate) news, which denotes the predictable component of market news. $\tilde{\eta}_{cf,t+1}$ ($\tilde{\eta}_{dr,t+1}$) is the innovation in cash-flow (discount-rate) news from the AR(2) processes and the unpredictable component of market news. γ^{cf} (γ^{dr}) denotes the cash-flow (discount-rate) timing skill. φ^{cf} (φ^{dr}) denotes the cash-flow (discount-rate) reaction. If fund managers reflect only past market news, we expect their timing coefficients to be insignificant when considering market-news reaction.

We find that market-news timing skills remain significant after controlling for market-news reactions. The bootstrap analyses of Eqs. (24) and (25) suggest that the $t_{\hat{\gamma}}$s of top market-news timers have p-values close to zero. The bootstrap analyses show that top-sorted funds in the strategies of convertible arbitrage, long-short equity, and multi-strategy reveal market cash-flow timing skills. Overall, our basic findings about timing skills remain unchanged. We also find significant evidence of market-news reactions across hedge funds.[6]

We then proceed to distinguish between reaction to and timing of market news by calculating the economic significance of the former by the same method used to evaluate the latter. We replace $\eta_{cf,t+1}$ with $\eta_{cf,t}$ in Eq. (21) and $\eta_{dr,t+1}$ with $\eta_{dr,t}$ in Eq. (22) and calculate their economic values. We again generate out-of-sample alphas of the five reaction portfolios for each timing measure as well as the alphas of portfolios 1 to 5. Part C of the Appendix reports these results. We find that cash-flow reaction generates economic value for investors. For example, the out-of-sample alpha in all funds for the portfolio of the top (bottom) 20% cash-flow reactors is 0.385% (0.182%) over the 12-month holding period. The spreads in out-of-sample alphas between the top and bottom cash-flow reactors are relatively large and significant for all the holding periods. Thus, funds' reaction to past cash-flow news is important (whether it contains fund managers' reactions to volatilities in market cash flows or managers' reactions to fund flows) and reflects managerial ability. Obviously, the group of top cash-flow timers is consistent with the group of top cash-flow reactors, implying that cash-flow timing can be replicated by reacting to past cash-flow news. We also find that discount-rate reaction does not produce economic value for investors.

[6] The results for market-news reactions are available on request.

V. Further Analyses

5.1 Alternative Factors

Fung and Hsieh (1997, 2001) find that most hedge-fund strategies earn option-like payoffs. Jagannathan and Korajczyk (1986) also find that if funds invest in stocks and options with option-like returns, they obtain artificial market timing without having actual timing ability. Thus, spurious timing can arise if funds hold some assets (i.e. options) that their market exposure changes with market news.

We consider two alternative models that contain the factors of market, size, value, momentum, and two option factors of Agarwal and Naik (2004) constructed from out-of-money options on the S&P 500 index. We insert these alternative factors in Eqs. (15) and (16) to re-examine the market-news timing skills. After adding option factors to our benchmark models, we find the same bootstrap results as in Section IV. Overall, our results do not suggest that our timing models are mis-specified.[7]

5.2 The Importance of the Suggested Timing Models

More importantly, we answer the key question of whether our suggested timing models can make a significant contribution to Fung and Hsieh's (2004) seven-factor model. Table 6 shows that the statistical significance of the cash-flow timing models (Eq. (21)), but not that of the discount-rate timing models (Eq. (22)), increase when our suggested timing measures are added to Fung and Hsieh's (2004) model. Panel A shows that adding the market cash-flow timing measure (γ_p^{cf}) to the seven-factor model increases the Adj.R^2s for the samples of all funds, hedge funds, and FoFs from 0.67 to 0.70, 0.78 to 0.82, and 0.55 to 0.57, respectively. The panel also reports that the squared error of regression (S.E.) drops from 0.74 to 0.72, 0.70 to 0.67, and 0.90 to 0.88 for the samples of all funds, hedge funds, and FoFs, respectively, when γ_p^{cf} is added to the seven-factor model. The γ_p^{cf}s are statistically significant in all the samples. In contrast, we find a statistical significance for market discount-rate timing measures (γ_p^{dr}) when adding them to the seven-factor model.

