Cash-flows, earnings, and time-varying expected stock returns

Prodosh Eugene Simlai
Department of Economics, University of North Dakota, Grand Forks, North Dakota, USA

Abstract

Purpose – The objective of this paper is to empirically evaluate alternative multifactor explanations of cash-flows and earnings momentum portfolios. It aims to examine whether the common risk factors, which are related to firm level accounting characteristics, can reflect the behavior of average portfolio returns based on such measures as cash-flows and earnings momentum in the presence of each other's systematic components and time-varying measures of volatility.

Design/methodology/approach – The paper uses monthly stock returns for all NYSE firms on CRSP database and constructs average portfolio returns between July 1951 and June 2008. It investigates the interdependence of stock returns for cash-flows and earnings momentum portfolios using their systematic components. The methodology is implemented by extending various characteristic-based factor models of returns.

Findings – The main finding of the study suggests that there is strong information transmission – both in the temporal variation and risk sensitivities of the average returns of cash-flows and earnings momentum portfolios. Also, there is compelling empirical evidence that the associated systematic components well complement the ability of common risk factors to explain the temporal behavior of all NYSE stocks.

Research limitations/implications – While the results are statistically significant, the effect of aggregate risk in factor model is dubious. An integration of other accruals based accounting characteristics would be an interesting issue to explore.

Practical implications – The goal of the paper is to examine how different combinations of empirically determined variables that are instrumental in the creation of style-specific benchmarks can capture the time-series variation of average portfolio returns. It will provide added value to scholars and investment professionals in making effective portfolio management decisions.

Originality/value – Compared to the existing literature, in the evaluation of earnings and cash-flows based measures, the paper focuses on the predictive power of the systematic components. It shows that paying close attention to the systematic components clearly provides additional information about the time-varying behavior of average stock returns. The findings that the economic characteristics of the firm can complement the comparative role of the systematic components of cash-flows and earnings add significantly to the literature.

Keywords Firm size, Book-to-market, Cash flow, Earnings, Systematic components, Factor models, United States of America.

Paper type Research paper

1. Introduction

The objective of this paper is to empirically evaluate alternative multifactor explanations of cash flows and earnings momentum. Specifically, it examines whether the common risk factors related to size (market equity, ME) and book-to-market equity (BE/ME),

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reflect the behavior of average portfolio returns based on such measures as cash flows and earnings performance in the presence of each other's systematic components and time-varying measures of volatility. The idea is to investigate the interdependence of stock returns for cash flows and earnings momentum portfolios using their systematic components, and examine the relative importance of common risk factors and volatility persistence in explaining the time-varying expected stock returns. Even though there exists a large literature on linkages and interactions between international stock markets, exchange rates, and stock prices (see e.g. Hamao *et al.*, 1990; Nieh and Lee, 2001; Baele, 2005), there has been little work done on information transmission as a factor in active portfolio formation strategies. In this paper we bridge that gap and examine the extent of information transmission between portfolios of stocks sorted by two widely known firm characteristics; they are – cash flows-to-price (C/P) and earnings-to-price (E/P).

Our goal is to examine how different combinations of empirically determined variables that are instrumental in the creation of style-specific benchmarks can capture the time series variation of average portfolio returns. Using monthly returns of all firms from NYSE universe between July 1951 and June 2008, we investigate information transmission between the portfolios of stocks sorted by C/P and E/P. For systematic components we use zero-investment portfolios with respect to C/P and E/P. In order to gauge volatility persistence we employ multifactor specification of Fama and French (1993) in conjunction with various versions of generalized autoregressive conditional heteroskedasticity (GARCH) model using the technique of Bolleslev and Wooldridge (1992). We investigate how the relevance of two firm performance measures is sensitive to the incorporation of their systematic components, economic characteristics such as firm size and book-to-market ratio, and volatility persistence.

There exist numerous works that study the contemporaneous associations between stock returns and firm characteristics such as earnings and cash flows[1]. Considerable attention has been paid to how earnings numbers are presented and their role as a measure of firm performance[2]. It has been argued that the level of accruals is a negative cross-sectional predictor of abnormal stock returns (Sloan, 1996). There is strong evidence that the other component of earnings, cash flows, is a positive cross-sectional predictor of returns (Desai *et al.*, 2004; Pincus *et al.*, 2007). Compare to the existing literature, in our evaluation of earnings and cash-flows-based measures, we focus on the predictive power of the systematic components. We find that even though there is no a priori reason to choose one over another, paying attention to the systematic components, in addition to volatility persistence, can provide additional information about the time-varying behavior of average stock returns[3]. In addition, the economic characteristics of the firm play a crucial role in complementing the comparative role of the systematic components of cash flows and earnings.

Throughout the paper, we emphasize on the role of common risk factors that are related to firm characteristics such as ME and BE/ME, and extrapolate the relevance of volatility persistence in the average stock returns based on cash flows and earnings performance. We emphasize the interrelationship between the systematic components of cash flows and earnings momentum, and test whether alternative volatility models can further influence the role of common risk factors. Our main findings suggest that there is strong information transmission – both in the temporal variation and risk sensitivities of the average returns of cash flows and earnings momentum portfolios. Also, there is compelling empirical evidence that volatility persistence can improve the ability of common risk factors to explain the temporal behavior of all NYSE stocks.

The remainder of the paper is organized as follows. In the next section we discuss the sample and various models of performance measurement used in this paper. The main empirical results are presented in Section 3. Section 4 investigates whether the results are spurious with a series of robustness tests. The evidence explains why our results are not the outcome of data mining. In Section 5 we conclude.

2. Data and models of performance measurement

2.1 Sample descriptions

We utilize monthly stock returns for all NYSE firms on CRSP US Stock database[4], and construct average portfolio returns between July 1951 and June 2008 (684 months). The source of accounting data is Compustat. We calculate returns for ten decile portfolios for all NYSE firms on the CRSP files at the end of each June using sorts on E/P and C/P. As in Fama and French (1995, 1996), for each portfolio formed in June of year t, the denominator of the ratios E/P and C/P is ME for the end of December of year $t-1$. For the numerator, E is earnings before extraordinary items, but after interest, depreciation, taxes, and preferred dividends, for the fiscal year ending in calendar year $t-1$. Similarly, C is E plus depreciation for the fiscal year ending in calendar year $t-1$. The dependent variable is based on excess returns on each of the ten portfolios from July 1951 through June 2008, for E/P and C/P separately. Among other variables used in the regression model, market return proxy is based on CRSP's value-weighted index on all NYSE stocks, and risk-free asset is the one-month Treasury bill (T-bill) rate obtained from FRED database at Federal Reserve Bank of St Louis.

In order to utilize mimicking risk factors in our risk model we follow Fama and French (1992a, b, 1993). The risk factor in returns mimicking size (or SMB) is the difference, each month, between average returns on the three small stock portfolios and the average of the three big stock portfolios. The risk factor in returns mimicking BE/ME (or HML) is the difference, each month, between the average of the returns on the two high-BE/ME portfolios and the two low-BE/ME portfolios. Both are obtained from Ken French.

