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Improving momentum returns using generalized linear models

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Abstract

We estimate the enduring momentum probabilities of past winners and losers continuing as future winners and losers by incorporating a comprehensive set of firm characteristics. Our results reveal that combining the price momentum signals and enduring momentum probabilities generates returns double those of the traditional price momentum strategy. Furthermore, the robust performance of the enduring momentum strategy cannot be fully attributed to factors such as seasonality, limits to arbitrage, and transaction costs.

KEYWORDS

enduring momentum probability, firm characteristics, momentum

JEL CLASSIFICATION

C13, C31, C53, G17

1 | INTRODUCTION

The price momentum strategy, where past winning firms continue to outperform while past losing firms persist in underperformance, remains one of the most puzzling anomalies in asset-pricing research (Fama, 1998). Researchers have identified that specific firm attributes and fundamental factors can enhance traditional price momentum returns by providing additional predictive information (e.g., Huang et al., 2019; Sagi & Seasholes, 2007). In this study, we employ a Cox Proportional Hazards (Cox PH) model (Cox, 1972), and five other generalized linear models (GLM), to

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identify stocks that deliver superior momentum returns. Our models integrate information from past momentum survival time and 37 firm characteristics to estimate the probability that a winner (loser) will continue being a winner (loser) over a 6-month investment period. This probability is referred to as the "enduring momentum probability".

Specifically, in the first stage of our estimation process, we identify winners and losers at the end of each month t based on their cumulative returns over the preceding 6-month period ($t-5$ to t). We then compute the momentum survival time for each winner and loser over the subsequent 6-month period ($t+1$ to $t+6$) by counting the number of months a winner or loser continues in its respective category.[1] We refer to this momentum survival time as 'enduring time'. We also calculate a large set of firm characteristics for each firm at the end of each month t. This process is repeated every month in our sample period to generate a time series of enduring time and firm characteristics.

In the second stage of our estimation process, we fit the enduring time and firm characteristics from month $t-60$ to month $t-6$ to the Cox PH model to estimate the model parameters.[2] The enduring momentum probability for a winner (loser) to remain in the winning (losing) group in the next six months ($t+1$ to $t+6$) is calculated by applying these parameters to the winner's (loser's) firm characteristics in month t. Finally, we establish our enduring momentum strategy by buying 10 winners and selling 10 losers in month t with the highest enduring momentum probabilities. We hold this long-short portfolio for six months and rebalance it on a monthly basis.

Our analysis reveals that the enduring momentum probabilities estimated by the Cox PH model for winners and losers are significantly associated with the persistence of stock returns. Firms with higher enduring momentum probabilities exhibit stronger return persistence compared to those with lower probabilities. In addition, we show that these probabilities play a critical role in predicting cross-sectional stock returns. By conditioning on a comprehensive set of 37 firm characteristics, the enduring momentum probabilities enhance traditional momentum returns, extending beyond the conventionally examined variables such as price momentum signals, book-to-market ratio, size, illiquidity ratio, and volatility. Our results show that the enduring momentum long-short portfolio achieves an average monthly return of 2.19%, nearly double the 1.12% return of the traditional price momentum portfolio (e.g., Jegadeesh & Titman, 1993). In addition to the Cox PH model, we employ five other GLMs, that is, Poisson, logit, fractional logit, linear probability, and OLS models, to estimate the enduring momentum probability and form long-short portfolios in a similar manner. We find that these portfolios also outperform the price momentum portfolio, although their performances are still inferior to the Cox PH portfolio's performance.

Since the superior performance of the enduring momentum strategy to the price momentum strategy is exhibited in both average portfolio returns and risk-adjusted returns, with the loser portfolio component apparently playing a central role in driving this outperformance, we investigate whether the returns are due to limits to arbitrage. Li et al. (2009) argue that trading winners is generally less costly than trading losers. Investors face fewer barriers when buying stocks than short selling, which is more complex and costly due to borrowing requirements, fees, regulatory constraints, and the risk of unlimited losses. Consistent with this perspective, studies by Shleifer and Vishny (1997) and Lamont and Thaler (2003) highlight how these barriers prevent arbitrageurs from effectively correcting market mispricing. Arena et al. (2008) suggest that momentum profits are associated with limits to arbitrage; however, our results show that the enduring momentum returns are unlikely attributable to limits to arbitrage. They prevail after we remove small stocks, volatile stocks, and illiquid stocks from the sample.

We also conduct numerous robustness checks on the performance of our enduring momentum strategy based on previous literature on price momentum. These include excluding the top 10% of microcap stocks (Asness et al., 2013), varying the portfolio holding period of up to 12 months (Jegadeesh & Titman, 1993), addressing the seasonal effect or long-term reversal of momentum performance (De Bondt & Thaler, 1985; Jegadeesh & Titman, 1993), extending the number of winners and losers in the portfolio, applying different weighting schemes (Korajczyk & Sadka, 2004), and adjusting for different risk factors (e.g., Barroso & Santa-Clara, 2015; Da et al., 2014). Overall, we show that the enduring momentum continues to show consistent results and outperforms the price momentum returns in most tests. Finally, our results indicate that the enduring momentum strategy performs well during market crashes and that it bears a higher break-even transaction cost than the price momentum strategy.

Our paper contributes to existing research on firm characteristics that moderate momentum returns. A growing body of literature highlights that momentum is intricately driven by various firm characteristics rather than solely by price signals (e.g., Daniel & Titman, 1999; Guo et al., 2022; Hong et al., 2000). We identify age, bid-ask spread, trading volume, leverage, maximum daily return, volatility, secured debt, and the sales-to-price ratio as the most critical characteristics in selecting stocks in enduring momentum portfolios. Several studies support the importance of these characteristics. For example, Lee and Swaminathan (2000) demonstrate that past trading volume predicts both the magnitude and persistence of price momentum. Forner et al. (2018) show that incorporating leverage on the short side of momentum portfolios can yield higher abnormal returns. Barroso and Santa-Clara (2015) find that the realized variance of daily returns is highly predictable, and scaling the long-short portfolio by its realized volatility results in substantial economic gains. Avramov et al. (2007) document a strong relationship between momentum and credit rating, where momentum profitability is higher for low-grade firms but non-existent among high-grade firms. Motivated by Daniel and Moskowitz (2016), this paper contributes to the literature on conditional momentum by comprehensively incorporating firm characteristics to refine momentum signals and develop an enhanced trading strategy, namely the enduring momentum strategy.

The remainder of this paper is organized as follows. Section 2 provides the data and methodology for estimating the enduring momentum probability and constructing an enduring momentum strategy. Section 3 presents the empirical results. Section 4 reports robustness check results, and Section 5 concludes the paper.

2 | DATA AND METHODOLOGY

2.1 | Data

We collect daily returns for all common stocks on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and Nasdaq from the Center for Research in Security Prices (CRSP) database. The monthly returns of all the individual firms used to construct the 6-month/6-month price momentum strategy are obtained by compounding their daily returns, and we exclude stocks with share prices less than $1 at the beginning of the holding month. In addition, we obtain data from the Compustat database and follow Green et al. (2017)[3] to construct 102 firm characteristics. Green et al. (2017) argue that data from January 1980 become robustly available. Thus, our analysis starts in January 1980 and ends in December 2018, covering 38 years.

To maximize the predictive ability of firm characteristics and ensure sufficient data for the Cox PH model and other GLM models to calculate the enduring momentum probability, we only retain firm characteristics with missing data of less than 5% over the entire sample period. In addition, we exclude all momentum variables to avoid the momentum effect in the construction of the enduring momentum strategy. After these screening criteria, 37 firm characteristics remain, and we provide their descriptions in Table A1. Finally, we collect the four Fama–French and Carhart factors (MKT, SMB, HML, and UMD)[4] from Kenneth French's data library.[5]

2.2 | Methodology

2.2.1 | Enduring momentum probability and enduring momentum strategy

This section introduces the terminology common to enduring momentum analysis and discusses the estimation of enduring momentum probability by applying the Cox PH model. It also introduces the difference between the enduring momentum and survival probability and describes how we use the estimated enduring momentum probability to construct the enduring momentum strategy. Figure 1 illustrates the steps and timeline for constructing the enduring momentum strategy. This estimation process includes two stages. In the first stage, we identify momentum winners

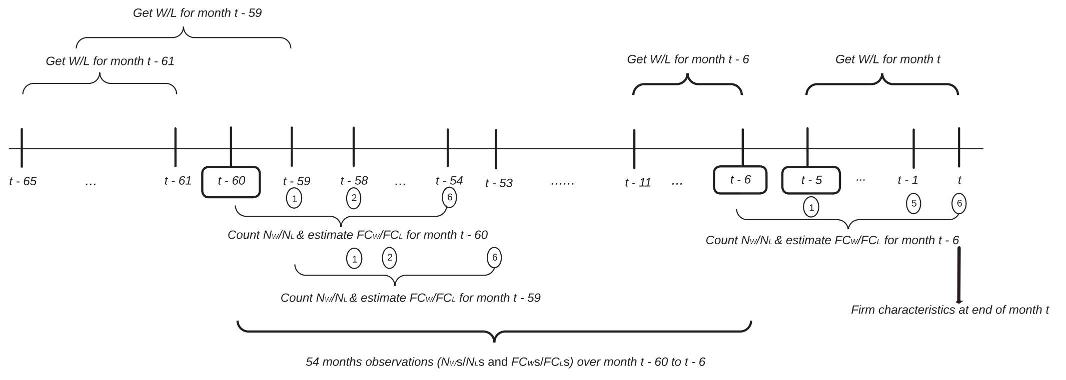

FIGURE 1 Steps and timeline to estimate the enduring momentum probability. First, at the end of each month, we identify momentum winners (W) and losers (L) based on their cumulative returns over the preceding 6-month period. Second, we determine the enduring time of each winner (N_W) or loser firm (N_L), calculated as the number of months it remains in its respective category during the subsequent 6-month period. The 37 firm characteristics associated with each winner (FC_W) or loser (FC_L) are also calculated or observed at the end of the month. These steps provide us with a time series of winners and losers, their enduring time, and firm characteristics throughout our sample period. Third, we use the time series data from month $t-60$ to month $t-6$ (i.e., 54 months) and fit the enduring time and firm characteristics into the Cox PH model to estimate the model parameters. Fourth, we compute the enduring momentum probability for a winner (loser) in month t to stay in the winning (losing) group in the following six months ($t+1$ to $t+6$) by applying these parameters to the winner's (loser's) firm characteristics in that month. Finally, we rank these enduring momentum probabilities and form our enduring momentum portfolio by buying 10 winners and selling 10 losers with the highest estimated enduring momentum probabilities. We hold this long-short portfolio for six months and rebalance it monthly.

and losers, count their enduring time, and compute their 37 firm characteristics. Specifically, at the end of each month t, we identify momentum winners and losers based on their cumulative returns over the preceding 6-month period ($t-5$ to t). Next, we determine the survival time of each winner (loser) firm, calculated as the number of months it remains in its respective category during the subsequent 6-month period (i.e., $t+1$ to $t+6$) and denote this enduring time as N_i^W (N_i^L). The 37 firm characteristics associated with each winner (loser) are also calculated or observed at the end of month t. These steps provide us with a time series of winners and losers, their enduring time, and firm characteristics throughout our sample period.

In the second stage of estimation, for each month t, we use the time series data from month $t-60$ to month $t-6$ (i.e., 54 months) and fit the enduring time and firm characteristics into the Cox PH model to estimate the model parameters. We then compute the enduring momentum probability for a winner (loser) in month t to stay in the winning (losing) group in the following six months ($t+1$ to $t+6$) by applying these parameters to the winner's (loser's) firm characteristics in that month. Finally, we rank these enduring momentum probabilities and form our enduring momentum portfolio by buying 10 winners and selling 10 losers with the highest estimated enduring momentum probabilities. We hold this long-short portfolio for six months and rebalance it monthly.