Overall, these results show that our suggested cash-flow timing measure, but not our discount-rate timing measure, improves the seven-factor model's statistical significance.

5.3 Cash-Flow and Discount-Rate Timing Measures: A Joint Timing Model

The analyses of this study rely on evaluating the performance of hedge funds using timing models which estimate the cash-flow and discount rate timing measures separately. In this subsection, we conduct a controlling check by merging the cash-flow and discount rate timing measures in joint timing models. To execute this check, we reconstruct timing models (17) and (18) as follows:

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[7] The results are not reported in this paper but are available on request.

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p^{cf} MKT_{t+1}(\eta_{cf,t+1} - \bar{\eta}_{cf}) + \gamma_p^{dr} MKT_{t+1}(\eta_{dr,t+1} - \bar{\eta}_{dr}) + \varepsilon_{p,t+1} \quad (26)$$

Table 6 Simple Regression Analysis

Panel A: Market cash-flow news

Classes of Funds	α_p	$\beta_{p,1}$	γ_p^{cf}	$\beta_{p,2}$	$\beta_{p,3}$	$\beta_{p,4}$	$\beta_{p,5}$	$\beta_{p,6}$	$\beta_{p,7}$	S.E	$Adj. R^2$
All Funds	0.0060	0.29		0.15	-1.66	-3.08	-0.018	0.007	0.039	0.74	0.67
	(0.00)	(0.012)		(0.03)	(-0.53)	(-0.07)	(-0.012)	(0.00)	(0.00)		
	0.0015	0.30	3.00	0.19	-1.69	-3.12	-0.1	0.014	0.037	0.72	0.70
	(0.00)	(0.00)	(0.00)	(0.015)	(-0.58)	(-0.05)	(-0.02)	(0.00)	(0.00)		
Hedge	0.0043	0.32		0.24	-2.97	-6.75	-0.018	0.015	0.037	0.70	0.78
Funds	(0.00)	(0.00)		(0.02)	(-0.42)	(0.00)	(0.00)	(0.00)	(0.00)		
	0.0022	0.39	3.30	0.30	-2.77	-6.66	-0.047	0.022	0.046	0.67	0.82
	(0.00)	(0.00)	(0.00)	(0.00)	(-0.36)	(0.00)	(0.00)	(0.00)	(0.00)		
Fund of	0.011	0.20		0.20	-1.10	-2.26	-0.05	0.03	0.022	0.90	0.55
Funds	(0.00)	(0.05)		(0.05)	(-0.72)	(-0.09)	(-0.12)	(0.00)	(0.04)		
	0.0088	0.26	2.75	0.24	-1.13	-2.33	-0.052	0.04	0.028	0.88	0.57
	(0.00)	(0.03)	(0.00)	(0.04)	(-0.66)	(-0.08)	(-0.14)	(0.00)	(0.00)		

Panel B: Market discount-rate news

Classes of funds	α_p	$\beta_{p,1}$	γ_p^{dr}	$\beta_{p,2}$	$\beta_{p,3}$	$\beta_{p,4}$	$\beta_{p,5}$	$\beta_{p,6}$	$\beta_{p,7}$	S.E	$Adj. R^2$
All Funds	0.0077	0.15		0.14	-1.36	-2.72	-0.009	0.004	0.030	0.84	0.62
	(0.00)	(0.09)		(0.09)	(-0.82)	(-0.19)	(-0.12)	(0.03)	(0.03)		
	0.0072	0.20	1.34	0.18	-1.68	-2.80	-0.02	0.04	0.04	0.79	0.65
	(0.00)	(0.05)	(0.20)	(0.02)	(-0.64)	(-0.05)	(-0.03)	(0.00)	(0.02)		
Hedge	0.005	0.30		0.22	-2.77	-6.66	-0.018	0.008	0.049	0.82	0.70
Funds	(0.00)	(0.00)		(0.03)	(0.59)	(0.00)	(0.00)	(0.00)	(0.00)		
	0.0044	0.37	1.38	0.29	-2.83	-6.75	-0.026	0.010	0.054	0.79	0.74
	(0.00)	(0.05)	(0.22)	(0.02)	(-0.44)	(0.00)	(0.00)	(0.00)	(0.00)		
Fund of	0.011	0.26		0.18	-0.79	-2.09	-0.007	0.0029	0.024	0.98	0.53
Funds	(0.03)	(0.07)		(0.05)	(-0.88)	(0.30)	(0.16)	(0.00)	(0.04)		
	0.007	0.33	0.98	0.20	-0.88	-2.19	-0.012	0.0036	0.033	0.95	0.56
	(0.00)	(0.01)	(0.50)	(0.06)	(0.80)	(0.24)	(0.10)	(0.00)	(0.02)		