In addition to the simple three-factor Fama and French (1993) risk model, we also use an extended four-factor model in the spirit of Carhart (1997) and Chordia and Shivakumar (2006). The idea is to use a second set of independent variable that is based on holding the highest decile and shorting the lowest decile portfolios. Also known as the zero-investment portfolio, it signifies the difference between two extreme portfolio returns: high and low. We refer the zero-investment portfolios with respect to C/P and E/P as CPM and EPM, respectively. Both EPM and CPM, which indicates winners minus losers, are empirical construction. There is no theoretical motivation to include them in an asset-pricing framework.

2.2 Models of performance measurement

Mean-variance analysis and the capital asset pricing model (CAPM) are the basic tools for any investment manager. In order to estimate the market model version of CAPM we use the following simple linear regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_i [R_{Mt} - R_{ft}] + \eta_{it} \tag{M1}$$

where R_{it} is the observed return on asset i for time t, R_{ft} the return on the risk-free asset, R_{Mt} the observed return on the market portfolio for time t, α_i is population intercept, and β_i the population slope coefficient.

In model M1, η_{it} is an error term which reflects the diversifiable, or unsystematic risk of asset i. It is typical to assume $\eta_{it} \sim iid(0, \sigma^2)$. Since 1992, through a series of tests, Fama and French (1992a, b, 1993) suggest that the so-called market β from (M1) does not suffice to explain expected stock returns. They propose a three-factor model that seems to give better descriptions of expected stock returns.

According to three-factor model, there are return premia associated with ME and BE/ME, and the time-series variation in expected returns can be captured using the following three factors: return on the market portfolio in excess of the risk-free rate of return; a zero net investment (spread) portfolio that is long in small firm stocks and short in large firm stocks (SMB); and a zero net investment (spread) portfolio that is long in high-BE/ME stocks and short in low-BE/ME stocks (HML). So in a world of three-factor risk model, the expected return of security i, is given by:

$$E(R_{it}) - R_{ft} = b_{it}\left[E(R_{Mt}) - R_{ft}\right] + s_{it}\,E(SMB_t) + h_{it}E(HML_t), \quad t = 1, \ldots, T$$

where b_{it}, s_{it}, and h_{it} are the slopes in the regression:

$$R_{it} - R_{ft} = a_{it} + b_{it}\left[R_{Mt} - R_{ft}\right] + s_{it}\,SMB_t + h_{it}\,HML_t + e_{it}, \quad t = 1, \ldots, T \tag{M2}$$

Therefore, a security's expected return depends on the sensitivity of its return to the market return, and two mimicking portfolios representing additional factors: SMB and HML, where SMB is the size-related factor and HML is the book-to-market-related factor[5]. For empirical illustration we implement two version of multirisk model M2 to analyze factor loadings of cash flows and earnings momentum portfolios. They are simple and extended version of three- and four-factor model. More specifically, for each type of C/P and E/P sorted portfolios, we analyze the following four specifications (for simplicity we ignore subscript i):

Model A1: For both C/P and E/P based portfolios:

$$R_t - R_{ft} = a + b\left[R_{Mt} - R_{ft}\right] + s(SMB_t) + h(HML_t) + \eta_t,$$
$$\eta_t|\mathcal{F}_{t-1} \sim iid\left(0, \sigma^2\right)$$

Model A2: For both C/P and E/P based portfolios:

$$R_t - R_{ft} = a + b\left[R_{Mt} - R_{ft}\right] + s(SMB_t) + h(HML_t) + \eta_t,$$
$$E[\eta_t|\mathcal{F}_{t-1}] = 0 \text{ and } E\left[\eta_t^2|\mathcal{F}_{t-1}\right] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2V_{t-1}.$$

Model A3: For C/P based portfolios:

$$R_t - R_{ft} = a + b\left[R_{Mt} - R_ft\right] + s(SMB_t) + h(HML_t) + p(EPM_t) + \eta_t,$$
$$E[\eta_t|\mathcal{F}_{t-1}] = 0 \text{ and } E\left[\eta_t^2|\mathcal{F}_{t-1}\right] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2V_{t-1}.$$

Model A4: For E/P based portfolios:

$$R_t - R_{ft} = a + b\left[R_{Mt} - R_{ft}\right] + s(SMB_t) + h(HML_t) + q(CPM_t) + \eta_t,$$
$$E[\eta_t|\mathcal{F}_{t-1}] = 0 \text{ and } E\left[\eta_t^2|\mathcal{F}_{t-1}\right] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2V_{t-1}.$$

where R_t–R_f is the return on a portfolio in excess of the one-month T-bill return; R_M–R_f is the excess market return; SMB and HML are value-weighted returns on factor mimicking portfolios for ME and BE/ME, respectively; EPM and CPM are the same for zero-investment portfolios based on E/P and C/P, respectively. Also, $\mathscr{F}_{t-1}$ is the information set available at time $t-1$, which may include various combinations of lagged endogenous and exogenous variables. In model specification A2-A4, for parsimonious representation of time-varying conditional variance, we utilize a simple GARCH(1, 1) model[6]. As mentioned by Anheluk and Simlai (2011), the framework enables us to test the exposure to volatility persistence in the presence of common risk factors[7]. The idea is that any shift in asset demand must be associated not only with changes in expected means but also with variances of the rates of return. This also brings us to the forefront of the renewed interest in the finance literature about the forecasting ability of the Fama-French risk factors[8].

3. Empirical results and interpretations

3.1 Behavior of stock returns based on cash flows and earnings

We start with the stylized empirical facts about the behavior of average stock returns based on various sorts using C/P and E/P ratio. Table I presents summary statistics for the explanatory returns (in percent) used in our regression. The reported statistics indicates that the average value of the market premium is quite high (0.58 percent per month) and statistically significant. Among other explanatory variables, size-related factor premium (i.e. average SMB returns) is statistically insignificant and small (0.21 percent per month) whereas book-to-market factor premium (i.e. average HML returns) is statistically significant and high (0.49 percent per month). There exist relatively low auto-correlation and the cross-correlations across regressors are very low. Table II presents descriptive statistics for all NYSE stocks sorted into C/P and E/P decile portfolios. Average firm size decreases as we move from lower to higher deciles. For average number of firms the relationship is U-shape. In contrast, the average ratio of sum of C/P and sum of ME shows an increasing trend when we move from lower to higher deciles. For the portfolios formed on E/P, the average ratio of sum of E/P and sum of ME increases monotonically from 0.02 for lowest decile to 0.19 for highest decile portfolios.