In the traditional Cox PH models, survival analysis is typically conducted over a continuous interval from $t=1$ to $t=\mathrm{T}$, with each subject i assigned a survival time T_i upon failure. However, in our analysis, the winners or losers formed at the end of month t to keep performing as winners or losers can only occur at discrete points over the 6-month holding period (i.e., from $t+1$ to $t+6$). Therefore, our enduring time variables, N_i^W for winners and N_i^L for losers, represent discrete survival time. For example, if firm i is identified as a winner at the end of formation month t and continues to be a winner in the second ($t+2$), fourth ($t+4$), and sixth months ($t+6$) of the holding period, the enduring time N_i^W for this winner firm is 3.

The below hazard function describes the relative likelihood of a winner or loser exiting the top or bottom decile group based on τ times ($0 \le \tau \le 6$) that it has survived in the top or bottom group:

$$\lambda(\tau|X) = \lim_{\Delta\tau \to 0} \frac{P(\tau \le T \le \tau + \Delta\tau | T \ge \tau, X, \beta)}{\Delta\tau}$$

$$= \frac{-dlogS(\tau|X)}{d\tau} = \frac{f(\tau|X)}{S(\tau|X)} = \lambda_0(\tau)\exp(\beta' X) \tag{1}$$

where $f(\tau|X)$ is the density function associated with the distribution of survival duration, $\lambda_0(\tau)$ is the baseline hazard function with all covariates equal to zero, β is a vector of the parameters, and X represents a set of 37 firm characteristics. The survival function $S(\tau|X) = Prob(T \ge \tau|X)$ is related to the hazard by:

$$S(\tau|X) = exp\left(-\int_0^\tau \lambda(u|X)du\right) = exp^{\left(-\int_0^\tau \lambda_0(u) exp^{\beta' X} du\right)},$$

$$= exp^{(-\Lambda_0(\tau)\exp(\beta' X))} = S_0(\tau)^{\exp(\beta' X)}, \tag{2}$$

where $\Lambda_0(\tau) = \int_0^\tau \lambda_0(u)du$ represents the baseline cumulative hazard function at time τ, and $S_0(\tau) = \exp(-\Lambda_0(\tau))$. Let x^* denote a particular value of X at the end of rolling window t. The estimated enduring momentum probability is defined by substituting estimators for the unknown quantities as:

$$\widehat{S}(\tau|x^*) = exp^{\left(-\widehat{\Lambda}_0(\tau)\exp\left(\widetilde{\beta'} X\right)\right)}, \tag{3}$$

At the end of each rolling window in month t, we obtain seven estimated enduring momentum probabilities[6] for each winner or loser to stay in the corresponding group during the 6-month holding period ($t+1$ to $t+6$), as τ ranges from one to six. For example, $\widehat{S}_{W/L}(6)$ ($\tau = 6$) represents the estimated enduring probability for a winner (W) or loser (L) to remain so throughout the 6-month holding period. Unlike the price momentum strategy to hold and sell all past winners and losers, our enduring momentum portfolio only includes the top 10 winners and top 10 losers with the highest estimated enduring probabilities, $\widehat{S}_W(6)$ and $\widehat{S}_L(6)$, respectively.

2.2.2 | Enduring momentum with general linear model (GLM) estimation

In this section, we introduce a series of generalized linear models, including the Poisson, logit, fractional logit, linear probability, and OLS models, to construct enduring momentum portfolios and compare their performances with the Cox PH. Although all five GLMs follow the same estimation procedure to facilitate a fair comparison with the Cox PH model, variations exist in the definition of the dependent variable due to the unique characteristics of each model.

We use the same enduring time variables, N_i^W and N_i^L, as the dependent variable in the Poisson and OLS models. Since in the logit model the dependent variable needs to be a binary, we define this variable, $y_i^{W(L)}$, as follows:

$$y_i^{W(L)} = \begin{cases} 1, & \dfrac{N_i^W(N_i^L)}{6} \ge 0.5 \\ 0, & \dfrac{N_i^W(N_i^L)}{6} < 0.5 \end{cases}. \tag{4}$$

In the fractional logit and linear probability models, the dependent variable is defined as in Equation (5) below:

$$D\_ratio_i^W\left(D\_ratio_i^L\right)=\frac{N_i^W\left(N_i^L\right)}{6}, \tag{5}$$

where $D\_ratio_i^W\left(D\_ratio_i^L\right)$ represents the enduring ratio for winner (loser) firm i, calculated by dividing its enduring time $N_i^W\left(N_i^L\right)$ by six. Using these dependent variables, we obtain the model parameters, estimate enduring momentum probabilities, and then construct enduring momentum portfolios in a similar manner as described above.

Compared with the Cox PH model, the above five GLMs are conventional methods commonly used in estimating the enduring momentum probabilities. However, there are some restrictions and limitations for these models. For example, the OLS model assumes that the effects are linear and additive. Moreover, the estimated enduring time fit in the Poisson, linear probability, and OLS models will cause the out-of-bound prediction problem that the estimated enduring probabilities of the Poisson model may exceed the total investment months (6) or the estimated enduring probabilities of the OLS and linear probability models may be less than 0. Besides, the Poisson model is required to adhere to the assumption E(Y) = V(Y), where the expected value of enduring time is equivalent to its variance. The dependent variable in the logit model is binary, which will compress the total number of enduring time information to 1 and 0. Since the Cox PH model is more flexible, as it is semi-parametric, it does not make strong assumptions about the shape of the baseline hazard function. Moreover, the Cox PH model produces greater statistical power than a logistic regression model with the same available follow-up data (Annesi et al., 1989; Cuzick, 1982). Given the above limitations of the five other GLMs compared to the Cox PH, our analysis mainly focuses on the enduring momentum probability (EMP) and enduring momentum portfolio/returns (EM) based on the Cox PH model unless otherwise specified.

2.2.3 | Autocorrelation regression

Sagi and Seasholes (2007) claim that some specific firm attributes (revenues, costs, and real options) restrict winners and losers, and that restricted winners and losers have more persistent expected returns. We test whether the enduring momentum probability is related to the persistence of stock returns. We first run the autoregression with a one-month lag (AR (1)) for each firm based on a 60-month rolling window:

$$r_{i,t-60:t}=a_{i,t}+\rho_{i,t}r_{i,t-61:t-1}+e_{i,t}, \tag{6}$$

where $r_{i,t-60:t}$ ($r_{i,t-61:t-1}$) is the stock return of firm i from month $t-60$ to t ($t-61$ to $t-1$). After obtaining the slope $\rho_{i,t}$ (the proxy for stock return persistency), we determine the relationship between the enduring momentum probability and the persistence of stock returns using the multiple cross-sectional regression over time as follows:

$$\rho_{h,t}=\alpha_{h,t}+\beta_{h,t}^{EMP}EMP_{h,t-1}+\varepsilon_{h,t}, \tag{7}$$

where $EMP_{h,t-1}$ represents the enduring momentum probabilities for the winner (h = W) or loser (h = L) firms, estimated at the end of month $t-1$. Subsequently, we calculate the average value of all estimated coefficients $\beta_{h,t}$ and its corresponding t value.

2.2.4 | Logit regression

We compare the performance of the estimated enduring momentum probability and the price momentum signal (i.e., past 6-month cumulative returns) in determining future winners or losers over the 6-month holding period using the following panel logit regression:

$$Y_{h,t} = a_h^k + \gamma_h^k x_{h,t}^k + \epsilon_{h,t}^k, \tag{8}$$

where $Y_{h,t}$ is a dummy variable equal to one for a winner ($h = \mathrm{W}$) or loser ($h = \mathrm{L}$) firm of price momentum identified at the end of month t to keep performing as a winner or loser in any month of the subsequent 6-month holding period and zero otherwise. $x_{h,t}^k$ is the estimated enduring momentum probability ($k = \mathrm{EMP}$) or the cumulative returns over the preceding 6-month period ($k = \mathrm{MOM}$) associated with that winner or loser. We also explore the explanatory ability of the enduring momentum probability after controlling for the price momentum signal as depicted in Equation (9) below.

$$Y_{h,t} = a_h + \gamma_h^{EMP} EMP_{h,t} + \gamma_h^{MOM} MOM_{h,t} + \epsilon_{h,t}, \tag{9}$$

where $Y_{h,t}$ is the same dummy variable as in Equation (8). $MOM_{h,t}$ is the price momentum signal for a winner ($h = \mathrm{W}$) or loser ($h = \mathrm{L}$). $EMP_{h,t}$ is the estimated enduring momentum probability for the same winner or loser.[7]

2.2.5 | Decomposition analysis

We compare the predictive ability of the enduring momentum probability and momentum signal in forecasting future returns using the following cross-sectional regressions:

$$r_{h,t+1} = a_h^k + \phi_h^k x_{h,t}^k + \epsilon_{h,t}^k, \tag{10}$$

where $r_{h,t+1}$ is the stock return for a winner ($h = \mathrm{W}$) or loser ($h = \mathrm{L}$) firm in month $t+1$. $x_{h,t}^k$ is the estimated enduring momentum probability ($k = \mathrm{EMP}$) or the price momentum signal ($k = \mathrm{MOM}$) for that winner or loser. We also include both EMP and MOM in the same predictive regression:

$$r_{h,t+1} = a_h^k + \phi_h^{EMP} EMP_{h,t} + \phi_h^{MOM} MOM_{h,t} + \varepsilon_{h,t+1}, \tag{11}$$

However, Hou and Loh (2016) argue that the traditional method of adding competing variables cannot quantify the explanatory fraction of candidate variables. They introduce a decomposition method to comprehensively evaluate the explained fraction of the candidate variables. We follow their method to detect whether the momentum signal can explain the return captured by the enduring momentum probability. We first explore whether enduring momentum probability affects the predictability of stock returns using the following cross-sectional regression:

$$r_{i,t+1} = \alpha_{h,t} + \eta_{h,t} EMP_{h,i,t} + \varepsilon_{h,i,t}, \tag{12}$$

where $r_{i,t+1}$ is the stock return of firm i in month $t+1$. $EMP_{h,i,t}$ is the enduring momentum probability for a winner ($h = \mathrm{W}$) or loser ($h = \mathrm{L}$) firm estimated in month t. We consider the price momentum return, $MOM_{h,i,t}$, as a candidate variable and examine the relationship between the $EMP_{h,i,t}$ and $MOM_{h,i,t}$ as follows:

$$EMP_{h,i,t} = a_{h,t} + \zeta_{h,t} MOM_{h,i,t} + \epsilon_{h,i,t}, \tag{13}$$

Subsequently, we decompose $EMP_{h,i,t}$ into two orthogonal components based on the estimated coefficients $\eta_{h,t}$ in Equation (12):

$$\eta_{h,t} = \frac{Cov(r_{h,i,t+1},\ EMP_{h,i,t})}{Var(EMP_{h,i,t})},$$
$$= \frac{Cov(r_{h,i,t+1},\ \zeta_{h,t}MOM_{h,i,t})}{Var(x_{i,j,t-1})} + \frac{Cov(r_{h,i,t+1},\ a_{h,t}+\epsilon_{h,i,t})}{Var(x_{i,j,t-1})},$$
$$= \eta^{C}_{h,t} + \eta^{R}_{h,t}, \tag{14}$$

where $\zeta_{h,t}MOM_{h,i,t}$ $(a_{h,t}+\epsilon_{h,i,t})$ is the related (residual) component of $EMP_{h,i,t}$. Finally, we use $\frac{\eta^{C}_{h,t}}{\eta_{h,t}}$ $\left(\frac{\eta^{R}_{h,t}}{\eta_{h,t}}\right)$ to calculate the explained (residual) fractions from the price momentum signal of winners (h = W) or losers (h = L) by estimating the mean and variance of the fractions over the whole regression period as follows:

$$\widehat{E}\left(\frac{\eta^{C}_{h,t}}{\eta_{h,t}}\right) \approx \frac{\overline{\eta}^{C}_{h,t}}{\overline{\eta}_{h,t}}, \widehat{E}\left(\frac{\eta^{R}_{h,t}}{\eta_{h,t}}\right) \approx \frac{\overline{\eta}^{R}_{h,t}}{\overline{\eta}_{h,t}}, \tag{15}$$

$$\widehat{Var}\left(\frac{\eta^{C}_{h,t}}{\eta_{h,t}}\right) \approx \frac{1}{T}\left(\frac{\overline{\eta}^{C}_{h,t}}{\overline{\eta}_{h,t}}\right)^{2}\left(\frac{\sigma^{2}_{\eta^{C}_{h,t}}}{\overline{\eta}^{C\,2}_{h,t}} + \frac{\sigma^{2}_{\eta_{h,t}}}{\overline{\eta}_{h,t}^{\,2}} - 2\frac{\widehat{\rho}_{\eta^{C}_{h,t},\eta_{h,t}}\sigma^{2}_{\eta^{C}_{h,t}}\sigma^{2}_{\eta_{h,t}}}{\overline{\eta}^{C}_{h,t}\overline{\eta}_{h,t}}\right), \tag{16}$$

$$\widehat{Var}\left(\frac{\eta^{R}_{h,t}}{\eta_{h,t}}\right) \approx \frac{1}{T}\left(\frac{\overline{\eta}^{R}_{h,t}}{\overline{\eta}_{h,t}}\right)^{2}\left(\frac{\sigma^{2}_{\eta^{R}_{h,t}}}{\overline{\eta}^{R\,2}_{h,t}} + \frac{\sigma^{2}_{\eta_{h,t}}}{\overline{\eta}_{h,t}^{\,2}} - 2\frac{\widehat{\rho}_{\eta^{R}_{h,t},\eta_{h,t}}\sigma^{2}_{\eta^{R}_{h,t}}\sigma^{2}_{\eta_{h,t}}}{\overline{\eta}^{R}_{h,t}\overline{\eta}_{h,t}}\right), \tag{17}$$

and,

$$t_{\frac{\overline{\eta}^{C}_{h,t}}{\overline{\eta}_{h,t}}} = \frac{\frac{\overline{\eta}^{C}_{h,t}}{\overline{\eta}_{h,t}}}{\sigma\left(\frac{\overline{\eta}^{C}_{h,t}}{\overline{\eta}_{h,t}}\right)}, t_{\frac{\overline{\eta}^{R}_{h,t}}{\overline{\eta}_{h,t}}} = \frac{\frac{\overline{\eta}^{R}_{h,t}}{\overline{\eta}_{h,t}}}{\sigma\left(\frac{\overline{\eta}^{R}_{h,t}}{\overline{\eta}_{h,t}}\right)}, \tag{18}$$

where $t_{\frac{\overline{\eta}^{C}_{h,t}}{\overline{\eta}_{h,t}}}\left(t_{\frac{\overline{\eta}^{R}_{h,t}}{\overline{\eta}_{h,t}}}\right)$ is the t value used to examine whether the explained (residual) fraction is significantly different from zero.

3 | EMPIRICAL RESULTS

3.1 | Summary statistics of firm characteristics

Table 1 summarizes the 37 firm characteristics from January 1980 to December 2018, presenting the mean, median, standard deviation (std), and the fifth (P5), twenty-fifth (P25), seventy-fifth (P75), and ninety-fifth (P95) percentile values. We can see that most firm characteristics are positive; for example, the average monthly return volatility (*retvol*) and idiosyncratic volatility (*idiovol*) are 3.0% and 7.0%, with standard deviations of 0.03 and 0.04, respectively, suggesting that stock returns are volatile over January 1980 to December 2018. Guo et al. (2022) show that the average monthly return volatility and idiosyncratic volatility are 2.5% and 2.3%, with standard deviations of 0.014 and 0.013 from July 1963 to December 2016.

Table 2 presents the Pearson correlations between the 37 firm characteristics and the estimated enduring momentum probabilities from January 1985 to December 2018. 25 of them display positive and statistically significant relationships with the estimated enduring momentum probabilities. For example, the results for *baspread*, *beta*, *bm*, *retvol*, *idiovol* indicate that winner and loser firms with higher bid-ask spread, beta, book-to-market ratio, return

TABLE 1 Summary statistics of firm characteristics.

N	Variables	Mean	Median	Std	P5	P25	P75	P95
1	age	11.32	9.00	9.18	1.00	4.00	16.00	31.00
2	baspread	0.06	0.04	0.07	0.01	0.02	0.06	0.15
3	beta	1.09	1.02	0.67	0.14	0.61	1.48	2.34
4	betasq	1.65	1.04	1.90	0.03	0.38	2.19	5.46
5	bm	0.69	0.55	0.64	0.06	0.30	0.91	1.85
6	bm_ia	26.86	0.05	772.36	−42.80	−0.36	0.65	6.74
7	cashdebt	−0.04	0.11	1.34	−1.27	0.01	0.26	0.82
8	cashpr	−0.95	−0.26	57.47	−53.92	−8.64	5.34	49.39
9	convind	0.12	0.00	0.33	0.00	0.00	0.00	1.00
10	currat	3.33	1.94	5.05	0.68	1.18	3.26	10.23
11	depr	0.29	0.17	0.42	0.05	0.11	0.31	0.88
12	dolvol	11.37	11.32	3.06	6.47	9.17	13.64	16.40
13	dy	0.02	0.00	0.03	0.00	0.00	0.02	0.07
14	ep	−0.04	0.04	0.36	−0.49	−0.02	0.08	0.17
15	herf	0.08	0.05	0.09	0.02	0.03	0.09	0.23
16	idiovol	0.07	0.06	0.04	0.02	0.04	0.09	0.14
17	ill	5.16	0.07	27.23	0.00	0.00	1.06	20.69
18	indmom	0.14	0.11	0.29	−0.26	−0.03	0.27	0.65
19	IPO	0.07	0.00	0.26	0.00	0.00	0.00	1.00
20	lev	2.23	0.64	4.77	0.04	0.22	1.88	10.03
21	maxret	0.08	0.05	0.08	0.01	0.03	0.09	0.22
22	mve	11.91	11.80	2.26	8.38	10.28	13.47	15.81
23	mve_ia	−201.51	−486.39	6479.43	−4861.02	−1723.79	−104.34	4157.84
24	pricedelay	0.16	0.07	1.05	−0.74	−0.05	0.33	1.24
25	quick	2.64	1.31	4.48	0.41	0.88	2.41	9.00
26	retvol	0.03	0.03	0.03	0.01	0.02	0.04	0.09
27	roic	−0.13	0.06	1.08	−1.01	−0.01	0.13	0.30
28	salecash	56.10	8.78	173.34	0.28	2.26	36.80	229.12
29	salerec	11.79	5.82	58.78	0.10	3.59	8.81	45.83
30	securedind	0.47	0.00	0.50	0.00	0.00	1.00	1.00
31	sin	0.01	0.00	0.09	0.00	0.00	0.00	0.00
32	sp	2.03	0.97	3.27	0.05	0.41	2.22	7.59
33	std_dolvol	0.87	0.80	0.42	0.32	0.53	1.15	1.65
34	std_turn	4.31	2.17	7.25	0.35	1.04	4.59	15.15
35	tang	0.54	0.54	0.16	0.25	0.46	0.62	0.82
36	turn	1.14	0.62	1.83	0.07	0.27	1.39	3.83
37	zerotrade	1.36	0.00	3.38	0.00	0.00	0.00	9.55

Note: This table reports the summary statistics of the 37 firm characteristics from January 1980 to December 2018. The definitions of these characteristic variables are presented in Table A1.

TABLE 2 Correlations with enduring momentum probability.

N	Variables	Corr	*p*-value
1	age	−0.13	<0.0001
2	baspread	0.25	<0.0001
3	beta	0.14	<0.0001
4	betasq	0.14	<0.0001
5	bm	0.05	<0.0001
6	bm_ia	0.29	<0.0001
7	cashdebt	−0.08	<0.0001
8	cashpr	0.00	0.1227
9	convind	0.02	<0.0001
10	currat	0.02	<0.0001
11	depr	0.04	<0.0001
12	dolvol	0.02	<0.0001
13	dy	−0.04	<0.0001
14	ep	−0.29	<0.0001
15	herf	0.01	<0.0001
16	idiovol	0.22	<0.0001
17	ill	−0.03	<0.0001
18	indmom	0.12	<0.0001
19	IPO	0.07	<0.0001
20	lev	0.10	<0.0001
21	maxret	0.32	<0.0001
22	mve	−0.07	<0.0001
23	mve_ia	−0.07	<0.0001
24	pricedelay	0.02	<0.0001
25	quick	0.02	<0.0001
26	retvol	0.34	<0.0001
27	roic	−0.10	<0.0001
28	salecash	−0.02	<0.0001
29	salerec	0.01	<0.0001
30	securedind	0.06	<0.0001
31	sin	0.00	0.4162
32	sp	0.16	<0.0001
33	std_dolvol	0.06	<0.0001
34	std_turn	0.33	<0.0001
35	tang	0.08	<0.0001
36	turn	0.26	<0.0001
37	zerotrade	−0.08	<0.0001

Note: This table reports the correlation between enduring momentum probability and firm characteristics from January 1985 to December 2018. The definitions of these characteristic variables are presented in Table A1.

volatility, and idiosyncratic volatility have higher probabilities to continue to be winners and losers over the following 6-month investment period, respectively. The results are consistent with the findings of Guo et al. (2022) which show that the stocks with high past returns tend to be those with high past idiosyncratic volatility and return volatility.

The Diff column in Panel A of Table A2 reports the average difference of each of the 37 firm characteristics calculated by averaging the monthly firm characteristics difference between the enduring momentum selected top ten winner (loser) firms and the non-selected firms within the same winner (loser) group from January 1985 to December 2018. Most firm characteristics are significantly higher for the enduring momentum selected winners and losers. For example, the monthly average bid-ask spread, *baspread*, is 0.06 and 0.01 higher for the enduring momentum's top ten winners and losers, respectively.

The construction of the traditional price momentum strategy assumes that past winners or losers will continue to perform as winners or losers. However, this assumption does not hold for all winners and losers. Therefore, we summarize the average enduring months and the proportion of past winners and losers to keep performing as future winners and losers during the 6-month holding period in Panel B of Table A2. The N column represents the total number of months for all past winners (losers) to keep performing as winners (losers) over the 6-month holding period. We report the corresponding marginal survival and cumulative fail proportions for winners (losers) in the second (fourth) and third (fifth) columns of Panel B. In the second (fourth) column, we can see that only 7% (6%) of past winners (losers) continue to be future winners (losers) throughout the 6-month holding period, whereas 74% (75%) of past winners (losers) will no longer appear in the top (bottom) decile group over the entire investment period. The last two rows in Panel B show that the average number of enduring months for winners and losers is approximately two.