Note: This table reports the results of simple least squares regression (OLS) analyses for all coefficients derived from Fung and Hsieh's (2004) seven-factor model and the suggested timing models for each of the fund samples:

$$r_{p,t+1} = \alpha_p^{cf} + \beta_{p,1} MKT_{t+1} + \gamma_p^{cf} MKT_{t+1}(\eta_{cf,t+1} - \bar{\eta}_{cf}) + \beta_{p,2} SMB_{t+1} + \beta_{p,3} CY_{t+1} + \beta_{p,4} CBY_{t+1} + \beta_{p,5} BTF_{t+1} + \beta_{p,6} ETF_{t+1} + \beta_{p,7} CTF_{t+1} + \varepsilon_{p,t+1}^{cf}$$

$$r_{p,t+1} = \alpha_p^{dr} + \beta_{p,1} MKT_{t+1} + \gamma_p^{dr} MKT_{t+1}(\eta_{dr,t+1} - \bar{\eta}_{dr}) + \beta_{p,2} SMB_{t+1} + \beta_{p,3} CY_{t+1} + \beta_{p,4} CBY_{t+1} + \beta_{p,5} BTF_{t+1} + \beta_{p,6} ETF_{t+1} + \beta_{p,7} CTF_{t+1} + \varepsilon_{p,t+1}^{dr}$$

where $r_{p,t+1}$ is the equal-weight excess return of fund p's sample in month $t+1$. MKT, SMB, CY, CBY, BTF, ETF, and CTF are defined as in Table 2. η_{dr} and η_{cf} denote the discount-rate and cash-flow news computed using Eq. (3) and Eq. (4), respectively. $\bar{\eta}_{dr}$ and $\bar{\eta}_{cf}$ denote the mean levels of discount-rate and cash-flow news, respectively. γ represents the timing skill. SE is the squared error of regression. We report the t-statistics of all regression coefficients along with their p-values.

We also reconstruct timing models (19) and (20) as follows:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p^{cf} MKT_{t+1}(\eta_{cf,t+1} - \bar{\eta}_{cf}) + \gamma_p^{dr} MKT_{t+1}(\eta_{dr,t+1} - \bar{\eta}_{dr}) + \sum_{j=1}^{J} \beta_j I_{j,t+1} + \varepsilon_{p,t+1} \quad (27)$$

Using the bootstrap procedures, Panel A in Table 7 reports still significant timing coefficients of market news (t-statistics less than 5%) at different tail percentiles after controlling for cash-flow and discount rate timing. For example, the $t_{\hat{\gamma}^{cf}}$s of the top 1%, 5%, and 10% timing funds in the sample of all funds are respectively 3.33, 2.28, and 2.10, with p-values of zero. The same results are found for hedge funds and FoFs. Regarding the strategies, the most top-sorted funds in the strategies of convertible arbitrage, long-short equity, and multi-strategy obtain p-values of less than 5%. Generally, we find poorer evidence of market news timing after controlling for both cash-flow timing and discount-rate timing in a joint timing model.

Table 7 Controlling for Cash-Flow and Discount-Rate Timing Measures in a Joint Timing Model