Panel A and B of Table III presents the average returns of all NYSE stock portfolios and zero-investment portfolios formed on C/P and E/P separately for four sub-periods (following the convention of Chordia and Shivakumar, 2006). For C/P sorted portfolios, except for the period July 1980-June 1989, the average return increases monotonically from lower deciles to higher deciles. For E/P momentum portfolios, irrespective of any

				Autocorrelation for lag					
Name	Mean	SD	t	1	2	12	Correlations		
				Explanatory returns					
$R_M - R_f$	0.58	4.51	3.36	0.04	0.02	0.01	1.00		
SMB	0.21	3.27	1.68	0.05	−0.04	0.02	0.21	1.00	
HML	0.49	2.54	5.05	0.09	0.03	0.01	−0.28	−0.22	1.00

Notes: R_M is the return of CRSP's value-weighted index on all NYSE stocks, and R_f is the one-month T-bill rate obtained from Ibbotson and associates. SMB (small minus big) is the difference each month between the simple average of the percent returns on the three small-stock portfolios and the simple average of the returns on the three bog-stock portfolios. HML (high minus low) is the difference each month between the simple average of the returns on the two high-BE/ME portfolios and the average of the returns on the two low-BE/ME portfolios

Table I.
Summary statistics for the explanatory returns

Table II. Descriptive statistics for portfolios formed on C/P and E/P

Portfolio formed on	Low	2	3	4	5	6	7	8	9	High
					Deciles					
					Average firm size					
C/P	1351.1	1243.7	1215.9	1058.7	1020.8	933.4	860.5	826.1	722.7	441.8
E/P	1450.3	1342.1	1220.5	1158.2	1151.7	997.5	854.2	726.3	710.7	435.1
					Average number of firms in portfolio					
C/P	382.4	255.1	233.2	231.6	225.7	235.2	232.0	235.1	256.5	371.7
E/P	390.2	263.4	222.7	218.3	213.1	218.3	219.4	234.1	247.6	315.7
					Average ratio					
Sum of C/P and Sum of ME	0.03	0.05	0.07	0.10	0.10	0.12	0.13	0.16	0.20	0.24
Sum of E/P and Sum of ME	0.02	0.04	0.06	0.08	0.09	0.10	0.12	0.15	0.16	0.19

Notes: For all ten portfolios, the portfolio formation months are in between 7/51 and 06/08. At the end of June of each year, all NYSE firms are allocated to ten portfolios based on their decile breakpoints formed from sorts on C/P and E/P. ME is size of the firms in a portfolio

Table III.
Descriptive statistics of average portfolio returns

	Low	2	3	4	5	Deciles 6	7	8	9	High	High-low
Panel A: C/P momentum portfolios											
July 1951-June 1972											
Mean (%)	0.43	0.47	0.52	0.55	0.58	0.59	0.83	0.90	0.92	1.14	0.71
t-statistics	2.53	2.92	2.24	2.45	2.87	2.31	3.21	2.94	2.87	3.14	2.54
July 1972-June 1979											
Mean (%)	−0.81	−0.25	−0.11	−0.02	0.07	0.16	0.21	0.44	0.68	0.72	1.53
t-statistics	−1.78	−0.89	−0.41	−0.23	0.37	0.55	0.39	1.27	1.98	2.09	2.51
July 1980-June 1989											
Mean (%)	0.26	0.44	0.53	0.68	0.72	0.67	0.75	0.81	0.82	0.91	0.65
t-statistics	0.65	1.08	1.54	1.76	1.82	1.69	1.99	1.95	2.01	2.42	2.07
July 1989-June 2008											
Mean (%)	0.54	0.61	0.64	0.70	0.73	0.78	0.81	0.83	0.86	0.88	0.34
t-statistics	1.64	1.89	2.65	2.21	2.33	2.58	2.98	2.14	2.46	3.01	1.77
Panel B: E/P momentum portfolios											
July 1951-June 1972											
Mean (%)	0.49	0.52	0.54	0.63	0.66	0.75	0.84	0.98	1.05	1.17	0.68
t-statistics	1.99	2.04	2.34	2.68	2.67	3.29	3.06	2.79	2.51	3.27	2.57
July 1972-June 1979											
Mean (%)	−0.33	−0.21	−0.11	−0.06	0.29	0.41	0.53	0.67	0.79	0.83	1.16
t-statistics	−1.57	−0.39	−0.21	−0.17	0.59	0.98	1.09	1.87	1.97	2.05	2.64
July 1980-June 1989											
Mean (%)	0.38	0.47	0.66	0.70	0.74	0.82	0.89	0.94	0.93	0.96	0.58
t-statistics	0.89	0.96	1.97	1.91	2.03	2.06	2.21	2.34	2.51	2.67	1.89
July 1989-June 2008											
Mean (%)	0.54	0.56	0.63	0.66	0.71	0.75	0.80	0.82	0.85	1.02	0.48
t-statistics	1.62	1.98	2.06	2.55	2.37	2.49	2.68	3.04	2.98	3.06	2.07

Notes: For all ten portfolios, the portfolio formation months are in between 7/51 and 06/08. The average return for C/P and E/P momentum portfolios are value-weighted simple returns in excess of the one-month bill rate calculated for each month. At the end of June of each year, all NYSE firms are allocated to ten portfolios based on their decile breakpoints formed from sorts on C/P and E/P. High-low signifies the difference between two extreme portfolios representing positive minus negative cash flows and earnings changes time period we consider, the same fact is true as well. The average return for C/P momentum is highest (0.69 percent per month) for period July 1951-June 1972, and lowest (0.11 percent per month) between July 1972 and June 1979. The highest and lowest average return for E/P momentum is 0.76 percent per month (for period July 1951-June 1972) and 0.28 percent per month (for period July 1972 through June 1979), respectively. The zero-investment portfolios have highest average value during July 1972-June 1979.

We consolidate our previous results from Tables I-III with the three-factor regression results from various panels of Tables IV and V. Over the entire period from July 1951 to June 2008, the monthly return increases for both C/P and E/P sorted portfolios. The difference in returns between the highest and lowest deciles of C/P portfolios is statistically and economically significant (0.49 percent per month and *t*-statistics of 2.60) with over 51 percent of the months having positive difference between highest and lowest decile. For the E/P sorted portfolios, around 53 percent of total months, the highest decile return beats the lowest decile counterpart, and the difference is statistically and economically significant (0.59 percent per month and *t*-statistics of 3.17). The implication of our result is consistent with both Foster *et al.* (1984) and Bernard and Thomas (1989). The difference in the highest and lowest deciles is robust over the entire sample as well as for most of the sub-periods.

Since the sorts of all NYSE stocks displays strong positive relations between average returns, average firm size, average number of firms, and C/P and E/P, it is imperative to see how we can explain the stock return variability with respect to firm characteristics. Panel B of Table IV represents the replication of Fama and French (1996) results for our extended time horizon. The results demonstrate that the three-factor model A1 clearly captures the pattern in average returns based on C/P ratio, and are strongly consistent with the implications of Lakonishok *et al.* (1994), and Fama and French (1996). The regression intercepts are very small and statistically insignificant for all ten deciles. The slopes on the market portfolio vary between 0.96 and 1.07, and are always statistically significant. The regression slopes on SMB and HML show some interesting patterns. Higher decile portfolios display larger slopes on both SMB and HML. For SMB, the regression slope estimates increases slowly from -0.09 percent per month to 0.15 percent per month. For HML, the pattern in the slope estimate is more pronounced; it increases gradually from -0.52 percent per month for lowest decile to 0.47 percent per month for highest decile. The loading on HML is statistically significant for nine out of ten deciles whereas the loading on SMB is statistically insignificant four deciles. This evidence, in addition to our earlier summary statistics from Table II, suggests that three-factor model A1 is very successful in capturing the variability of the average return for C/P sorted portfolios.