Table 3 reports the partial likelihood estimates of enduring momentum portfolio returns and marginal differences in R^2 when each firm characteristic is dropped. We estimate the impact of each firm characteristic on the enduring momentum probability using the Cox PH specification in Equation (1). Each beta estimate reflects the partial impact of a firm characteristic on the probabilities of winners (losers) surviving as winners (losers) over the investment period, holding the estimated enduring time constant. Besides, a positive (negative) coefficient estimate implies a shorter (longer) enduring time because the survival time is inversely related to the hazard rate. The results in Table 3 suggest that out of the 37 characteristics, 9 (8) characteristics are statistically significantly associated with a longer enduring time for winners (losers) while 20 (21) other characteristics exhibit significantly shorter effects on the enduring time. Interestingly, many characteristics share positive/shorter impacts on the enduring time of both winners and losers such as idiosyncratic volatility, *idiovol*, and size, *mve*, whereas only two statistically significant characteristics, systematic risk, *beta*, and secured debt indicator, *securedind*, exhibit common longer effects on the enduring time of both groups. In addition, many other characteristics show opposite effects, including bid-ask spread, *baspread*, return volatility, *retvol*, and maximum daily return in the formation month, *maxret*. Both winners and losers have eight firm characteristics that do not show a statistical significance at the 10% level on their respective enduring time. However, only the current ratio, *currat*, quick ratio, *quick*, price delay, *pricedelay*, are insignificant for both groups. The other five characteristics are statistically significant in the winner regression and insignificant in the loser regression and vice versa.

The two ΔR^2 columns show the R^2 difference between the Cox PH model that incorporates all 37 firm characteristics in the regression and the model obtained by iteratively excluding each characteristic. Therefore, ΔR^2 indicates the marginal impact of an individual firm characteristic on the enduring time. The results show that the magnitude of maximum daily return in the formation month, *maxret*, has the largest contribution to the enduring time of winners. Its ΔR^2 of 0.22% is equivalent to 8% of the full regression R^2 of 2.77%. Other characteristics such as *baspread*, sales to price ratio, *sp*, the number of zero trading days in the formation month, *zerotrade*, also have relatively large impact on winners' enduring time. For the impacts on losers' enduring time, *maxret* also has the largest contribution. Its ΔR^2 of 0.36% is equivalent to 11% of the full regression R^2 of 3.38% for losers. Following *maxret* are return volatility, *retvol*, leverage, *lev*, dollar trading volume, *dolvol*, and firm age, *age*, in exerting their impacts on

TABLE 3 Partial likelihood estimates of enduring momentum portfolio returns.

		Winners			Losers		
N	Variable	β	p-value	ΔR^2	β	p-value	ΔR^2
1	age	0.00	0.0002	0.01%	0.01	<0.0001	0.14%
2	baspread	−1.96	<0.0001	0.14%	0.75	<0.0001	0.03%
3	beta	−0.09	<0.0001	0.03%	−0.05	0.0002	0.00%
4	betasq	0.02	<0.0001	0.01%	0.01	0.0774	0.00%
5	bm	0.01	0.0057	0.01%	0.06	<0.0001	0.09%
6	bm_ia	0.00	<0.0001	0.02%	0.00	0.0685	0.00%
7	cashdebt	−0.01	0.0006	0.00%	0.01	<0.0001	0.01%
8	cashpr	0.00	0.1084	0.00%	0.00	0.0416	0.00%
9	convind	0.04	<0.0001	0.02%	−0.08	<0.0001	0.05%
10	currat	0.00	0.998	0.00%	0.00	0.9157	0.00%
11	depr	−0.03	<0.0001	0.02%	0.03	<0.0001	0.00%
12	dolvol	0.01	0.0124	0.00%	−0.07	<0.0001	0.15%
13	dy	1.19	<0.0001	0.06%	0.02	0.8945	0.00%
14	ep	0.04	<0.0001	0.02%	−0.01	0.6340	0.00%
15	herf	0.07	0.0123	0.00%	−0.35	<0.0001	0.04%
16	idiovol	0.22	0.0297	0.01%	0.41	0.0008	0.01%
17	ill	0.00	0.295	0.00%	0.00	<0.0001	0.01%
18	indmom	0.02	0.0034	0.00%	0.01	0.1872	0.00%
19	IPO	−0.01	0.5865	0.00%	−0.12	<0.0001	0.09%
20	Lev	0.00	0.0998	0.00%	−0.01	<0.0001	0.15%
21	maxret	−1.65	<0.0001	0.22%	1.51	<0.0001	0.36%
22	mve	0.03	<0.0001	0.02%	0.04	<0.0001	0.07%
23	mve_ia	0.00	<0.0001	0.02%	0.00	<0.0001	0.03%
24	pricedelay	0.00	0.5654	0.00%	0.00	0.2684	0.00%
25	quick	0.00	0.4073	0.00%	0.00	0.3334	0.00%
26	retvol	3.46	<0.0001	0.05%	−4.94	<0.0001	0.29%
27	roic	0.00	0.0917	0.00%	0.01	0.0031	0.01%
28	salecash	0.00	<0.0001	0.02%	0.00	0.1007	0.00%
29	salerec	0.00	0.0206	0.00%	0.00	<0.0001	0.01%
30	securedind	−0.05	<0.0001	0.08%	−0.04	<0.0001	0.02%
31	sin	−0.08	0.0023	0.00%	0.08	0.0345	0.00%
32	sp	−0.01	<0.0001	0.13%	0.01	<0.0001	0.04%
33	std_dolvol	−0.01	0.5408	0.00%	0.06	<0.0001	0.00%
34	std_turn	0.00	0.0005	0.01%	0.00	<0.0001	0.03%
35	tang	−0.21	<0.0001	0.08%	0.05	0.0454	0.00%
36	turn	0.00	0.1749	0.00%	0.00	0.0934	0.04%
37	zerotrade	0.02	<0.0001	0.11%	0.00	0.8696	0.00%
	R^2	2.77%			3.38%		

Note: This table reports the partial likelihood estimates of enduring momentum portfolio returns from January 1985 to December 2018. The β and p-value columns indicate the partial likelihood estimated coefficients from Equation (1) and corresponding p-value for all 37 firm characteristics. The R^2 in the last row represents the coefficient of determination for the Cox PH model utilizing all 37 firm characteristics for winner and loser firms, respectively. Moreover, the marginal difference in R^2 when each firm characteristic is dropped is presented in the ΔR^2 column, highlighting the impact of each characteristic on the model's explanatory power.

the enduring time of losers. Overall, while many characteristics exhibit statistically significant effects on the enduring time of winners and losers, the above characteristics are particularly important for investors in selecting future winners and losers for their long-short portfolios.

Table A3 reports the summary statistics of the estimated enduring momentum probabilities for all winners and losers, which include the average, standard deviation, median, maximum, and minimum estimated probabilities of all enduring months. At the end of each month *t*, we estimate the probability of each winner or loser firm continuing as a winner or loser for one (two, three, four, five, and six) month (months) over the entire 6-month holding period. We then calculate the cross-sectional average, median, standard deviation, maximum, and minimum values of all estimated enduring momentum probabilities. Finally, we consider the time series average of each statistic across all months. Panel B of Table A3 shows that the average estimated enduring momentum probability for winners to appear for one (six) month(s) over the 6-month holding period is 58% (5%), and these statistics are similar for losers.

3.2 | Returns of price momentum and enduring momentum strategies

Table 4 reports the monthly average return of the traditional price momentum (PM) and that of the enduring momentum portfolio constructed based on the Cox PH model (EM) and five other GLMs: Poisson, Logit, fractional logit (Frac Logit), linear probability model (LPM), and ordinary least squares (OLS). We describe the formation and investment process in Sections 2.2.1 and 2.2.2. The results in Panel A suggest that all five GLMs consistently yield statistically significant positive returns. Moreover, among the five GLM estimations, the Poisson (OLS) model produces the highest (lowest) monthly average enduring momentum return of 1.97% (1.69%). All these GLM models outperform the traditional price momentum's monthly average return of 1.12% displayed in the PM column in Panel B. However, their performances are inferior to the EM, which boasts a monthly average return of 2.19%.

Apart from PM and EM results, we also report the monthly average return for the long-short portfolio of winners and losers that are not picked for the enduring momentum portfolio. We denote this portfolio as non-EM and show that it earns an average return of 0.63% a month. The return difference between EM and PM in the EM-PM column demonstrates that our enduring momentum strategy based on the Cox PH model produces an average of 1.07% higher monthly return than the traditional price momentum strategy. Moreover, the loser firms in EM generate a 1.01% lower monthly return compared to their corresponding counterparts in PM, suggesting that the outperformance of EM primarily stems from the loser portfolio. Furthermore, the last column shows that compared to the portfolio constructed based on the non-enduring momentum strategy, the enduring momentum strategy generates an average of 1.56% higher monthly return, and this is also driven by loser stocks.

Panel C reports the value-weighted and probability-weighted EM returns, and the portfolio return of a combined strategy that is constructed based on the most popular momentum stocks selected by all six models. Returns in the value-weighted EM use firms' market capitalizations as weights, while those in the probability-weighted EM employ the estimated enduring momentum probabilities at the beginning of each month as weights. The results show that all three long-short portfolios yield significant monthly average returns, with the probability-weighted EM achieving the highest monthly return of 2.13%, followed by the combined portfolio of 2.06% a month.

Figures 2 and 3 present the time series patterns of the EM and non-EM portfolio returns over January 1985 to December 2018. In Figure 2, the return shown in a particular year is the average of monthly returns in that year. In Figure 3, the annual return is cumulative across all months in a year. The results show that EM outperforms non-EM in most years of our sample period and that EM's cumulative return is approximately five times more than that of non-EM.

3.3 | Enduring momentum predictive ability

This subsection investigates the relationship between stock returns and winner/loser indicators based on the Fama-Macbeth (FM) regression. Concurrently, we consider the impact of 37 firm characteristics and past returns. Utilizing

TABLE 4 Momentum returns of price momentum and generalized regression models.

Panel A: Enduring momentum returns of five GLMs

	Poisson	Logit	Frac logit	LPM	OLS
Winners	1.22%***	1.27%***	1.22%***	1.22%***	1.16%***
	[2.50]	[2.60]	[2.47]	[2.48]	[2.34]
Losers	−0.74%	−0.54%	−0.69%	−0.57%	−0.53%
	[−1.17]	[−0.87]	[−1.10]	[−0.92]	[−0.83]
WML	1.97%***	1.80%***	1.92%***	1.79%***	1.69%***
	[3.91]	[3.73]	[3.80]	[3.69]	[3.30]

Panel B: Returns of price momentum and Cox PH enduring momentum portfolios

	PM	EM	Non-EM	EM-PM	EM-NonEM
Winners	1.32%***	1.38%***	1.40%***	0.06%	−0.02%
	[3.96]	[2.77]	[4.21]	[0.22]	[−0.08]
Losers	0.19%	−0.81%	0.78%	−1.01%***	−1.59%***
	[0.39]	[−1.29]	[1.58]	[−3.39]	[5.14]
WML	1.12%***	2.19%***	0.63%*	1.07%***	1.56%***
	[3.20]	[4.24]	[1.79]	[2.58]	[3.69]

Panel C: Value- and probability-weighted Cox PH enduring momentum returns

	Value-weighted EM	Probability-weighted EM	Combined
Winners	1.40%***	1.30%***	1.26%***
	[2.63]	[2.58]	[2.45]
Losers	−0.04%	−0.83%	−0.80%
	[−0.07]	[−1.31]	[−1.25]
WML	1.45%***	2.13%***	2.06%***
	[2.55]	[4.04]	[3.86]

Note: This table reports the momentum returns generated by various generalized regression models from January 1985 to December 2018. Panel A presents the monthly average enduring portfolio returns by applying the five popular GLMs, including the Poisson, Logit, fractional logit (Frac Logit), linear probability model (LPM), and ordinary least squares (OLS) models. Panel B reports the monthly average returns of the price momentum (PM), Cox PH enduring momentum (EM), and non-enduring momentum (Non-EM) portfolios. The return differences between EM, PM, and Non-EM are also reported in Panel B. Panel C reports the value-weighted and probability-weighted EM returns, and the portfolio return of a combined strategy that is constructed based on the most popular momentum stocks selected by all six GLMs. Returns in the value-weighted EM use firms' market capitalization as weights, while those in the probability-weighted EM employ the estimated enduring momentum probabilities at the beginning of each month as weights. *t*-statistics are in brackets. * and *** indicate statistical significance at the 10% and 1% levels, respectively.