Strategies	N	1%	5%	10%	10%	5%	1%
		Bottom t-statistics for $\hat{\gamma}^{cf}$			Top t-statistics for $\hat{\gamma}^{cf}$		
All Funds	3,568	-2.77 (0.00)	-1.32 (0.32)	-1.50 (0.37)	2.10 (0.00)	2.28 (0.00)	3.33 (0.00)
Hedge funds	2,417	-3.86 (0.00)	-2.56 (0.00)	-1.67 (0.16)	2.05 (0.02)	2.54 (0.00)	3.73 (0.00)
Fund of Funds	1,151	-1.53 (0.26)	-0.14 (1.08)	-0.07 (1.12)	2.00 (0.00)	2.42 (0.00)	3.24 (0.00)
		Bottom t-statistics for $\hat{\gamma}^{dr}$			Top t-statistics for $\hat{\gamma}^{dr}$		
All Funds	3,568	-1.65 (0.17)	-1.12 (0.74)	-0.77 (0.96)	0.78 (1.09)	0.70 (0.90)	1.87 (0.00)
Hedge funds	2,417	-3.08 (0.00)	-1.18 (0.37)	-0.86 (0.75)	0.38 (1.10)	1.00 (1.22)	2.11 (0.00)
Fund of Funds	1,151	-0.31 (1.15)	-0.06 (1.12)	-0.11 (0.86)	0.16 (1.15)	0.68 (1.22)	1.67 (0.16)

Note: This table reports the bootstrap results for market news timing by controlling for both cash-flow timing and discount-rate timing in a joint timing model. We estimate our timing models for each fund as follows:

$$r_{p,t+1} = \alpha_p + \beta_{p,1} MKT_{t+1} + \gamma_p^{cf} MKT_{t+1}(\eta_{cf,t+1} - \bar{\eta}_{cf}) + \gamma_p^{dr} MKT_{t+1}(\eta_{dr,t+1} - \bar{\eta}_{dr}) + \beta_{p,2} SMB_{t+1} + \beta_{p,3} CY_{t+1} + \beta_{p,4} CBY_{t+1} + \beta_{p,5} BTF_{t+1} + \beta_{p,6} ETF_{t+1} + \beta_{p,7} CTF_{t+1} + \varepsilon_{p,t+1},$$

where $r_{p,t+1}$ denotes the excess return on each fund in month $t+1$. MKT, SMB, CY, CBY, BTF, ETF, and CTF are defined as in Table 2. η_{dr} and η_{cf} denote the discount-rate and cash-flow news computed by Eq. (3) and Eq. (4), respectively. $\bar{\eta}_{dr}$ and $\bar{\eta}_{cf}$ are the mean levels of discount-rate and cash-flow news, respectively. γ^{cf} and γ^{dr} represent the cash-flow timing and discount-rate timing, respectively. We report the sorted t-statistics of the timing coefficients across individual funds and the p-values of the bootstrap simulations. The number of resampling repetitions is 10,000.

VI. Conclusions

This paper explores a new dimension of fund managers' timing skill, namely their ability to time market news, and examines whether managers have any capacity to adjust their portfolios' market exposure as market news changes. Using 3,568 share-oriented hedge funds operating from 1994 to 2017, we evaluate market-news timing skills at the individual fund level and find strong evidence of market cash-flow timing.

Specially, fund managers increase their market exposure when stock market news is high, and their effects are economically and statistically significant. The bootstrap analyses suggest that top-sorted cash-flow timers can be attributed to sampling variation, while the same results are not found for top-sorted discount-rate timers. Cash-flow timing ability persists over time and can add value for fund investors. The top-sorted cash-flow (discount-rate) timing funds outperform the bottom cash-flow (discount-rate) timing funds by 3.168% to 3.768% (1.80–2.436%) p.a. on a risk-adjusted basis. Our findings suggest that cash-flow timing indicates managerial ability, implying that it is an important source of fund alphas. We also distinguish between timing skills and reactions to market news and find that market-news timers, especially cash-flow timers, generate remarkable investment values.

Overall, the study of fund managers' market-news timing skills highlights the importance of incorporating market news in investment decisions.

References

Admati, A. R., Bhattacharya, S., Pfleiderer, P., and Ross, S. A. (1986), 'On timing and selectivity', *The Journal of Finance* 41 (3): 715–730.

Agarwal, V., Fos, V., and Jiang, W. (2013), 'Inferring reporting-related biases in hedge fund databases from hedge fund equity holdings', *Management Science* 59 (6): 1271–1289.

Agarwal, V. and Naik, N. Y. (2004), 'Risks and portfolio decisions involving hedge funds', *Review of Financial Studies* 17 (1): 63–98.