The pattern in the intercept and slope estimates for the E/P sorted portfolios are given in panel B of Table V. Similar to C/P-based portfolios, here the three-factor model A1 transforms the average returns and common risk factors into intercepts that are close to zero and statistically insignificant. The average loading on the broad market portfolio is 1.00 percent per month which is always statistically and economically meaningful. The loadings on both SMB and HML increases monotonically from lower to higher decile portfolios even though HML slopes are always larger in magnitude. The overall pattern of statistically robust loadings of C/P and E/P deciles on HML indicates that the strong stocks (characterized by low C/P and E/P) have lower returns, and relatively distressed stocks (characterized by high C/P and E/P) have higher returns.

Table IV.
Three-factor regression results for C/P portfolios

	Deciles										
	Low	2	3	4	5	6	7	8	9	High	CPM
Panel A: Mean, standard deviations and t-statistics of excess returns											
Mean (%)	0.43	0.51	0.58	0.61	0.62	0.70	0.78	0.82	0.85	0.92	0.49
SD	5.21	4.67	4.21	4.19	4.22	4.17	4.37	3.95	4.58	4.16	4.92
t-statistics	2.16	2.85	3.60	3.80	3.84	4.39	4.66	5.43	4.85	5.78	2.60
Panel B: Estimation of simple three-factor model											
a	0.04	0.09	0.01	−0.03	−0.05	0.07	0.04	0.06	0.01	0.04	0.02
b	1.01*	0.98*	0.96*	1.00*	0.97*	0.99*	0.98*	1.02*	1.03*	1.07*	0.04
s	−0.09	−0.12*	−0.14*	−0.16*	0.02	0.05	0.10	0.12*	0.14*	0.15*	0.21*
h	−0.52*	−0.20*	−0.04	0.07*	0.13*	0.19*	0.27*	0.32*	0.44*	0.47*	0.78*
Adjusted R^2	0.87	0.88	0.82	0.76	0.75	0.79	0.71	0.73	0.66	0.64	0.60
Panel C: Estimation of three-factor model with GARCH(1,1) error process											
a	0.03	0.09*	0.04	−0.01	0.04	−0.05	0.07	0.11	0.05	0.03	0.02
b	0.97*	0.99*	1.02*	0.96*	1.01*	0.97*	0.98*	1.03*	1.00*	1.07*	0.04
s	−0.03	−0.04	−0.01	−0.06	−0.07	−0.09	−0.06	0.01	−0.03	0.10*	0.16*
h	−0.43*	−0.28*	−0.09	0.03	0.14*	0.27*	0.31*	0.45*	0.47*	0.51*	0.87*
d_1	0.11*	0.13*	0.17*	0.11*	0.12*	0.05	0.19*	0.19*	0.10*	0.11*	0.09*
d_2	0.79*	0.80*	0.79*	0.82*	0.84*	0.82*	0.77*	0.78*	0.86*	0.84*	0.83*
Adjusted R^2	0.92	0.90	0.89	0.88	0.89	0.93	0.87	0.90	0.85	0.88	0.81

Notes: For all ten portfolios, the portfolio formation months are in between 7/51 and 06/08. The dependent variable is value-weighted simple returns in excess of the one-month bill rate calculated for each month. At the end of June of each year, all NYSE firms are allocated to ten portfolios based on their decile breakpoints formed from sorts on C/P. For panel B we use the model: $R_t - R_f = a + b[R_M - R_f] + s(SMB) + h(HML) + \eta_t$, $\eta_t | \mathscr{F}_{t-1} \sim iid(0, \sigma^2)$ and for panel C we use the model: $R_t - R_f = a + b[R_M - R_f] + s(SMB) + h(HML) + \eta_t$ with $E[\eta_t | \mathscr{F}_{t-1}] = 0$ and $E[\eta_t^2 | \mathscr{F}_{t-1}] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2 V_{t-1}$. CPM is cash flow based zero-investment portfolio. It signifies the difference between two extreme portfolios representing positive minus negative cash flows changes. The regression R^2 is adjusted for degrees of freedom. *Implies the coefficient is significant at 5 percent level

Table V. Three-factor regression results for E/P portfolios

	Deciles										
	Low	2	3	4	5	6	7	8	9	High	EPM
Panel A: Mean, standard deviations and t-statistics of excess returns											
Mean (%)	0.45	0.50	0.56	0.63	0.66	0.71	0.81	0.90	0.96	1.04	0.59
SD	4.52	3.96	4.02	4.03	4.62	4.21	4.27	3.92	4.09	4.61	4.87
t-statistics	2.60	3.30	3.64	4.09	3.73	4.41	4.96	6.00	6.13	5.90	3.17
Panel B: Estimation of simple three-factor model											
a	0.02	0.05	−0.06	0.05	0.03	0.02	−0.01	0.10*	0.09	0.08	0.03
b	1.02*	0.95*	0.99*	0.91*	1.05*	0.96*	0.94*	1.02*	1.01*	1.10*	0.05
s	−0.01	−0.10*	−0.12*	−0.10*	−0.11*	0.04	−0.06*	0.07	0.09	0.16*	0.12*
h	−0.49*	−0.27*	0.06	0.17	0.21*	0.33*	0.41*	0.47*	0.51*	0.63*	1.21*
Adjusted R^2	0.83	0.84	0.80	0.78	0.72	0.62	0.64	0.63	0.54	0.64	0.53
Panel C: Estimation of three-factor model with GARCH(1,1) error process											
a	0.06	−0.01	0.02	0.05	−0.07	0.05	0.03	0.11*	0.09	0.08	0.04
b	1.01*	0.95*	0.96*	0.92*	1.05*	0.99*	0.96*	1.03*	1.01*	1.09*	0.07
s	0.02	−0.09*	−0.02*	−0.07*	0.06*	0.09*	−0.07*	0.01	0.07*	0.10*	0.15*
h	−0.47*	−0.28*	0.03	0.11 *	0.09*	0.18*	0.27*	0.39*	0.50*	0.62*	1.10*
d_1	0.07*	0.09*	0.11*	0.10*	0.12*	0.11*	0.09*	0.10*	0.13*	0.08*	0.09*
d_2	0.88*	0.87*	0.85*	0.79*	0.79*	0.84*	0.86*	0.83*	0.85*	0.86*	0.89*
Adjusted R^2	0.89	0.92	0.87	0.83	0.85	0.79	0.83	0.84	0.83	0.87	0.85

Notes: For all ten portfolios, the portfolio formation months are in between 7/51 and 06/08. The dependent variable is value-weighted simple returns in excess of the one-month bill rate calculated for each month. At the end of June of each year, all NYSE firms are allocated to ten portfolios based on their decile breakpoints formed from sorts on E/P. For panel B we use the model: $R_t - R_f = a + b[R_M - R_f] + s(SMB) + h(HML) + \eta_t$, $\eta_t | \mathscr{F}_{t-1} \sim iid\,(0,\sigma^2)$ and for panel C we use the model: $R_t - R_f = a + b[R_M - R_f] + s(SMB) + h(HML) + \eta_t$ with $E[\eta_t | \mathscr{F}_{t-1}] = 0$ and $E[\eta_t^2 | \mathscr{F}_{t-1}] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2V_{t-1}$. EPM is earnings based zero-investment portfolio. It signifies the difference between two extreme portfolios representing positive minus negative earnings changes. The regression R^2 is adjusted for degrees of freedom. *Implies the coefficient is significant at 5 percent level