Fama-MacBeth regression, Guo et al. (2022) successfully identified firm fundamentals as the most promising factor among established momentum explanations.

In each month, we calculate stocks' average monthly returns over the holding period. We then regress these returns on an EM indicator that is equal to one for enduring momentum stocks, and zero otherwise. We also include the past returns and the 37 firm characteristics as additional control variables. We report the average values for the intercept, EM indicator, adjusted R^2, and number of observations in Panels A, B, and C of Table 5, respectively. We do not report the coefficients for control variables to save space. The results in Panel A without any control variables show that enduring momentum winners do not earn significantly higher returns in the holding period than

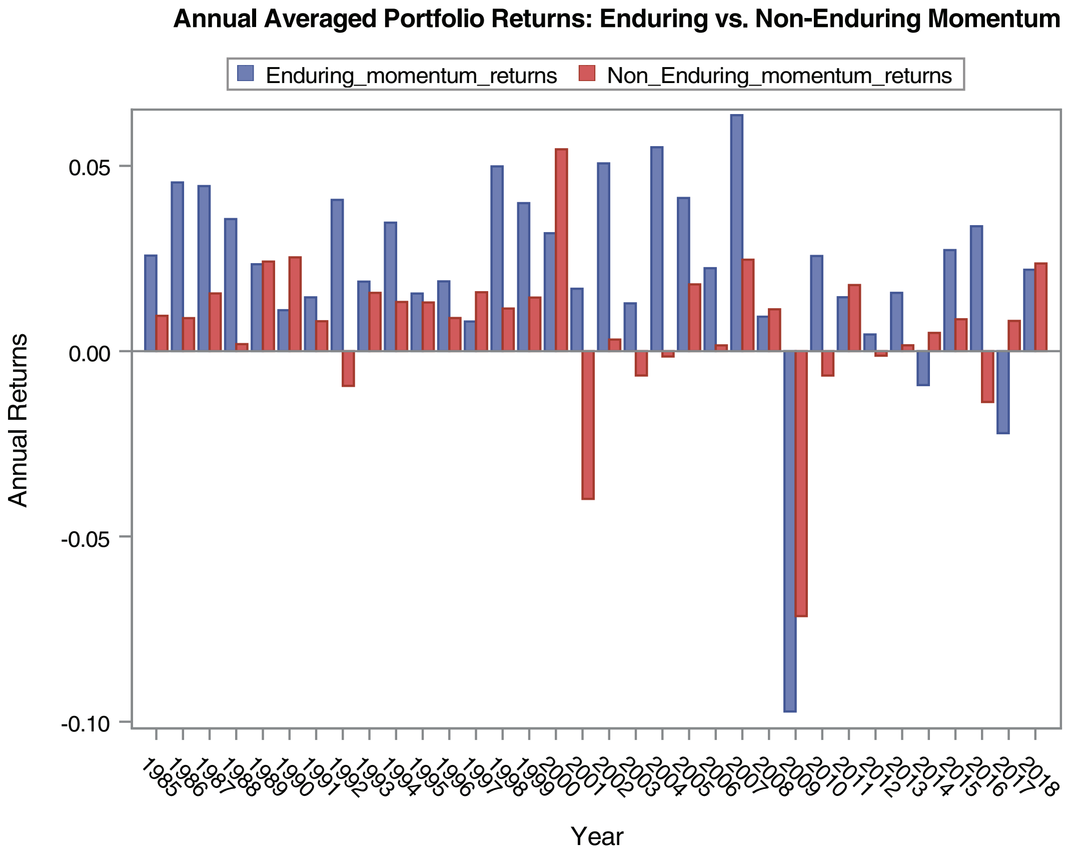

FIGURE 2 Enduring and non-enduring momentum portfolio returns. This figure presents the performance of enduring momentum and non-enduring momentum portfolios from January 1985 to December 2018. The enduring momentum portfolio is constructed by buying the top ten winner firms and selling the top ten loser firms with the highest enduring momentum probabilities estimated by the Cox PH model. The non-enduring momentum portfolio is constructed by buying winners and selling losers that are not selected for the enduring momentum portfolio. The return shown in a particular year is the average of monthly returns in that year.

non-enduring winners. However, enduring momentum losers exhibit significantly lower holding returns than non-enduring losers. These results are consistent with those in Table 4 and suggest that the outperformance of the enduring momentum portfolio is driven mainly by the loser stocks. In Panels B and C, we find consistent patterns even after controlling for past month returns and firm characteristics.

3.4 | Risk-adjusted returns

Table 6 presents the risk-adjusted returns for the price momentum and enduring momentum strategies based on the Capital Asset Pricing Model (Sharpe, 1964), Fama and French's (1992) three-factor model, and Carhart's (1997) four-factor model. The results show that EM excess returns, that is, alpha, remain positive and statistically significant across the three factor models. For example, in the Carhart four-factor model, alpha is 0.0143, suggesting that the EM earns an average return of 1.43% a month during our sample period. The results for PM in the last three columns in Table 6 show markedly smaller values for alpha compared to those for EM. PM's alpha even becomes insignificant after controlling for the four popular risk factors. These results confirm our previous findings regarding the superiority of the enduring momentum strategy to the traditional price momentum strategy.

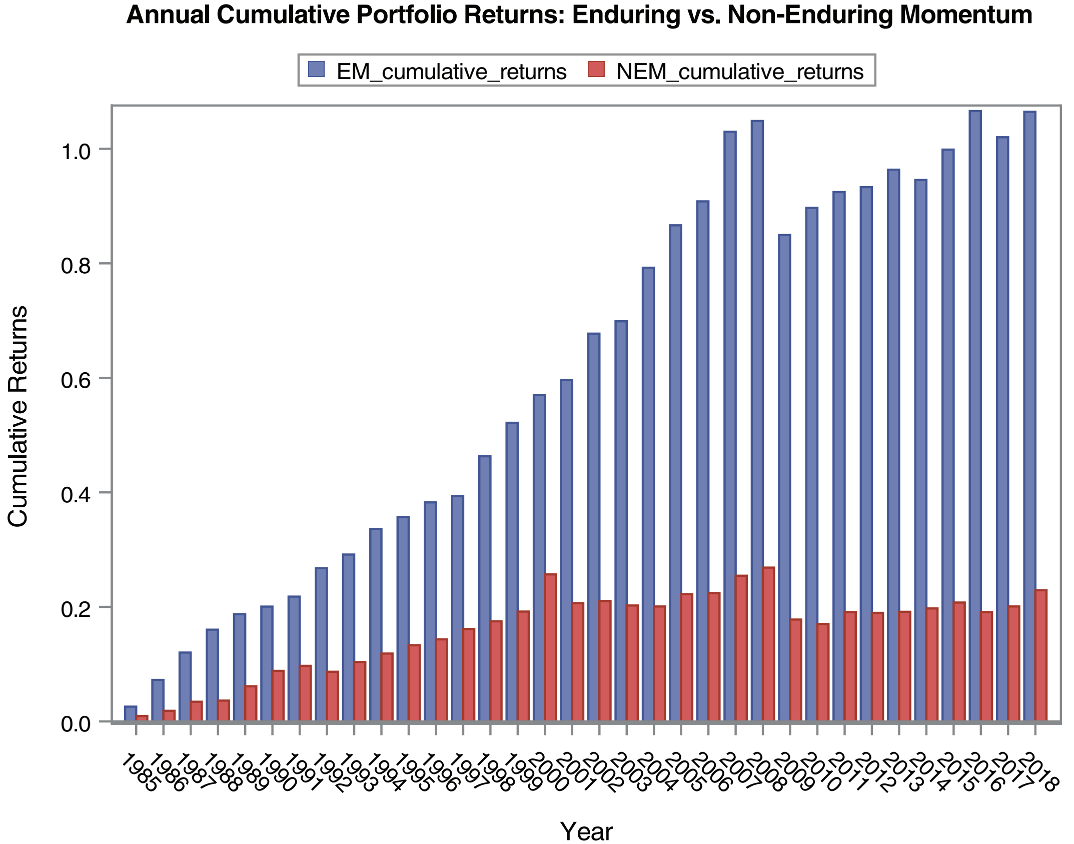

FIGURE 3 Enduring and non-enduring momentum cumulative portfolio returns. This figure presents the cumulative returns of enduring momentum and non-enduring momentum portfolios from January 1985 to December 2018. The enduring momentum portfolio is constructed by buying the top ten winner firms and selling the top ten loser firms with the highest enduring momentum probabilities estimated by the Cox PH model. The non-enduring momentum portfolio is constructed by buying winners and selling losers that are not selected for the enduring momentum portfolio. The annual return is cumulative across all months in a year.

4 | ADDITIONAL ROBUSTNESS CHECKS

This section examines the validity of our empirical findings through a comprehensive series of robustness tests. The initial robustness test set focuses on validating the enduring momentum probability. We then explore enduring momentum returns by excluding micro stocks, varying sample sizes, and investment horizons. In addition, we investigate the seasonal effects, detect the limits of arbitrage effects, probe long-term reversal effects, evaluate the risk-managed momentum factor and the information discreteness (ID) index, and assess returns during market crashes, turnover ratio, and break-even costs.

4.1 | Predictive ability of enduring momentum probability

In this section, we examine the predictive ability of the Cox PH model's enduring momentum probability (EMP) in explaining the persistence of stock returns and detecting future winner and loser firms. Sections 2.2.3 and 2.2.4 describe the methodologies, and Table A4 shows the regression results. Panel A shows positive and significant values

TABLE 5 Fama-Macbeth regression results.

	Intercept	EM indicator	R^2	N
Panel A: Enduring momentum winner/loser indicator only				
Winners	0.0135***	−0.0111	0.0067	385
	[8.85]	[−0.62]		
Losers	0.0242***	−0.0348***	0.0078	272
	[3.30]	[−5.16]		
Panel B: Enduring momentum winner/loser indicator with past returns				
Winners	0.0136***	−0.0008	0.0148	385
	[8.93]	[−0.45]		
Losers	0.0138**	−0.0322***	0.0184	272
	[1.99]	[−4.76]		
Panel C: Enduring momentum winner/loser indicators with past returns and 37 firm characteristics				
Winners	0.0265***	−0.0019	0.1893	385
	[5.24]	[−1.00]		
Losers	−0.0119***	−0.0059***	0.1897	272
	[−3.75]	[−2.32]		

Note: This table reports the Fama-Macbeth (FM) regression results. In each month, we regress the average monthly holding returns on an EM indicator that is equal to one for enduring momentum stocks and zero otherwise. We include the past-month return and the 37 firm characteristics as additional control variables in Panels B and C, respectively. We report the average values for the intercept, EM indicator, adjusted R^2, and number of observations in this table and do not show the coefficients for control variables to save space. The *t*-statistics in brackets are calculated using Newey and West (1987) standard errors. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

TABLE 6 Risk-adjusted portfolio returns.

