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Cashflow risk, systematic earnings revisions, and the cross-section of stock returns[☆]

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The returns of stocks are partially driven by changes in their expected cashflow. Using revisions in analyst earnings forecasts, we construct an analyst earnings beta that measures the covariance between the cashflow innovations of an asset and those of the market. A higher analyst earnings beta implies greater sensitivity to marketwide revisions in expected cashflow, and therefore higher systematic risk. Our analyst earnings beta captures exposure to macroeconomic fluctuations and has a positive risk premium that provides a partial explanation for the value premium, size premium, and long-term return reversals. From 1984 to 2005, 55.1% of the return variation across book-to-market, size, and long-term return reversal portfolios is captured by their analyst earnings betas.

1. Introduction

A key insight of financial economics is that expected returns are determined by systematic risk. The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) measures systematic risk using a return beta that is computed as the covariance between the returns of an individual stock and those of the market. However, the empirical asset pricing literature has identified cross-sectional return variation that is not attributable to the return-based CAPM beta.[1]

Despite the empirical challenges confronting CAPM, stock returns are driven by a combination of changes in expected discount rates and cashflows (Campbell and Shiller, 1988). Cashflow risk, which captures the comovement between the cashflow innovations of a stock and those of the market, is therefore an important source of systematic risk that links stock returns directly to fundamentals. As emphasized in Campbell and Vuolteenaho (2004), this link is crucial to investors with a long-term buy-and-hold perspective.

In this paper we derive a novel measure of cashflow risk using revisions in analysts' consensus earnings forecasts. Analyst forecasts are an important set of expectations regarding future cashflows since numerous empirical studies such as Givoly and Lakonishok (1979), Imhoff and Lobo (1984), and Lys and Sohn (1990) show a

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[1] Schwert (2003) contains an excellent and comprehensive survey of financial market anomalies.

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strong relationship between their revisions and stock returns.[2] Jagannathan and Baldaque da Silva (2002) and Chen and Zhao (2007) report that cashflow innovations derived from analyst earnings forecasts explain a large portion of stock return variability. However, our focus is on the *covariance* between analyst forecast revisions. In particular, we examine whether systematic cashflow risk measured using analyst forecast revisions can explain cross-sectional variation in average returns. Commonality in analyst forecast revisions clearly poses a serious cashflow risk to investors. For example, downward forecast revisions across a wide cross-section of stocks lead to undiversifiable stock price reductions. To date, however, the systematic risk associated with analyst forecast revisions has not been examined. Our paper defines an earnings beta that bridges two important strands of literature by demonstrating that the cashflow risk captured by analyst forecast revisions explains cross-sectional return variation.

The estimation of our analyst earnings beta (hereafter, earnings beta) proceeds in several steps. First, for each stock in our sample, we collect consensus analyst earnings forecasts for the current fiscal year and the next fiscal year along with a long-term earnings growth forecast. These consensus forecasts are then aggregated at the portfolio-level each month, which alleviates the noise associated with firm-specific forecasts. Second, we extend the horizon of these portfolio-level earnings forecasts using a procedure that parallels the approach in Frankel and Lee (1998) and Pástor, Sinha, and Swaminathan (2008) by assuming future earnings growth is mean-reverting. Third, we convert these extended forecasts into portfolio-level expected cashflows following Vuolteenaho (2002). Cashflow innovations are then computed as monthly revisions in these cashflow expectations to mitigate forecast biases that persist beyond one month. Finally, a portfolio's earnings beta is computed as the covariance between its cashflow innovations and those of the market. Intuitively, a higher analyst earnings beta implies greater sensitivity to marketwide revisions in expected cashflows, and therefore higher systematic risk.

The earnings beta has several advantages over cashflow risk measures in the prior literature. First, the availability of analyst earnings forecasts over a range of future maturities allows us to directly measure *revisions in expected cashflow* across several horizons. In contrast, alternative cashflow risk measures resort to using forward-looking realized earnings (Cohen, Polk, and Vuolteenaho, 2008; Da, 2009), imposing parametric assumptions on the evolution of cashflow (Hansen, Heaton, and Li, 2008), or implementing a vector autoregression that depends on a specific choice of state variables (Bansal, Dittmar, and Lundblad, 2005; Campbell and Vuolteenaho, 2004; Campbell, Polk, and Vuolteenaho, 2008). Second, the frequent revisions in analyst earnings forecasts enable us to estimate our cashflow innovations at monthly frequencies, while cashflow risk measures derived from dividend and accounting data are updated at most quarterly. Higher-frequency data produce more efficient risk estimates.

During the period from 1984 to 2005, we estimate the earnings betas for 10 book-to-market, 10 size, and 10 past long-term return sorted portfolios. These 30 portfolios are examined since the persistent cross-sectional return variation associated with book-to-market, size, and past long-term return characteristics challenges common benchmark models (Fama and French, 1993; DeBondt and Thaler, 1985). We find that earnings betas are higher for value stocks and small stocks than for growth stocks and large stocks, respectively. In addition, past long-term losers have higher earnings betas than past long-term winners. Differences between the earnings betas of the extreme portfolios are highly significant. Overall, our earnings beta simultaneously explains more than 55% of the cross-sectional return variation across book-to-market, size, and long-term reversal portfolios. Furthermore, the estimated market price of cashflow risk is positive (63 bp per month) and significant. A battery of robustness tests confirms that our conclusions regarding cashflow risk are not driven by poor statistical inferences associated with a small sample, a specific sample period, a specific weighting scheme, nor assumptions regarding cashflow payout rates.