Aggarwal, R. K. and Jorion, P. (2010), 'Hidden Survivorship in Hedge Fund Returns', *Financial Analysts Journal* 66 (2): 69–74.

Ang, A. and Bekaert, G. (2007), 'Stock return predictability: Is it there?', *Review of Financial Studies* 20 (3): 651–707.

Atanasov, V. and Nitschka, T. (2015), 'Foreign Currency Returns and Systematic Risks', *Journal of Financial and Quantitative Analysis* 50 (1/2): 231–250.

Bühlmann, P. (1997), 'Sieve bootstrap for time series', *Bernoulli* 3 (2): 123–148.

Busse, J. A. (1999), 'Volatility timing in mutual funds: Evidence from daily returns', *Review of Financial Studies* 12 (5): 1009–1041.

Campbell, J. Y. (1991), 'A variance decomposition for stock returns', *The Economic Journal* 101 (4): 157–179.

Campbell, J. Y. (1993), 'Intertemporal Asset Pricing Without Consumption Data', *American Economic Review* 83 (3): 487–512.

Campbell, J. Y., Giglio, S., and Polk, C. (2013), 'Hard Time', *Review of Asset Pricing Studies* 3 (1): 95–132.

Campbell, J. Y. and Vuolteenaho, T. (2004), 'Bad Beta, Good Beta', *American Economic Review* 94 (5): 1249–1275.

Campbell, J. Y. and Shiller, R. J. (1988), 'The dividend-price ratio and expectations of future dividends and discount factors', *Review of Financial Studies* 1 (3): 195–228.

Cao, C., Chen, Y., Liang, B., and Lo, A. W. (2013), 'Can hedge funds time market liquidity?', *Journal of Financial Economics* 109 (2): 493–516.

Chen, Y. (2007), 'Timing Ability in the Focus Market of Hedge Funds', *Journal of Investment Management* 5 (1): 66–98.

Chen, Y. (2011), 'Derivatives use and risk taking: Evidence from the hedge fund industry', *Journal of Financial and Quantitative Analysis* 46 (4): 1073–1106.

Chen, L., Da, Z., and Priestley, R. (2012), 'Dividend smoothing and predictability', *Management Science* 58 (10): 1834–1853.

Chen, Y., Ferson, W., and Peters, H. (2010), 'Measuring the timing ability and performance of bond mutual funds,' *Journal of Financial Economics* 98 (1): 72–89.

Chen, Z. and Knez, P. (1996), 'Portfolio performance measurement: Theory and applications', *Review of Financial Studies* 9 (2): 511–555.

Chen, L. and Zhao, X. (2009), 'Return decomposition', *Review of Financial Studies* 22 (12): 5213–5249.

Christopherson, J. A., Ferson, W. E., and Glassman, D. A. (1998), 'Conditioning manager alphas on economic information: Another look at the persistence of performance', *Review of Financial Studies* 11 (1): 111–142.

Cowles, A. (1933), 'Can stock market forecasters forecast?', *Econometrica* 1 (3): 309–324.

Epstein, L. G. and Zin, S. E. (1991), 'Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis', *Journal of Political Economy* 99 (2): 263–286.

Fama, E. and French, K. R. (1993), 'Common Risk Factors in the Returns on Stocks and Bonds,' *Journal of Financial Economics* 33 (1): 3–56.

Fama, E. and French, K. R. (2010), 'Luck versus skill in the cross section of mutual fund returns', *The Journal of Finance* 65 (5): 1915–1947.

Ferson, W. E. and Schadt, R. W. (1996), 'Measuring fund strategy and performance in changing economic conditions', *The Journal of Finance* 51 (2): 425–460.

Fung, W. and Hsieh, D. A. (1997), ‘Empirical characteristics of dynamic trading strategies: The case of hedge funds’, *Review of Financial Studies* 10 (2): 275–302.

Fung, W. and Hsieh, D. A. (2000), ‘Performance characteristics of hedge funds and CTA funds: Natural versus spurious biases’, *Journal of Financial and Quantitative Analysis* 35 (3): 291–307.

Fung, W. and Hsieh, D. A. (2001), ‘The risk in hedge fund strategies: Theory and evidence from trend followers’, *Review of Financial Studies* 14 (2): 313–341.