	Panel A: Enduring momentum			Panel B: Price momentum		
	CAPM	FF3	Carhart4	CAPM	FF3	Carhart4
alpha	0.2570***	0.0270***	0.0143***	0.0143***	0.0148***	0.0034
	[4.97]	[5.22]	[3.38]	[4.03]	[4.15]	[1.49]
MKT	−0.0035***	−0.0044***	−0.0006	−0.0033***	−0.0033***	0.0001
	[−3.00]	[−3.65]	[−0.57]	[−4.09]	[−3.99]	[0.22]
SMB		0.0021	0.0025*		−0.0018	−0.0015*
		[1.22]	[1.75]		[−1.48]	[−1.95]
HML		−0.0040**	0.0014		−0.0021*	0.0026***
		[−2.11]	[0.87]		[−1.65]	[3.12]
UMD			0.0084***			0.0075***
			[14.87]			[24.61]
R^2	0.0217	0.0398	0.3801	0.0396	0.0489	0.6199
N	408	408	408	408	408	408

Note: This table presents the risk-adjusted returns for enduring momentum and price momentum portfolios from the CAPM, Fama–French three-factor, and Carhart four-factor models. The last row reports the total number of regression observations. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

for β_{EMP} from Equation (7), indicating that EMP is significantly related to the persistence of stock returns for both winner and loser firms. Panel B presents the results of Equations (8) and (9). For the winner portfolio, both γ_W^{EMP} and γ_W^{MOM} are positive and highly statistically significant, suggesting that past returns, MOM, and EMP can individually predict future winners. More importantly, the predictive ability of EMP remains strong after controlling the effect of MOM. We observe a similar pattern for the loser portfolio. The positive coefficient of EMP indicates that a higher EMP is associated with a higher likelihood that the current loser stock is also a future loser stock. The negative coefficient of MOM indicates that lower past returns increase the likelihood of being a loser in the future. The predictive power of EMP survives the inclusion of MOM in the regression, as shown in the last column in Panel B. We also estimate Equation (9) using OLS regression as an alternative to logit regression and report the results in Panel C. We still observe a significant predictive power of EMP across the winner and loser portfolios.

We next examine the predictive ability of EMP in forecasting future stock returns. We estimate Equations (10) and (11) and report their results in Panel A of Table A5. The results for EMP alone indicate that EMP has a significant power to forecast future stock returns. The coefficients, ϕ_W^{EMP} and ϕ_L^{EMP} are positive and negative for winner and loser portfolios, respectively. This suggests that higher enduring momentum probabilities lead to higher (lower) future returns for winners (losers), which is consistent with the portfolio results in Table 4. The results for past returns, however, show that the effect of MOM effect on future returns is only significant for loser firms and that its effect does not explain away the forecasting power of EMP, as shown in the last column. In Panel B, we decompose the effect of EMP into 2 components: an explained component representing how much MOM shares its predictive impact with EMP and a residual component representing the magnitude of EMP predictive power that is not shared with MOM. We present this methodology in Section 2.2.5 following Hou and Loh (2016). We find that the momentum signal fails to share the predictive information that the enduring momentum probability provides in forecasting stock returns for winner and loser firms. The magnitude of the explained fraction is small and statistically insignificant for winner firms and significantly negative for loser firms.

Overall, in this section we show that the enduring momentum probability is strongly associated with the persistence of returns, able to detect future winners and losers and forecast their returns. More importantly, its predictive information is not shared by the price momentum signal based on past returns.

4.2 | Excluding micro stocks, varying investment firm numbers, different investment horizons, and weighting schemes

This subsection examines how the results change by investigating four separate sample adjustments. First, we follow Asness et al. (2013) to rank all the stocks into ten groups based on their market capitalization in descending order at the beginning of each month and then exclude the group with the smallest market capitalization. Second, we expand the number of stocks to be included in the enduring momentum portfolio to 20 and 30 instead of 10 as in the main analysis. Third, we include the 3, 9, and 12 months as alternative investment periods and show the portfolio returns using equal weighting and value weighting. The results reported in Tables A6–A8 generally show that the enduring momentum returns remain robust and mostly larger than the price momentum returns.

4.3 | Seasonal effect

Jegadeesh and Titman (1993) document a seasonal behavior of the price momentum strategy: loser firms generate significantly higher returns than winner firms in January. McLean and Pontiff (2016) find that anomalies decay over time. Thus, we examine the performance of the enduring momentum and price momentum strategies in the January and non-January periods, report the results in Panel A of Table A9, and explore the performance of the two strategies during the earlier and later periods of our sample in Panel B.

The results show that the enduring momentum strategy is less affected by seasonality and shows consistent long-short returns over time than the price momentum strategy. Consistent with Jegadeesh and Titman (1993), we find that the PM return is negative for January and positive in other months. The EM return, however, remains positive in both January and other months. The results for subsample periods indicate that both EM and PM strategies generate lower long-short portfolio returns during the 2000.01–2018.12 period than during the 1985.01–1999.12 period, consistent with the findings of McLean and Pontiff (2016). However, both subperiod returns are significantly higher for EM than for PM portfolios.

4.4 | Limits of arbitrage

Our results in Table 4 and other Tables A6–A8 apparently indicate that the outperformance of the EM over the PM is mainly driven by the performance of loser firms. In this section, we investigate whether this is due to limits to arbitrage. Researchers have argued that limits to arbitrage prevent arbitrageurs from correcting market mispricing effectively (e.g., Shleifer and Vishny, 1997; Lamont and Thaler, 2003) and these limits tend to be more constrained when investors sell short stocks than when they buy them (e.g., Li et al., 2009). Stringent borrowing requirements, fees, regulatory constraints, and the risk of unlimited losses are among the limits to arbitrage. Arena et al. (2008) suggest that momentum profits are associated with limits to arbitrage.

We use popular proxies for limits to arbitrage: size, illiquidity, and return volatility, and reconstruct the enduring momentum and price momentum portfolios by excluding from our sample 20% of firms with the smallest market capitalization, highest illiquidity, and highest return volatility. For the sake of comparison, we alternatively exclude 20 firms that are largest in size, lowest in illiquidity, and lowest in return volatility. We present the portfolio returns in Table A10. The results in the 2nd column show that the long-short portfolio returns remain positive and significant in each instance of excluding stocks with high limits to arbitrage. The return difference between EM and PM portfolios is still positive and significant, except when volatility is used in the screening. The exclusion of firms with the least limits to arbitrage does not materially alter the portfolio returns of the two strategies and their differences, as compared to the results in Table 4.

4.5 | Long-term reversal effects

The long-term reversal effect is a widely recognized anomaly in asset pricing (e.g., Balvers & Wu, 2006; De Bondt & Thaler, 1985; Spierdijk et al., 2012). Stocks that have performed poorly over a long time tend to have higher returns in the future, while stocks that have performed well over a long period tend to have lower returns. This section examines whether the winners and losers from month $t-12$ to $t-24$ tend to have reversal performance after time t in enduring momentum. We report the performance of the enduring momentum portfolio in Table A11 for both equal-weighted and value-weighted returns. The results show that the average long-short portfolio return is 1.62% (1.58%) a month, statistically significant at the 1% level, suggesting that long-term reversal does not have a significant impact on the enduring momentum performance.

4.6 | Risk-managed momentum factor

Barroso and Santa-Clara (2015) find that the performance of price momentum could be enhanced by effectively managing its risk by using realized volatility to scale the long-short portfolio return. This section compares the risk-managed momentum strategy with the enduring momentum strategy. We first follow Barroso and Santa-Clara (2015) to construct the risk-managed momentum strategy with the same sample period as the enduring momentum strategy. We then regress the enduring momentum portfolio returns on the four popular risk factors plus this risk-managed momentum return factor, denoted by WML*, and report the results in Table A12.

The results in Panel A show that the EM portfolio continues generating significant returns after controlling for all five risk factors. The value of Alpha ranges from 1.24% to 1.53% across the four regression specifications. However, the PM portfolio returns turn insignificant or even negative as soon as WML* is included in the regression. These results indicate that the risk-managed momentum strategy fails to explain away the enduring momentum strategy's returns.

4.7 | Information discreteness index

Da et al. (2014) argue that investors' limited attention to information that arrives continuously in small amounts causes stronger momentum observed in stocks with more continuous information. They create the information discreteness (ID) index based on past returns and the proportion difference between positive and negative prices to measure a stock's ID. Following Da et al. (2014), we construct the ID for each stock using daily returns over the past 12 months, rank them into quintiles, and buy the stocks in the top group of continuous information and sell those in the bottom group of discrete information. The long-short portfolio is held for six months and rebalanced monthly. We include these ID-based monthly returns in the factor model regression. The results reported in Table A13 suggest that information discreteness does not have an impact on the risk-adjusted returns for the EM portfolio. All alpha coefficients are relatively large and statistically significant at the 1% level. The results for the PM portfolio are relatively similar to those in Panel B of Table 6.

4.8 | Returns when market crashes

Table A14 reports the enduring momentum returns when financial market crashes occur. The results suggest that the enduring momentum strategy successfully avoids market crashes. Specifically, the EM portfolio yields positive returns during the top eight crashes in the aggregate financial market while its return is significantly less negative for the other two market crashes.

4.9 | Turnover ratio and breakeven transaction cost

In many studies, a price momentum portfolio usually has a higher turnover ratio than a market portfolio. This section examines whether high turnover-related transaction costs offset the overperformance of the price momentum and enduring momentum strategies. Following Brandt et al. (2009), we calculate the turnover ratio in month t as the summation of the absolute values of the weight changes of all securities in the corresponding portfolio between months $t-1$ and t. We report the turnover ratio and breakeven cost for the price momentum and enduring momentum in Table A15. We find that the turnover ratio for winners (losers) of the enduring momentum strategy is 1.3101 (1.138), and this is higher than the turnover ratio of 0.7398 (0.7587) for winners (losers) of the price momentum strategy.[8] However, the breakeven cost for the EM portfolio is 0.95%, higher than 0.81% for the PM portfolio. This result suggests that while it takes 81 basis points for the price momentum portfolio to break even, a transaction cost of 95 basis points will make the enduring momentum portfolio achieve zero returns. For comparison's sake, both these break-even costs are higher than real-world transaction costs of 8.37 basis points for long-short trades and 9.61 basis points for implementation shortfall (Frazzini et al., 2018).

5 | CONCLUSION

This study utilizes information from 37 firm characteristics and a Cox PH model to estimate the enduring momentum probabilities that winner and loser firms continue to be winners and losers over the next investment period. Instead of trading on all past winners and losers, we construct the enduring momentum strategy by buying the top ten past winners and selling the top ten past losers with the highest estimated enduring momentum probabilities.

Our results indicate that the enduring momentum strategy generates significantly higher returns than the traditional price momentum strategy. This finding remains robust when the enduring momentum probabilities are estimated by the five alternative GLMs models: Poisson, Logit, fractional logit, linear probability model, and ordinary least squares. Moreover, we show that the enduring momentum indicator plays an important role in predicting cross-sectional stock returns, even after controlling for past returns and various firm-specific characteristics. Besides, traditional models, including the CAPM, Fama–French three-factor, and Carhart four-factor model, fail to explain the enduring momentum anomaly even after we augment them with a risk-managed momentum factor or an information discrete index.

Enduring momentum returns withstand a series of robustness tests. Firstly, we find that the enduring momentum probabilities for winner and loser firms are significantly related to the persistence of stock returns, successfully detect future winners and losers, and show significant ability in forecasting future returns. Secondly, enduring momentum returns are held after excluding microcap stocks, varying the number of selected firms, and applying various weighting schemes and investment horizons. Thirdly, positive returns are consistently observed with the enduring momentum strategy in January and non-January periods and surpassing the price momentum strategy across all subsamples. Fourthly, the enduring momentum returns prove resilient against arbitrage limits and long-term reversal effects. Finally, the enduring momentum portfolio performs well during market crashes and has a higher breakeven transaction cost than the price momentum portfolio.

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ENDNOTES

[1] Given our monthly data, the survival time in our study is discrete rather than continuous as in the traditional survival analysis.

[2] Note that the data from months $t-5$ to t are used to compute the enduring time for winners and losers in month $t-6$.

[3] We thank Jeremiah Green for providing the SAS code on his webpage: https://sites.google.com/site/jeremiahrgreenacctg/home.

[4] MKT: market excess return; SMB is the return difference between small-capitalization firms and big-capitalization firms; HML is the return difference between high book-to-market and low book-to-market firms; UMD is the return difference between momentum winner and loser stocks.