3.2 Volatility persistence and the role of common risk factors

The evidence so far suggests that the three-factor model A1 is very successful in explaining the average portfolio returns of our sets of deciles based on past C/P and E/P performance. But a hint of the issue that we are interested in is hidden in the coefficient of determination. The average adjusted R^2 for C/P and E/P sorted portfolio is 0.76 and 0.70, respectively, leaving us with a huge unexplained variation. In addition, as we mentioned in Section 3, the incorporation of conditional homoskedasticity may reduce the explanatory power of model. This leads us to extend the three-factor model by incorporating GARCH(1, 1) error process, represented by model A2. In A2, we keep the mean specification of A1 intact but extend the framework that includes the provision of time-varying conditional heteroskedasticity[9].

Panel C of Table IV reports the A2 estimation results for C/P sorted portfolios. The basic tenet of the result remains the same (i.e. as in panel B of Table IV). The intercepts are still small and insignificant for almost all ten deciles. The regression slope of the broad market portfolio stays close its mean of 1.01 percent per month and always displays statistically significant *t*-statistics. The loadings on SMB increase monotonically from lower to higher deciles; except that the number of insignificant SMB slope estimates decreases. Also, consistent with Fama and French (1996) and Chordia and Shivakumar (2006), the loadings on HML increase monotonically from the loser portfolio to the winner portfolio. For eight out of ten portfolios, the persistent parameter $(d_1 + d_2)$ estimates exceeds statistically significant value of 0.95. The real benefit of the incorporation of conditional heteroskedasticity can be seen in the improvement in the coefficient of determination. In fact, for all ten decile portfolios based on C/P ratio, we see an improvement of adjusted R^2. The average value of adjusted R^2 through A2 is 0.89 instead of 0.76 using A1.

For E/P sorted portfolios, the behavior of the A2 regression slopes and intercepts, reported in panel C of Table V, are similar as well. This is not a surprise given the make-up of the data. The regression intercepts becomes small and insignificant. The average value of the market portfolio slopes stays close to its monthly average. Higher decile E/P portfolios display larger slopes on SMB and especially HML. Even though the average loading on HML is slightly smaller in the present case (for panel B it is 0.20 and for panel C it is 0.14), patterns in the loadings are statistically and economically meaningful.

The estimated persistence parameter is also robust (exceeds 0.95 in seven out of ten deciles) and statistically significant. As in the case of C/P-based portfolios, the main improvement seems to be the coefficient of determination. Compare to the previous average of 0.70, the new average value of R^2 jumps to 0.85. Another interpretation of the above results is that, by incorporating GARCH process, we may have picked up some effect of omitted variables from the simple three-factor model A1, and a portion of non-normality of the regression disturbance terms.

3.3 Variability of stock returns based on four-factor model

In order to study the interrelationship between C/P and E/P-based portfolios, we extend the three-factor model A2 by including zero-investment portfolios as an independent variable. The idea is to see whether the systematic component of C/P or E/P can explain each other's payoff. As Chordia and Shivakumar (2006) mentioned, since the zero-investment portfolios are well diversified, their returns reflect only systematic information. Therefore, the four-factor model A3 and A4 should guide us about the direction of the causality and complementary explanatory power of the risk factors to explain the payoffs to both portfolio strategies in the presence of systematic information.

Panels A and B of Table VI report the estimation results of models A3 and A4, respectively. The regression intercepts are still insignificant. The coefficient of SMB and HML shows no fundamental difference in their respective loadings. Both of their slope estimates decreases monotonically from loser portfolio to winner portfolio, although the loading of HML is stronger for higher deciles. Interestingly the coefficient of EPM is highly significant for eight out of ten deciles, and increases monotonically from −0.34 percent for the loser portfolio to 0.33 percent for the winner portfolio. In contrast, the coefficient of CPM is significant for nine out of ten portfolios, and also gradually increases from −0.33 percent for the lowest decile to 0.36 percent for the highest decile. The overall pattern indicates that the portfolio returns of firms based on C/P and E/P ratios varies systematically with EPM and CPM factors, respectively. Therefore, the augmented four-factor model is successful in capturing the time series variation in cash flows and earnings momentum portfolios. Clearly, there is a strong information transmission in risk sensitivities of both C/P and E/P sorted portfolios. To the best of our knowledge, there is no study which shows this exposure of cash flows and earnings momentum portfolios with respect to each other's systematic factor.

The effect of volatility persistence is also visible from the estimated slope parameters of the conditional variance part. For the C/P sorted portfolios, the estimation of the persistence parameter $d_1 + d_2$ is at least equal to 0.95 for seven out of ten decile portfolios. In fact for four decile portfolios the sum is above 0.96, suggesting a strong presence of persistent shocks to the conditional variance. For the E/P-based portfolios, the volatility persistence is statistically significant but not as strong as the C/P sorted portfolios. The most remarkable impact of the incorporation of conditional heteroskedasticity can be seen in the improved coefficient of determination. The average value of adjusted R^2 emerging from the estimated four-factor model is 0.94 and 0.92 for C/P and E/P, respectively. They marked a significant improvement over other two versions of three-factor models (i.e. A1 or A2). This further implies that, not only the systematic factors based on cash flows and earnings momentum subsumes the corresponding payoffs to the E/P and C/P sorted portfolios, respectively, they also help to improve the overall explanatory power of the model.

Note that our specifications A1 through A4 are the simplest possible way to explain anomalies. In any empirical test of these models, one would have to assume that the mispricing parameters α's are constant over time. A common alternative is to incorporate a time-varying version of the α. For example, one may complement model A1 with time varying α by $\alpha_{it} = \alpha_{i0} + \alpha_{i1}'Z_t$, where Z_t is a $L \times 1$ vector of mean zero information variables known at time t. Following the previous literature we perform similar experiment and use the following instrumental variables: the dividend yield, the spread between Baa and Aaa corporate bond yields, the spread between a ten-year and a one-year Treasury bond yields, short-term T-bill rate. The idea behind α_{it} is to find a proxy which is not independent of the aggregate economic conditions. We test the presence of time-varying α by using the following hypothesis *H0*: $\alpha_{i1} = 0$. Our estimated results indicate that the aggregate economic conditions may provide a correct proxy and α_{i1} is economically significant around 50 percent of the time. The results, however, indicates that, the incorporation of α_{it} have no qualitative bearings upon the role of volatility persistence in the presence of common risk factors.