Fung, W. and Hsieh, D. A. (2004), ‘Hedge fund benchmarks: A risk-based approach’, *Financial Analyst Journal* 60 (5): 65–80.

Galsband, V. (2012), ‘Downside risk of international stock returns’, *Journal of Banking and Finance* 36 (8): 2379–2388.

Hall, P., Horowitz, J. L., and Jing, B.-Y. (1995), ‘On blocking rules for the bootstrap with dependent data’, *Biometrika* 82 (3): 561–574.

Henriksson, R. D. and Merton, R. C. (1981), ‘On market timing and investment performance II: Statistical procedures for evaluating forecasting skills’, *Journal of Business* 54 (4): 513–534.

Jagannathan, R. and Korajczyk, R. A. (1986), ‘Assessing the market timing performance of managed portfolios’, *Journal of Business* 59 (2): 217–235.

Jagannathan, R., Malakhov, A., and Novikov, D. (2010), ‘Do hot hands exist among hedge fund managers? An empirical evaluation’, *The Journal of Finance* 65 (1): 217–255.

Kosowski, R., Timmermann, A., Wermers, R., and White, H. (2006), ‘Can mutual fund “stars” really pick stocks? New evidence from a bootstrap analysis’, *Journal of Finance* 61 (6): 2551–2595.

Lan, C. and Wermers, R. (2016), ‘Cashflow Timing vs. Discount-Rate Timing: A Decomposition of Mutual Fund Market-Timing Skills’, Working Paper, UNSW and University of Maryland.

Mitchell, M. and Pulvino, T. (2001), ‘Characteristics of risk and return in risk arbitrage’, *The Journal of Finance* 56 (6): 2135–2176.

Newey, K. D. and Newey, W. K. (1987), ‘A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix’, *Econometrica* 55 (3): 703–708.

Patton, A. J. (2009), ‘Are “Market Neutral” Hedge Funds Really Market Neutral?’, *The Review of Financial Studies* 22 (7): 2495–2530.

Patton, A. J. and Ramadorai, T. (2013), ‘On the dynamics of hedge fund risk exposures’, *The Journal of Finance* 68 (2): 597–635.

Shanken, J. (1990), ‘Intertemporal asset pricing: An empirical investigation’, *Journal of Econometrics* 45 (1-2): 99–120.

Treynor, J. L. and Mazuy, K. K. (1966), ‘Can mutual funds outguess the market?’, *Harvard Business Review* 44 (4): 131–136.

Weil, P. (1989), ‘The Equity Premium Puzzle and the Risk-Free Rate Puzzle’, *Journal of Monetary Economics* 24 (3): 401–421.

Appendix

A. Market News and Hedge Fund Biases

Fung and Hsieh (1997, 2000) examine the three biases of survivorship, backfilling, and selection using hedge fund data. In this study, we construct our sample on the basis of the survivorship and backfilling biases and examine their effects on timing skills. We summarise these sorting exercises, and the detailed results are available on request.

Following the literature, we first use survivorship bias by considering both dead and live funds. We then consider backfill bias in which hedge funds can backfill their historical performance when they are added to a database. Fung and Hsieh (2000) find a 343-day backfill period for hedge funds by using the TASS data till September 1999. They also find annual backfill biases of 1.4% and 0.7% in the average returns of hedge funds and FoFs, respectively. We have a 24-month backfill period in our sample and thus discard the period for each fund by using fund returns after the date when the fund is entered into the TASS database. Excluding the backfill period leads to a decrease of 3,824 funds (2,619 hedge funds and 1,205 FoFs) in our sample size.

Furthermore, we use the bias of the Aggarwal and Jorion (2010) master-feeder duplicates on the hedge fund data. Specifically, TASS reports two databases of “live” funds and “graveyard” funds which keep track of dead funds and starts in 1994. Many funds stop reporting at some points due to either liquidation or other reasons. We use the graveyard database to minimise survivorship biases. We omit duplicate classes from the same fund family. Moreover, we only retain funds that provide returns in US dollars. While eliminating duplicate classes and funds providing returns in currencies other than US dollars is enough to omit most situations of the same fund appearing multiple times in the data, it does not completely resolve the problem. For example, two funds can appear in the database, be run by the same manager, and have the same name due to one fund having the designation “onshore” and the other having the designation “offshore”. As another example, two funds can have the same manager and the same name due to one fund being an “LP” (limited partnership) and the other being “limited” or an “investment company”. These situations often happen in fund companies set up with a master-feeder fund structure, where multiple feeder funds channel capital to one investing master fund. In these situations, if the funds are duplicates (for example, if the returns are 0.99 correlated or more), we omit one of the duplicates.