[5] We thank Kenneth French for providing the data on his website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

[6] The seven estimated enduring momentum probabilities illustrate the seven different occurrences for past winners (losers) to continue to be winners (losers) in the following 6-month investment period, ranging from 0 to 6 times. We only focus on the probability of six occurrences ($\tau = 6$) in our analysis.

[7] We also perform the OLS regression as an alternative to the logit regression.

[8] Compared with the price momentum strategy, which selects 385 winners and 272 losers each month, the enduring momentum strategy in the last row of Table A15 selects only 10 winners and 10 losers per month. This smaller pool can explain why the enduring momentum strategy's turnover ratio exceeds 100%.

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APPENDIX A

TABLE A1 Definitions of firm characteristics.

N	Acronym	Variable	Reference	Definitions of characteristics
1	age	Firm age	Jiang et al. (2005)	Number of years since the company's IPO year
2	baspread	Bid-ask spread	Amihud and Mendelson (1989)	Monthly averaged daily bid-ask spread divided by averaged daily spread
3	beta	Beta	Fama and MacBeth (1973)	Estimated market beta based on weekly returns and equal-weighted market returns for 3 years ending month $t-1$ with at least 52 weeks of returns
4	betasq	Beta squared	Fama and MacBeth (1973)	Market beta squared
5	bm	Book-to-market equity	Rosenberg, Reid, and Lanstein (1985)	Book value of equity divided by fiscal year-end market capitalization
6	bm_ia	Industry-adjusted book to market	Asness et al. (2000)	Industry adjusted book-to-market ratio
7	cashdebt	Cash-flow-to-debt	Ou and Penman (1989)	Earnings before depreciation and extraordinary items divided by the average of total liabilities
8	cashpr	Cash productivity	Chandrashekar and Rao (2009)	Fiscal year-end market capitalization plus long-term liabilities minus total assets scaled by cash and cash equivalents
9	convind	Convertible debt indicator	Valta (2016)	A dummy variable equal to 1 for a company that has convertible debt obligations, zero otherwise
10	currat	Current ratio	Ou and Penman (1989)	Current assets divided by current liabilities
11	depr	Depreciation / PP&E	Holthausen and Larcker (1992)	Depreciation divided by PP&E
12	dolvol	Dollar trading volume	Chordia et al. (2001)	Stock price times natural log of trading volume stock price from month $t-2$
13	dy	Dividend to price	Litzenberger and Ramaswamy (1982)	Annual total dividends divided by fiscal year-end market capitalization
14	ep	Earnings to price	Basu (1977)	Annual income before extraordinary items divided by fiscal year-end market cap
15	herf	Industry sales concentration	Hou and Robinson (2006)	2-digit SIC-fiscal-year sales concentration (sum of the squared percentages of sales in the industry for each company).
16	idiovol	Idiosyncratic return volatility	Ali et al. (2003)	Standard deviation of residuals of weekly returns on weekly equal-weighted market returns for 3 years before month-end
17	ill	Illiquidity	Amihud (2002)	Average of absolute daily return divided by daily dollar volume
18	indmom	Industry momentum	Moskowitz and Grinblatt (1999)	Equal-weighted average industry 12-month returns
19	IPO	New equity issue	Loughran and Ritter (1995)	An indicator equals 1 if the first year available on CRSP monthly stock file

TABLE A1 (Continued)

N	Acronym	Variable	Reference	Definitions of characteristics
20	lev	Leverage	Bhandari (1988)	Total liabilities divided by fiscal year-end market capitalization
21	maxret	Maximum daily return	Bali et al. (2011)	Maximum daily return during calendar month $t-1$
22	mve	Size	Banz (1981)	Natural logarithm of market capitalization at the end of month $t-1$
23	mve_ia	Industry-adjusted size	Asness et al. (2000)	2-digit SIC industry-adjusted fiscal year-end market capitalization
24	pricedelay	Price delay	Hou and Moskowitz (2005)	The proportion of variation in weekly returns for 36 months ending in month $t-1$ explained by 4 lags of weekly market returns incremental to contemporaneous market return
25	quick	Quick ratio	Ou and Penman (1989)	Value of current assets minus inventory divided by current liabilities
26	retvol	Return volatility	Ang et al. (2006)	The standard deviation of daily returns from month $t-1$
27	roic	Return on invested capital	Brown and Rowe (2007)	Annual earnings before interest and taxes minus non-operating income divided by non-cash enterprise value
28	salecash	Sales to cash	Ou and Penman (1989)	Annual sales divided by cash and cash equivalents
29	salerec	Sales to receivables	Ou and Penman (1989)	Annual sales divided by accounts receivable
30	securedind	Secured debt indicator	Valta (2016)	An indicator equal to 1 if the company has secured debt obligations
31	sin	Sin stocks	Hong and Kacperczyk (2009)	An indicator variable equal to 1 if a company's primary industry classification is in beer or alcohol, smoke or tobacco, or gaming
32	sp	Sales to price	Barbee et al. (1996)	Annual operating revenue divided by fiscal year-end market capitalization
33	std_dolvol	Volatility of liquidity	Chordia et al. (2001)	The monthly standard deviation of daily dollar trading volume
34	std_turn	Volatility of liquidity	Chordia et al. (2001)	The monthly standard deviation of daily share turnover
35	tang	Debt capacity/firm tangibility	Almeida and Campello (2007)	Cash holdings $+0.715\times$ receivables $+0.547\times$ inventory $+0.535\times$ PPE/total assets
36	turn	Share turnover	Datar et al. (1998)	Average monthly trading volume for the most recent three months scaled by the number of shares outstanding in the current month
37	zerotrade	Zero trading days	Liu (2006)	Turnover weighted number of zero trading days for most recent 1 month

Note: This table presents detailed definitions of the 37 firm characteristics applied in this study to estimate the enduring momentum probability.

TABLE A2 Firm characteristics differences and enduring proportions.

Panel A: Firm characteristics difference between EM and non-EM stocks					
		Winners		Losers	
N	Variables	Diff	*t*-value	Diff	*t*-value
1	age	−2.41	−17.55	−3.42	−25.26
2	baspread	0.06	33.82	0.01	10.76
3	beta	0.09	4.76	0.25	14.79
4	betasq	0.39	7.02	0.93	14.26
5	bm	0.23	10.36	−0.13	−6.68
6	bm_ia	270.59	2.70	272.87	3.07
7	cashdebt	−0.38	−12.18	−0.44	−6.74
8	cashpr	−9.12	−10.63	7.72	6.16
9	convind	−0.02	−4.20	0.11	13.10
10	currat	0.02	0.21	0.91	6.77
11	depr	0.12	9.33	0.01	0.49
12	dolvol	−2.44	−44.36	2.27	34.09
13	dy	−0.01	−4.43	0.00	3.28
14	ep	−0.50	−10.28	−0.08	−5.45
15	herf	0.01	3.00	0.01	3.82
16	idiovol	0.03	36.41	0.01	8.98
17	ill	7.40	8.97	−4.69	−14.84
18	indmom	0.01	0.95	0.02	2.93
19	IPO	0.01	1.41	0.11	14.66
20	lev	1.75	9.53	1.81	4.84
21	maxret	0.19	40.40	−3.42	2.37
22	mve	−1.69	−55.78	0.67	13.75
23	mve_ia	−841.04	−16.84	278.49	2.79
24	pricedelay	0.10	5.15	0.02	1.33
25	quick	0.04	0.41	0.87	7.74
26	retvol	0.05	39.81	0.02	34.54
27	roic	−0.61	−10.10	−0.40	−8.44
28	salecash	3.04	1.02	−11.03	−4.18
29	salerec	5.50	8.00	1.57	2.70
30	securedind	0.11	12.03	0.00	0.53
31	sin	0.01	3.52	0.00	−1.10
32	sp	3.65	12.50	−0.58	−10.92
33	std_dolvol	0.41	41.75	−0.06	−8.01
34	std_turn	11.42	17.44	20.44	31.00
35	tang	0.04	10.00	0.03	7.51
36	turn	0.55	7.04	3.49	30.60
37	zerotrade	0.55	8.27	−0.89	−17.28

TABLE A2 (Continued)

Panel B: Proportion of past winners (losers) to be future winners (losers)				
	Winners		Losers	
N	Marginal	Cumulative	Marginal	Cumulative
0	0.26	0.74	0.25	0.75
1	0.21	0.52	0.22	0.53
2	0.17	0.36	0.17	0.36
3	0.13	0.23	0.13	0.23
4	0.10	0.14	0.10	0.13
5	0.07	0.06	0.08	0.06
6	0.07	0.00	0.06	0.00
Mean	2.06		2.06	
Median	2.00		2.00	

Note: The Diff column in Panel A reports the average difference of each of the 37 firm characteristics calculated by averaging the monthly firm characteristic differences between the enduring momentum selected top ten winner (loser) firms, EM, and the non-selected firms within the same winner (loser) group, non-EM, from January 1985 to December 2018. We also show the corresponding *t* values. The N column in Panel B represents the total number of months for all past winners (losers) to keep performing as winners (losers) over the 6-month holding period. Marginal and Cumulative columns denote the corresponding marginal survival and cumulative fail proportions for winners (losers).

TABLE A3 Summary statistics of the enduring momentum probability.

N Panel A: Winners	Mean	Std	Median	Max	Min
1	0.58	0.07	0.58	0.78	0.31
2	0.43	0.80	0.42	0.68	0.17
3	0.30	0. 80	0.30	0.58	0.08
4	0.20	0.07	0.19	0.48	0.04
5	0.12	0.06	0.11	0.38	0.01
6	0.05	0.04	0.04	0.25	0.00
N Panel B: Losers	Mean	Std	Median	Max	Min
1	0.58	0.09	0.59	0.79	0.24
2	0.43	0.10	0.43	0.69	0.12
3	0.30	0.10	0.29	0.59	0.05
4	0.19	0.08	0.19	0.48	0.02
5	0.11	0.06	0.10	0.37	0.01
6	0.05	0.04	0.03	0.24	0.00

Note: This table reports the summary statistics of the enduring momentum probability from the Cox PH model for winner and loser firms.

TABLE A4 Detecting future winners/losers with enduring momentum probability.

Panel A: Enduring momentum probability and persistency of stock returns	Winners	Losers
β_{EMP}	0.1033***	0.3767***
t-value	[5.07]	[15.76]
R^2	0.0080	0.0181

Panel B: Enduring momentum probability detecting future winners/losers (Logit)				
Winners	γ_W^{EMP}	2.8596***		1.0711***
	p-value	[<0.0001]		[<0.0001]
	γ_W^{MOM}		0.5088***	0.4882***
	p-value		[<0.0001]	[<0.0001]
	R^2	0.0119	0.0679	0.0694
Losers	γ_L^{EMP}	4.7710***		3.6054***
	p-value	[<0.0001]		[<0.0001]
	γ_L^{MOM}		−1.5889***	−1.4265***
	p-value		[<0.0001]	[<0.0001]
	R^2	0.0260	0.0511	0.0645
Panel C: Enduring momentum probability detecting future winners/losers (OLS)				
Winners	γ_W^{EMP}	0.7268***		0.4049***
	t-value	[30.52]		[15.16]
	γ_W^{MOM}		0.0659***	0.0608***
	t-value		[20.93]	[19.57]
	R^2	0.0069	0.0240	0.0260
Losers	γ_L^{EMP}	1.2584***		0.8838***
	t-value	[24.83]		[19.63]
	γ_L^{MOM}		−0.4962***	−0.4415***
	t-value		[−63.53]	[−53.63]
	R^2	0.0153	0.0351	0.0416

Note: This table assesses the predictive ability of the enduring momentum probability (EMP) in explaining the persistence of stock returns and detecting future winner and loser firms. Sections 2.2.3 and 2.2.4 in the main text describe the methodologies. Panel A reports the results of Equation (7) while Panel B shows the logit regression results of Equations (8) and (9). Panel C contains the results of Equations (8) and (9) using OLS regression. We report the regression observations in parentheses in the first column. t-statistics (p-value) associated with each coefficient are in brackets (parentheses) for Panels A and C (B). *** indicates statistical significance at the 1% level.