Table VI.
Four-factor regression results for C/P and E/P portfolios

	Low	2	3	4	5	Deciles 6	7	8	9	High	High-low
Panel A: Estimation of four-factor model A3											
a	0.03	0.08	−0.06	−0.02	−0.02	−0.01	0.09	0.10	0.06	0.09	−0.01
b	1.07*	0.97*	1.02*	1.01*	0.96*	0.99*	0.95*	0.98*	1.03*	1.01*	0.02
s	0.03	−0.05	−0.07*	−0.12*	−0.09	−0.10*	−0.09	−0.01	−0.08	0.09*	0.11*
h	−0.21*	−0.13*	0.06	0.07	0.13*	0.14*	0.15*	0.19*	0.24*	0.29*	0.31*
p	−0.34*	−0.09	0.08	0.12*	0.19*	0.23*	0.27*	0.28*	0.30*	0.33*	0.66*
d_1	0.22*	0.20*	0.19*	0.11*	0.14*	0.19*	0.20*	0.23*	0.10*	0.09*	0.13*
d_2	0.70*	0.75*	0.73*	0.76*	0.82*	0.79*	0.75*	0.74*	0.82*	0.88*	0.81*
Adjusted R^2	0.94	0.96	0.92	0.96	0.93	0.95	0.94	0.91	0.92	0.93	0.92
Panel B: Estimation of four-factor model A4											
a	0.05	0.05	0.03	0.02	−0.03	0.11	0.10	0.13*	0.06	0.10	0.04
b	1.01*	0.95*	0.98*	0.95*	1.04*	0.94*	0.97*	1.03*	1.10*	1.08*	0.04
s	0.05	−0.04	−0.09*	−0.08*	−0.10*	−0.09*	−0.09*	−0.03	0.02	0.17*	0.16*
h	−0.23*	−0.12*	−0.06*	−0.01	0.00	0.11*	0.19*	0.24*	0.30*	0.33*	0.46*
q	−0.33*	−0.16*	0.09*	0.04	0.16*	0.15*	0.13*	0.23*	0.28*	0.36*	0.52*
d_1	0.11*	0.16*	0.17*	0.10*	0.15*	0.13*	0.09*	0.09*	0.11*	0.15*	0.11*
d_2	0.82*	0.80*	0.82*	0.83*	0.82*	0.79*	0.88*	0.86*	0.86*	0.82*	0.83*
Adjusted R^2	0.92	0.95	0.94	0.91	0.89	0.89	0.93	0.90	0.94	0.92	0.89

Notes: For all ten portfolios, the portfolio formation months are in between 7/51 and 06/08. The dependent variable is value-weighted simple returns in excess of the one-month bill rate calculated for each month. At the end of June of each year, all NYSE firms are allocated to ten portfolios based on their decile breakpoints formed from sorts on C/P and E/P. For panel A we use the model: $R_t - R_f = a + b[R_M - R_f] + s(SMB) + h(HML) + p(EPM) + \eta_t$, $\eta_t | \mathscr{F}_{t-1} \sim iid\,(0,\sigma^2)$ and for panel B we use the model: $R_t - R_f = a + b[R_M - R_f] + s(SMB) + h(HML) + q(CPM) + \eta_t$ with $E[\eta_t | \mathscr{F}_{t-1}] = 0$ and $E[\eta_t^2 | \mathscr{F}_{t-1}] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2 V_{t-1}$. CPM and EPM is cash flow and earnings based zero-investment portfolio respectively. They signify the difference between two extreme portfolios representing positive minus negative cash flow and earnings changes. The regression R^2 is adjusted for degrees of freedom. *Implies the coefficient is significant at 5 percent level

3.4 Does firm size play any role?

It is a well-known fact that small capitalization stocks in the US market realize higher return than large capitalization stocks (Schwert, 2003)[10]. In this section we provide an empirical evaluation of the size factor. We show that, if we control for market capitalization, the risk models A3 and A4 still produces a valid story as predictor of average portfolio return based on C/P and E/P ratios. Since we are using only NYSE universe, it is instructive that if size plays any controlling role, the relation between estimated risk loadings and average portfolio returns should be weaker than Table VI suggests. In this section we show that the conditional regressions with respect to the average firm size factors successfully captures substantial time-series variation in the average stock returns for both C/P and E/P sorted portfolios. Following Simlai (2009), we use the following two conditional models to present the results of our time-series tests that controls for firm size:

Model A5: For C/P based portfolios:

$$\begin{aligned} R_t - R_{ft} &= a + b[R_{Mt} - R_{ft}] + [s_1 + s_2 \ln(ME_t)](SMB_t) \\ &\quad + h(HML_t) + p(EPM_t) + \eta_t, \\ E[\eta_t|\mathcal{F}_{t-1}] = 0 \quad &\text{and} \quad E[\eta_t^2|\mathcal{F}_{t-1}] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2 V_{t-1}. \end{aligned}$$

Model A6: For E/P based portfolios:

$$\begin{aligned} R_t - R_{ft} &= a + b[R_{Mt} - R_{ft}] + [s_1 + s_2 \ln(ME_t)](SMB_t) \\ &\quad + h(HML_t) + q(CPM_t) + \eta_t, \\ E[\eta_t|\mathcal{F}_{t-1}] = 0 \quad &\text{and} \quad E[\eta_t^2|\mathcal{F}_{t-1}] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2 V_{t-1}. \end{aligned}$$

Table VII presents the estimated results. For panels A and B we estimate the conditional version of the multirisk model, given by A5 and A6. Both utilize the instrument $\ln(ME_t)$ to track time-varying risks. The results indicates that even after using the conditioning variable, the conditional loadings on SMB are systematically related for both C/P and E/P sorted decile portfolios. The loadings on SMB, the mimicking return for the size factor, go up as we move from lower decile to upper decile portfolios. Hence, SMB factor do not fail to capture the variation in stock returns related to size effect that is missed by the market premium and HML. Similarly, there is unambiguous evidence to support the success of HML factor to capture the variation in average stock returns. It is related to BE/ME effect and is missed by market premium and SMB.

Overall, there are two implications from the pieces of evidence of Table VII. First, even after controlling for size, value stocks loadings on HML, and zero-investment portfolios are lower than growth stocks. Second, the story of a risk factor hiding under the disguise of market capitalization is not entirely credible. Stocks with larger C/P and higher E/P are associated with higher risk and therefore requires a higher expected rate of return. Finally, the volatility persistence parameter also plays a non-trivial role for most of the decile portfolios. Following the explanations of Merton's (1973) ICAPM, we can interpret the time-varying conditional variance as a proxy for investment opportunities over time. Interestingly, the average explanatory power left out of the model does not show any significant changes.