More precisely, funds are selected as follows. If two (or more) funds from the same management company have a duplicate series of returns for the months in which both report, and one fund started later than the other, then we keep the oldest fund or the fund with the longest return series. If two funds have duplicate series for the months in which both report and one fund stops reporting before the other, we again keep the fund with the longer return series. If two funds have duplicate series and the same months for which they report, we keep the larger of the two funds by initial AUM. To avoid double-counting assets, we retain the AUM only for the fund whose return series we include. This is because, in many cases, the smaller fund is a feeder fund for the larger master fund, which suggests that the feeder fund's AUM could be already included in the master fund's AUM. Conversely, situations may exist without double-counting of assets (e.g. side-by-side onshore and offshore funds or side-by-side funds denominated in different currencies); in such cases, we understate the aggregate AUM for that manager.

Excluding the fund data affected by the biases of survivorship, backfilling, and master-feeder duplicates leads to a decrease of 3,568 share-oriented funds (1,122 FoFs and 2,446 hedge funds) in our sample size for the period 1994 to 2017.

B. Definitions of the VAR State Variables

The VAR state variables comprise (1) the excess market returns, calculated as the log excess returns of the Center for Research in Security Prices (CRSP) value-weight index; (2) the term yield spread (TY), calculated as the annualised spread between the 10-year constant maturity taxable bond yield and the yield on short-run taxable notes, and as the spread between the market yield on US Treasury securities at 10-year constant maturity, quoted on an investment basis from the Federal Reserve, and the annualised three-month US Treasury bill rate; (3) the market-smoothed price-earnings ratio, calculated as the log ratio of the S&P 500 price index to a 10-year moving average of the S&P 500 earnings; and (4) the small-stock value spread,[8] calculated as the spread between the log book-to-market ratio of small growth and small value stocks.

To check robustness, we use Chen and Zhao's (2009) alternative state variables, which consist of (1) the one-year price-earnings ratio, calculated as the log ratio of the S&P 500 price index to the one-year moving average of the S&P 500 earnings; (2) the dividend yield, calculated as the dividend-price ratio of the S&P 500 index; (3) the book-to-market spread, calculated as the log spread between book-to-market equity and value for growth portfolios; (4) inflation, calculated as the monthly rate of changes in the consumer price index; and (5) stock variance, calculated as the cross-sectional variance of the 25 size- and book-to-market ratio sorted Fama and French (1993) stock portfolios.[9]

C. Timing vs. Reaction to Market News

We proceed here to examine the distinction between reaction to and timing of market news by calculating the economic significance of the former using the same method used to value the latter. We replace $\eta_{cf,t+1}$ with $\eta_{cf,t}$ in Eq. (21) and $\eta_{dr,t+1}$ with $\eta_{dr,t}$ in Eq. (22), and calculate their economic values. For each timing measure, we again generate the

[8] The data are available in the Kenneth R. French data library.

[9] The detailed results of this check are available on request and are robust to our baseline results documented in section IV.

out-of-sample alphas of the five reaction portfolios as well as the alphas of portfolios 1 to 5.