TABLE A5 Forecasting future returns with enduring momentum probability.

Panel A: OLS regression				
Winners	ϕ_W^{EMP}	0.0696**		0.0717***
		[2.23]		[2.41]
	ϕ_W^{MOM}		−0.0004	−0.0018
			[−0.22]	[−1.11]
Losers	ϕ_L^{EMP}	−0.2687***		−0.3230***
		[−8.31]		[−10.17]
	ϕ_L^{MOM}		−0.0948***	−0.1220***
			[−5.73]	[−7.23]
	R^2	0.0108	0.0106	0.0207

Panel B: Decomposition	Explained fraction	Residual fraction
Winners	0.0324	0.9676***
	[0.32]	[9.61]
Losers	−0.1322***	1.1322***
	[−3.13]	[26.81]

Note: Panel A presents the regression results of equations (10) and (11) to examine the predictive ability of EMP in forecasting future stock returns. In Panel B, we decompose the effect of EMP into 2 components: an explained component representing how much MOM shares its predictive impact with EMP and a residual component representing the magnitude of EMP predictive power that is not shared with MOM. We present this methodology in Section 2.2.5 following Hou and Loh (2016). *t*-statistics are in brackets. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

TABLE A6 Portfolio returns after excluding micro stocks.

	Price momentum	Enduring momentum	Difference
Winners	1.31%***	1.45%***	0.13%
	[3.90]	[2.88]	[0.44]
Losers	0.06%	−0.31%	−0.51%*
	[0.11]	[−0.50]	[−1.89]
WML	1.26%***	1.76%***	0.63%
	[3.49]	[3.45]	[1.61]

Note: This table shows the average monthly portfolio returns for price and enduring momentum and their difference after excluding the 10% micro stocks at the beginning of each month. *t*-statistics are in brackets. *** and * indicate statistical significance at the 1% and 10% levels, respectively.

TABLE A7 Enduring momentum returns with 20 and 30 selected firms.

	Enduring momentum	Price momentum	Difference
Panel A: Top 20 firms			
Winners	1.51%***	1.32%***	0.19%
	[3.21]	[3.96]	[0.82]
Losers	−0.45%	0.19%	−0.65%***
	[−0.75]	[0.39]	[−2.69]
WML	1.96%***	1.12%***	0.84%***
	[4.24]	[3.20]	[2.51]
Panel B: Top 30 firms			
Winners	1.56%***	1.32%***	0.24%
	[3.48]	[3.96]	[1.24]
Losers	−0.26%	0.19%	−0.46%**
	[−0.45]	[0.39]	[−2.20]
WML	1.83%***	1.12%***	0.70%***
	[4.36]	[3.20]	[2.57]

Note: This table reports the monthly returns of enduring momentum portfolios that select the top 20 (in Panel A) and 30 firms (in Panel B) with the highest enduring momentum probabilities, as well as the monthly returns of the price momentum portfolio. *t*-statistics are in brackets. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

TABLE A8 Portfolio returns with different investment periods.

K=	3	6	9	12
Panel A: Price momentum (Equal weighting)				
Winners	1.36%***	1.32%***	1.25%***	1.13%***
	[4.07]	[3.96]	[3.75]	[3.40]
Losers	0.17%	0.19%	0.29%	0.42%
	[0.33]	[0.39]	[0.61]	[0.91]
WML	1.20%***	1.12%***	0.96%***	0.71%***
	[3.21]	[3.20]	[3.12]	[2.66]
Panel B: Enduring momentum (Equal weighting)				
Winners	1.06%**	1.38%***	1.32%***	1.37%***
	[2.02]	[3.96]	[2.80]	[2.82]
Losers	−0.36%	−0.81%	−0.51%	−0.47%
	[−0.56]	[−1.29]	[−0.81]	[−0.76]
WML	1.42%***	2.19%***	1.83%***	1.84%***
	[2.59]	[4.24]	[3.81]	[4.14]
Panel C: Enduring momentum (Value weighting)				
Winners	1.29%**	1.40%***	1.41%***	1.38%***
	[2.20]	[2.63]	[2.72]	[2.67]
Losers	0.00%	−0.04%	0.22%	0.19%
	[0.00]	[−0.07]	[0.35]	[0.31]
WML	1.29%**	1.45%***	1.19%**	1.19%***
	[2.00]	[2.55]	[2.31]	[2.55]

Note: This table reports the average monthly portfolio returns for the price momentum in Panel A and the equal-weighted and value-weighted enduring momentum in Panels B and C, respectively. These portfolios are constructed based on 6-month lagged returns and held for K months ($K = 3, 6, 9, 12$). *t*-statistics are in brackets. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

TABLE A9 Seasonal effect and subsample performance.

	Enduring momentum	Price momentum	Difference
Panel A: Seasonal effects			
January	1.79%	−0.50%**	2.29%***
	[0.85]	[2.19]	[2.93]
Feb-Dec	2.38%***	1.78%***	0.60%
	[4.49]	[5.63]	[1.56]
Panel B: Subsample periods performance			
1985.01–1999.12	3.21%***	2.02%***	1.19%*
	[5.54]	[6.04]	[1.94]
2000.01–2018.12	1.63%**	0.57%	1.07%*
	[2.04]	[0.97]	[1.92]

Note: This table reports the average returns for January and non-January periods of the enduring momentum and price momentum strategies in Panel A and their portfolio for the 1985.01–1999.12 and 2000.01–2018.12 subsamples in Panel B. We calculate their difference in the last column of each panel. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE A10 Limits of arbitrage effect.

Strategy	WML	WML	WML
Panel A: Excluding 20% firms with highest limits to arbitrage			
Smallest size		**Highest illiquidity**	**Highest volatility**
Price momentum	1.19%***	1.23%***	0.85%***
	[3.52]	[3.49]	[3.40]
Enduring momentum	1.97%***	2.07%***	1.15%***
	[4.02]	[4.19]	[3.03]
Difference	0.78%**	0.84%**	0.30%
	[2.02]	[2.28]	[1.02]
Strategy	**WML**	**WML**	**WML**
Panel B: Excluding 20% firms with lowest limits to arbitrage			
Largest size		**Lowest illiquidity**	**Lowest volatility**
Price momentum	1.29%***	1.25%***	1.29%***
	[3.60]	[3.62]	[3.44]
Enduring momentum	2.47%***	2.41%***	2.29%***
	[4.83]	[4.61]	[4.39]
Difference	1.18%***	1.16%***	0.99%***
	[2.91]	[2.86]	[2.45]

Note: This table reports the enduring momentum and price momentum strategies' average long-short returns after excluding the top/bottom 20% of stocks based on size, liquidity, or volatility. *t*-statistics are in brackets. *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

TABLE A11 Long-term return reversal effect.

	Equal weighting	Value weighting
Winners	1.28%***	1.42%***
	[2.52]	[2.58]
Losers	−0.34%	−0.16%
	[−0.56]	[−0.26]
WML	1.62%***	1.58%***
	[3.01]	[3.01]

Note: This table reports the monthly portfolio returns for equal-weighted and value-weighted enduring momentums after considering the long-term reversal effects. *t*-statistics are in brackets. *** indicates statistical significance at the 1% level.

TABLE A12 The effect of risk-managed momentum returns.

Panel A: Enduring momentum					Panel B: Price momentum			
Alpha	0.0124***	0.0147***	0.0153***	0.0142***	−0.0002	−0.0009	−0.0011***	−0.0017
	[2.55]	[3.01]	[3.14]	[3.29]	[−1.37]	[−0.44]	[−6.08]	[−0.92]
MKT		−0.0032***	−0.0041***	−0.0006		−0.0028***	−0.0029***	−0.0013***
		[−2.97]	[−3.72]	[−0.59]		[−6.16]	[−6.08]	[−2.91]
SMB			0.0042***	0.0024*			0.0011	0.0003
			[2.62]	[1.75]			[1.52]	[0.43]
HML			−0.0020	0.0013			0.0005	0.0021***
			[−1.16]	[0.86]			[0.74]	[3.22]
UMD				0.0008***				0.0039***
				[10.70]				[11.89]
WML*	0.7757***	0.7670***	0.7839***	0.0168	1.0735***	1.0657***	1.0750***	0.7149***
	[8.96]	[8.94]	[9.10]	[0.16]	[27.94]	[28.95]	[28.80]	[16.19]
R^2	0.1652	0.1829	0.2178	0.3801	0.3210	0.3475	0.3490	0.6398
N	408	408	408	408	408	408	408	408

Note: This table reports the risk-adjusted returns for the momentum strategies from three asset pricing models (CAPM, FF3, Carhart4) plus the risk-managed momentum (WML*) factor. WML* is from Barroso and Santa-Clara (2015), which adjusts momentum returns from the past 6-month realized variances. *t*-statistics are in brackets. *** and * indicate statistical significance at the 1% and 10% levels, respectively.

TABLE A13 The effect of information discreteness.

Panel A: Enduring momentum					Panel B: Price momentum			
Alpha	0.0316***	0.0328***	0.0333***	0.0204***	0.0163***	0.0175***	0.0177***	0.0031
								[1.06]
	[5.76]	[5.97]	[6.03]	[4.25]	[3.74]	[4.01]	[3.99]	
MK		−0.0023*	−0.0031***	−0.0007		−0.0022***	−0.0022**	0.0004
T		[−1.93]	[−2.33]	[−0.65]		[−2.33]	[−2.11]	[0.60]
SMB			0.0045***	0.0042***			−0.0012	−0.0015*
			[2.54]	[2.85]			[−0.88]	[−1.65]
HML			−0.0005	0.0019			−0.0006	0.0021*
			[−0.22]	[1.07]			[−0.34]	[1.91]
UMD				0.0071***				0.0080***
				[10.79]				[19.94]
ID	0.1819	0.1558	0.1586	0.0262	0.4211***	0.3961***	0.3964***	0.2466***
	[1.13]	[0.97]	[0.99]	[0.19]	[3.28]	[3.10]	[3.10]	[2.95]
R^2	0.0044	0.0172	0.0437	0.3231	0.0363	0.0543	0.0568	0.6030
N	408	408	408	408	408	408	408	408

Note: This table reports the risk-adjusted returns from three asset pricing models (CAPM, FF3, Carhart4) plus the information discreteness (ID) index. The ID index is proposed by Da et al. (2014) and constructed based on past returns and the proportion difference between positive and negative prices. *t*-statistics are in brackets. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

TABLE A14 Enduring momentum returns when market crashes.

	Date	Market	Enduring momentum
1	198,710	−21.58%	11.98%
2	200,810	−16.70%	11.70%
3	199,808	−14.31%	7.00%
4	200,209	−10.90%	9.79%
5	200,902	−10.36%	5.48%
6	200,102	−9.10%	7.35%
7	201,812	−9.09%	4.69%
8	199,008	−9.08%	5.88%
9	200,809	−8.55%	−1.04%
10	198,609	−8.32%	−0.94%

Note: This table reports the enduring momentum returns in the top 10 months of the lowest market returns during our sample period.

TABLE A15 Turnover ratio and breakeven transaction cost.

	Turnover ratio		Break-even cost
Strategies	Winners	Losers	Zero return
Price momentum	0.7398	0.7587	0.0081
Enduring momentum	1.3101	1.1381	0.0095

Note: This table shows turnover ratios and corresponding breakeven costs for the price momentum and enduring momentum strategies.