We have also experimented with a version of the conditional model where we control for firm size and book-to-market at the same time. The result indicates that the magnitude and significance of the intercepts are no different. The coefficients on

Table VII.
Conditional four-factor regression results for C/P and E/P portfolios

	Low	2	3	4	5	Deciles 6	7	8	9	High	High-low
Panel A: Estimation of four-factor model A5											
a	0.01	0.10	0.07	−0.03	−0.03	0.09	0.06	0.04	0.05	0.02	0.00
b	0.98*	0.99*	1.00*	0.95*	0.97*	0.96*	1.03*	0.99*	0.95*	1.01*	0.02
s_1	0.19*	0.38*	0.52*	0.35*	0.46*	0.27*	0.24*	0.42*	0.51*	0.59*	0.25*
s_2	0.01	0.04	−0.12*	−0.13*	−0.08*	−0.03	−0.01	−0.09	−0.13*	−0.07	−0.14*
h	−0.24*	−0.16*	−0.13*	−0.09*	−0.05	0.03	0.10*	0.18*	0.25*	0.30*	0.32*
p	−0.29*	−0.13	0.04	0.09	0.11	0.13*	0.15*	0.19*	0.22*	0.24*	0.52*
d_1	0.10*	0.12*	0.13*	0.09*	0.12*	0.10*	0.13*	0.11*	0.08	0.05	0.10*
d_2	0.87*	0.82*	0.81*	0.89*	0.83*	0.83*	0.79*	0.83*	0.87*	0.81*	0.83*
Adjusted R^2	0.95	0.97	0.96	0.96	0.96	0.94	0.95	0.90	0.93	0.95	0.94
Panel B: Estimation of four-factor model A6											
a	0.02	0.01	−0.02	−0.04	−0.04	0.08	0.10	0.12*	0.08	0.04	0.01
b	1.00*	0.95*	0.96*	0.98*	1.01*	0.96*	0.99*	0.98*	1.01*	1.05*	0.05
s_1	0.32*	0.51*	0.42*	0.50*	0.39*	0.24*	0.41*	0.33*	0.36*	0.49*	0.53*
s_2	0.06	0.05	−0.10*	−0.13*	−0.09*	−0.07	−0.13*	−0.09*	−0.13*	−0.12*	−0.11*
h	−0.11	−0.13*	−0.18*	−0.16*	−0.06	0.16*	0.19*	0.24*	0.30*	0.34*	0.42*
q	−0.32*	−0.13*	0.01	0.08	0.09*	0.09*	0.13*	0.18*	0.22*	0.28*	0.47*
d_1	0.07*	0.09*	0.12*	0.10*	0.13*	0.10*	0.09*	0.12*	0.11*	0.10*	0.11*
d_2	0.78*	0.89*	0.85*	0.86*	0.82*	0.87*	0.89*	0.84*	0.86*	0.85*	0.84*
Adjusted R^2	0.93	0.94	0.94	0.93	0.90	0.92	0.94	0.91	0.93	0.94	0.90

Notes: For all ten portfolios, the portfolio formation months are in between 7/51 and 06/08. The dependent variable is value-weighted simple returns in excess of the one-month bill rate calculated for each month. At the end of June of each year, all NYSE firms are allocated to ten portfolios based on their decile breakpoints formed from sorts on C/P and E/P. For panel A we use the model: $R_t - R_f = a + b[R_M + R_f] + [s_1 + s_2 \ln(ME_t)](SMB) + h(HML) + p(EPM) + \eta_t$, $E[\eta_t|\mathscr{F}_{t-1}] = 0$, $E[\eta_t^2|\mathscr{F}_{t-1}] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2 V_{t-1}$. For panel B we use the model: $R_t - R_f = a + b[R_M + R_f] + [s_1 + s_2 \ln(MR_t)](SMB) + h(HML) + q(CPM) + \eta_t$, $E[\eta_t|\mathscr{F}_{t-1}] = 0$, $E[\eta_t^2|\mathscr{F}_{t-1}] = V_t = d_0 + d_1\eta_{t-1}^2 + d_2 V_{t-1}$ CPM and EPM is cash flow and earnings based zero-investment portfolio respectively. They signify the difference between two extreme portfolios representing positive minus negative cash flow and earnings changes. The regression R^2 is adjusted for degrees of freedom. *Implies the coefficient is significant at 5 percent level the explanatory variables show a similar spread across the portfolios as well. Overall, what we observe is no significant improvement compared to what we already have in Table VII. In fact in terms of adjusted R^2 and root mean square error we see small marginal deterioration. This implies that the controlling for book to market may not complement the role of our multifactor models. There is valid reason why the above fact is true. Unlike ME and two price ratios (i.e. C/P and E/P), which are flow variables, by all means the ratio BE/ME is a stock variable. Since the dispersion associated with BE/ME is very small over time, it fails to generate economically significant effect on the conditional loadings of HML.

4. Robustness checks

The predictive ability of the systematic factors based on cash flows and earnings seems to be appealing but there can be many concerns in their analytical role in the model. First, there is no guarantee that the exposure of C/P and E/P portfolios to the earnings and cash-flows-based systematic information is stable across sub-periods. Second, by estimating over the entire sample period only, our model may not reflect the actual temporal variation in risk loading. And finally, there is a possibility that the results are driven by some "invisible hands" and the inference are actuated by small-sample biases. In order to avoid these problems and to check the robustness of our results we consider three different experiments: we replicate our analysis for various sub-periods, rolling window, and bootstrap methods. We call them sub-period regression estimates, rolling window estimates, and bootstrap estimates, respectively.

4.1 Sub-period regression estimates

Panel A of Table VIII reports the relevant output for EPM and CPM coefficient in model A3 and A4, respectively[11]. Both slope coefficients of EPM and CPM seem to be stable across various sub-periods. They depicts monotonically increasing trend from the loser portfolio to the winner portfolio; an empirical artifact we already saw in Table VI. The sub-period July 1972-June 1979 produces the highest average value for EPM and CPM as 0.13 and 0.11, respectively. The largest number of statistically significant EPM slopes is for the sub-period July 1951-June 1972. The corresponding figure for CPM is for the sub-period July 1972 through June 1979. Overall, even for various sub-periods, both earnings and cash-flows-based systematic component do not fail to capture the variability in the returns on sets of deciles formed on C/P and E/P sorted portfolios.

4.2 Rolling window and bootstrapped estimates

Similar observation can be noted as we interpret the rolling window estimates from panel B of Table VIII. We obtain the results by estimating our four-factor models, represented by A3 and A4, for each month between July 1951 and June 2008 period using a rolling window of 60 prior monthly returns. The five-year rolling regression slope estimates suggests that our four-factor model correctly captures the temporal variation in the loadings of both cash flows and earnings-based factors. The average value of EPM slopes rolling window estimates is 0.05 (for CPM it is 0.08) indicating that even though true loadings are not constant, the estimates of period-by-period loading is close to what we obtain in Table VI.