Table A.1 Economic Value of Market News Reaction: Out-of-Sample Alphas

Portfolios	All Funds				Hedge Funds			
	k = 3	k = 6	k = 9	k = 12	k = 3	k = 6	k = 9	k = 12
Panel A: Market cash-flow reaction								
P1 (Top timers)	0.355 (2.60)	0.345 (2.50)	0.324 (2.17)	0.344 (2.77)	0.372 (2.87)	0.362 (2.93)	0.366 (2.76)	0.385 (2.57)
P2	0.262 (2.68)	0.234 (2.30)	0.242 (2.38)	0.260 (2.58)	0.340 (3.93)	0.324 (3.69)	0.311 (3.45)	0.304 (3.33)
P3	0.224 (2.53)	0.221 (2.32)	0.234 (2.45)	0.249 (2.63)	0.328 (4.14)	0.345 (4.32)	0.332 (4.25)	0.320 (3.94)
P4	0.202 (2.42)	0.207 (2.50)	0.213 (2.59)	0.225 (2.22)	0.260 (2.52)	0.274 (2.76)	0.280 (2.95)	0.290 (3.47)
P5 (Bottom timers)	0.105 (1.00)	0.118 (0.82)	0.122 (0.98)	0.131 (1.12)	0.142 (1.25)	0.156 (1.39)	0.163 (1.53)	0.182 (1.72)
P1-5	0.25 (2.66)	0.227 (2.52)	0.202 (2.38)	0.213 (2.42)	0.230 (2.54)	0.206 (2.40)	0.203 (2.39)	0.203 (2.39)
Panel B: Market discount-rate reaction								
P1 (Top timers)	0.175 (1.33)	0.170 (1.30)	0.162 (1.24)	0.182 (1.37)	0.198 (1.42)	0.193 (1.39)	0.196 (1.41)	0.222 (1.67)
P2	0.140 (1.12)	0.136 (1.07)	0.142 (1.14)	0.156 (1.38)	0.177 (1.66)	0.165 (1.50)	0.155 (1.34)	0.140 (1.18)
P3	0.124 (1.00)	0.119 (0.94)	0.127 (0.98)	0.135 (1.08)	0.154 (1.28)	0.148 (1.18)	0.140 (1.12)	0.125 (1.04)
P4	0.102 (0.90)	0.095 (0.84)	0.106 (0.95)	0.115 (1.00)	0.124 (1.09)	0.118 (1.05)	0.112 (1.02)	0.105 (0.99)
P5 (Bottom timers)	0.084 (0.77)	0.076 (0.69)	0.088 (0.82)	0.094 (0.87)	0.098 (0.93)	0.097 (0.91)	0.095 (0.89)	0.076 (0.64)
P1-5	0.091 (0.84)	0.094 (0.98)	0.074 (0.71)	0.088 (0.82)	0.100 (0.95)	0.096 (0.90)	0.101 (0.93)	0.146 (1.21)

Note: This table reports the out-of-sample alphas of the portfolios for different extents of reacting to past market news. For each month, we sort five portfolios into the funds' cash-flow reaction coefficients resulting from the past 36 months and then hold the portfolios for different *K*-month periods. We repeat the above sorting exercise for the funds' discount-rate reaction coefficients. Panels A and B report the out-of-sample alphas (in % per month) of the seven-factor models generated from the post-ranking returns for the cash-flow and discount-rate reaction coefficients, respectively. T-statistics are estimated by autocorrelation-consistent standard errors and Newey and West heteroskedasticity with two lags in parentheses.

Table A.1 reports these results, and Panel A shows that cash-flow reaction generates economic value for investors. For example, over the 12-month holding period, the out-of-sample alpha in all funds for the portfolio of the top 20% of cash-flow reactors is 0.385%, while the alpha of the bottom 20% of cash-flow reactors is 0.182%. The spreads in out-of-sample alphas between the top and bottom market cash-flow reactors are relatively large and significant for all 3-, 6-, 9-, and 12-month holding periods. Thus, a fund's reaction to past cash-flow news is important (whether it contains a fund manager's reaction to volatilities in market cash flows or a manager's reaction to fund flows) and reflects managerial ability.

Obviously, the group of top cash-flow timers is consistent with the group of top cash-flow reactors, implying that cash-flow timing can be replicated by reacting to past cash-flow news.

Panel B of Table A.1 shows that market discount-rate reaction does not produce economic value for investors. For example, over the 12-month holding period, the out-of-sample alpha in all funds for the portfolio of the top 20% of discount-rate reactors is 0.222%, while the alpha of the bottom 20% of discount-rate reactors is 0.076%. The spreads in out-of-sample alphas between the top and bottom discount-rate reactors is statistically insignificant for all the holding periods. Obviously, the group of top discount-rate timers is not consistent with the group of top discount-rate reactors, implying that discount-rate timing cannot be replicated by reacting to past discount-rate news.