Finally, in panel C of Table VIII we present results from the randomization-bootstrap experiment[12]. We calculate the bootstrap standard errors using the number of bootstrap replications $B = 1{,}000$. We use the empirical standard deviation of a series

Table VIII.
Robustness checks of four-factor regressions for C/P and E/P

	Deciles									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Sub period regression estimates										
July 1951-June 1972										
EPM	−0.48*	−0.12*	−0.04	0.07	0.06	0.18*	0.16*	0.26*	0.33*	0.35*
CPM	−0.36*	−0.18*	−0.03	−0.01	0.08	0.10	0.11	0.18*	0.19*	0.26*
July 1972-June 1979										
EPM	−0.27*	−0.01	0.04	0.10	0.14	0.17*	0.20*	0.27*	0.31*	0.37*
CPM	−0.44*	−0.13*	−0.09	0.03	0.15*	0.22*	0.25*	0.34*	0.41*	0.40*
July 1980-June 1989										
EPM	−0.34*	−0.15*	−0.03	−0.01	0.05	0.10	0.13	0.17*	0.22	0.19*
CPM	−0.31*	−0.07	0.04	0.11	0.04	0.12	0.13	0.15*	0.15*	0.18*
July 1989-June 2008										
EPM	−0.30*	−0.12	−0.07	−0.03	0.10	0.11	0.14*	0.16*	0.28*	0.30*
CPM	−0.29*	−0.06	−0.07	−0.03	0.01	0.08	0.10	0.13*	0.30*	0.38*
Panel B: Rolling window estimates										
July 1951-June 2008										
EPM	−0.39*	−0.10	−0.03	0.05	0.10	0.11	0.13*	0.15*	0.21*	0.25*
SD	0.11	0.08	0.08	0.10	0.11	0.13	0.12	0.10	0.12	0.16
CPM	−0.35*	−0.10	0.02	0.03	0.08	0.16*	0.18*	0.21*	0.26*	0.28*
SD	0.09	0.16	0.09	0.09	0.09	0.11	0.09	0.13	0.17	0.14
Panel C: Bootstrapped estimates										
July 1951-June 2008										
EPM	−0.38*	−0.11	0.06	0.05	0.12	0.14*	0.15*	0.17*	0.24*	0.29*
SE	0.03	0.02	0.01	0.03	0.03	0.05	0.02	0.11	0.07	0.10
CPM	−0.33*	−0.05	0.06	0.09	0.11	0.14*	0.17*	0.19*	0.24*	0.33*
SE	0.02	0.03	0.03	0.01	0.03	0.06	0.03	0.04	0.09	0.13

Notes: CPM and EPM is cash flows and earnings based zero-investment portfolio, respectively. They signify the difference between two extreme portfolios representing positive minus negative cash flow and earnings changes. In panel B, we report CPM and EPM slopes in five-year rolling four-factor regression models. The four-factor models are estimated each month of the 7/51 to 6/08 period using a rolling window of 60 prior monthly returns. In panel C, we report results from the randomization-bootstrap tests. We calculate the bootstrap standard errors using number of bootstrap replications $B = 1{,}000$. In panel A, *implies the coefficient is significant at 5 percent level of bootstrap replications of model parameters to approximate the standard error of the estimators. The implications of the bootstrapped standard errors are similar to previous t-statistics generated from standard errors that are robust to serial correlation and heteroskedasticity in the residuals. Overall, the robustness check results strongly support our earlier finding that temporal variation in the exposure of cash flow and earnings momentum portfolios is strongly captured by EPM and CPM factors, respectively. This further suggests that our results are not the outcome of implicit data mining.

5. Conclusions

In this paper, we investigate the role of common risk factors in the variability of average returns of cash flows and earnings-based portfolio. Our study documents that there exists strong information transmission between the excess return of ten deciles portfolios formed on C/P and E/P ratio. We also argue that volatility persistence can improve the performance of common risk factors for explaining the temporal variation in both C/P and E/P sorted average portfolio returns. We observe that the systematic component of C/P and E/P sorted portfolios, in terms of a zero-investment strategy, can significantly capture the time-series variation as well. Also, by investigating our results through a battery of robustness checks, we demonstrate that corrections for serial correlation and heteroskedasticity are not too conservative at all. In summary, our empirical results help to narrow the search for an explanation of cash flows and earnings interrelationship, and demonstrate the benefit for acknowledging new predictable variables that have not been previously known in the literature.

Notes

1. See Bernard (1989) and Lev (1989) for a summary of this evidence from the earlier literature.
2. See, for example, Bhattacharya *et al.* (2003), Bradshaw and Sloan (2002), Brown and Sivakumar (2003).
3. Similar messages were reported by FASB (1980, Para 54) and Bernstein (1993). This is also in accordance with Sloan (1996); according to him (p. 291) "[…] the accrual and cash flow components of current earnings have different implications for the assessment of future earnings. While both components contribute to current earnings, current earnings performance is less likely to persist if it is attributable primarily to the accrual component of earnings as opposed to the cash flow component."
4. It was the maximum attainable sample period during the time we wrote this paper.
5. There exist various explanations for the success of the SMB and HML factors. Some of them are based on data snooping and other backfill bias (Lo and MacKinlay, 1990; Kothari *et al.*, 1995). Fama and French (1996, 2008), however, counted that even in the data set of Kothari *et al.* (1995) size is still an important determinant of expected returns. Gomes *et al.* (2003) suggests that success of Fama-French model may lie on the problems in the measurement of β. Ferson *et al.* (1999) argue that even when some attributes are unrelated to risk, portfolios sorted on attributes may work as risk factors. Daniel and Titman (1997) suggest that stocks characteristics such as behavioral biases, and not risks, are priced in the cross-section of average returns.
6. Note that, even though there are other forms of GARCH (including GARCH in mean) model with richer specification, inclusion of them hardly improves the forecasting performance (results are available upon request). That's why simple GARCH(1, 1) specification serves our basic purpose.
7. As a model of conditional volatility of returns GARCH specifications are widely used for some time. For example, some of the earlier works includes French *et al.* (1987) who model

the market volatility by GARCH(1, 2) process. Bollerslev *et al.* (1988) utilizes a multivariate GARCH model to display time-varying risk premiums. Reyes (1999) and Simlai (2009) show that accounting for GARCH effects in the market model yields better β estimates. Recently Fu (2009) uses the exponential GARCH models to estimate expected idiosyncratic volatilities.

8. See, for example, recent papers by Petkova (2006), Fu (2009) and references cited therein.
9. Even though not reported, to investigate the dependence structure of the disturbance term of the three-factor model A1, we evaluate various summary statistics about the sample moments and test for dependence of the estimated residuals and their squares. Based on the sample skewness and kurtosis, Jarque-Bera normality tests, Ljung-Box Q-statistics, and battery of GARCH tests we identify symmetric GARCH(1, 1) as an appropriate model. Also, since our results suggest that almost all the time the persistence parameter is less than one, we restrict our discussion to the stationary case.
10. Even though the outperformance of small capitalization stocks over large capitalization stocks has become weaker, there is evidence that it exists and is an international fact as well.
11. To conserve space, we only report the slope coefficients of CPM and EPM in Table VIII. The full regression results are available from the authors upon request.
12. There are several ways to conduct a bootstrap experiment. It can be carried out by bootstrapping either the distribution of the parameter of interest or the distribution of the t-statistics that involves standard error of the estimator. In our case, both methods produce almost similar results.

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About the author

Prodosh Eugene Simlai is Associate Professor of Economics at the University of North Dakota, USA. His teaching and research interest includes general financial markets, empirical asset pricing, portfolio management, and microstructure impacts of efficiencies. He has authored numerous articles in economics and finance journals, as well as book chapters. He is an active member of the American Economic Association, American Finance Association, Midwest Finance Association, and Southwestern Finance Association. He has worked in various consultancy positions, and has given numerous seminars on risk modeling and the econometrics of financial markets. Prodosh Eugene Simlai received his PhD in Economics and MS in Finance both from the University of Illinois at Urbana-Champaign, USA.