We also analyze the source of the commonality in analyst earnings forecast revisions that define our earnings beta. Flannery and Protopapadakis (2002) argue that the real economy simultaneously affects the cashflows of many firms. We find evidence that our earnings beta reflects exposure to macroeconomic fluctuations. For example, the cashflow innovations of past long-term losers are more sensitive to the credit spread than the cashflow innovations of past long-term winners. Intuitively, firms with relatively poor past performance have greater leverage, and experience larger decreases in expected cashflow when corporate borrowing costs rise. Furthermore, the cashflow innovations of value stocks and small stocks are more sensitive to inflation than growth stocks and large stocks, respectively. Specifically, the expected (nominal) cashflows from growth stocks and large stocks increase with inflation while value stocks and small stocks experience a decrease in their expected cashflows. Thus, growth firms and large firms appear to be better at maintaining their margins. Moreover, Feldstein (1980) demonstrates that inflation reduces the value of tax-deductible depreciation under historical-cost accounting. As value firms have proportionately larger book values, they experience greater reductions in after-tax cashflow as a consequence of inflation.

Although analyst forecast revisions and their cross-sectional covariances are highly informative, analyst earnings forecasts may contain biases. To examine the impact of any "residual" bias on the estimated earnings betas, we regress portfolio-level cashflow innovations on a comprehensive list of stock characteristics that have been previously identified as being associated with analyst

[2] Womack (1996) reports that stock prices react to the announcement of analyst buy/sell recommendations, while Brav and Lehavy (2003) show the influence of price targets on stock prices. However, stock recommendations and price targets are less direct proxies for cashflow expectations.

forecast biases.[3] These characteristics include firm size, analyst coverage, and earnings-to-price ratios as well as previous stock returns, earnings revisions, and earnings surprises (LaPorta, 1996; Frankel and Lee, 1998; Jegadeesh, Kim, Krische, and Lee, 2004; Scherbina, 2004; Hughes, Liu, and Su, 2008). The unpredictable components of the cashflow innovations, which likely represent cashflow risk, produce almost identical earnings betas as the original cashflow innovations. In contrast, earnings betas estimated from the predictable components of our cashflow innovations, which capture analyst forecast biases, are close to zero and exhibit very little variation across the portfolios. These results confirm that our earnings beta estimates are unlikely to be influenced by analyst forecast biases.

For comparison, we also implement an alternative cashflow risk measure that uses the popular vector autoregression (VAR) specification for expected returns in Campbell and Vuolteenaho (2004). This alternative cashflow beta is less adept at simultaneously explaining the value premium, size premium, and long-term return reversals than our earnings beta. Moreover, consistent with the recent findings of Chen and Zhao (2008), this cashflow beta is sensitive to the choice of VAR state variables.

Overall, we provide a novel approach for measuring cashflow risk using analyst forecast revisions. The remainder of this paper begins in Section 2 with a description of our data. Section 3 relates analyst earnings forecasts to the cashflow component of stock returns and describes the estimation of our earnings beta. Section 4 then presents our empirical results regarding the earnings beta estimates and cross-sectional returns along with evidence that our earnings beta captures exposure to macroeconomic fluctuations. Section 5 demonstrates the robustness of our earnings beta, while Section 6 concludes and offers suggestions for future research.

2. Data description

Our sample of analyst earnings forecasts is obtained from the Institutional Broker's Estimate System (IBES) Summary unadjusted file. IBES produces these consensus earnings forecasts each month, typically on the third Thursday of the month. We initially include all unadjusted consensus earnings forecasts from 1984 to 2005. Unadjusted IBES forecasts are not adjusted by share splits after their issuance date.[4]

We retain 545,165 firm-month observations, with each observation including a firm's earnings in the previous year ($A0_t$), consensus earnings forecasts for the current and subsequent fiscal year ($A1_t$, $A2_t$), along with its long-term growth forecast (LTG_t). The earnings forecasts are denominated in dollars per share, with the t subscript denoting when a forecast is employed. The long-term growth forecast represents an annualized percentage growth rate. This forecast has no fixed maturity date but pertains to the next three to five years. Quarterly forecasts are not utilized because of seasonality effects. Although a minimum analyst coverage filter is not imposed, qualitatively similar results are obtained in a smaller subsample that requires at least three analysts for each forecast maturity. Our conclusions are also robust to defining the consensus forecast as the median forecast.

On average, there are approximately 2,000 stocks in each month's sample, comprising 72.2% of the entire US stock universe in terms of market capitalization, according to Panel A of Table 1. Hence, our sample is representative of the broader universe of US stocks. NYSE, Amex, and Nasdaq account for 52.0%, 4.1%, and 43.9% of these stocks, respectively. Finally, our sample contains relatively large stocks whose average market capitalization is about \$2.6 billion dollars.

The resulting data set is then merged with the Compustat/Chicago Research into Securities Prices (CRSP) merged data set whenever price and/or accounting variables are needed. Observations with negative book values are eliminated when constructing the book-to-market ratios. Share splits are also accounted for using the split factor in CRSP. Every June, stocks are sorted into 10 size portfolios and 10 book-to-market portfolios following Fama and French (1996).[5] We also sort stocks into 10 long-term reversal portfolios according to their past three-year returns one year before portfolio formation. DeBondt and Thaler (1985) report that past long-term winners underperform past long-term losers. Equally weighted monthly portfolio returns are computed for each portfolio. For stock delistings, we use CRSP delisting returns whenever possible. Otherwise, we follow Shumway (1997) and assign a return of −0.3 to firms delisted for performance-related reasons (delisting code is 500 or in [520, 584]).

For comparison with LTG_t, the dollar-denominated consensus earnings forecast $A1_t$ is converted into an implied annualized percentage growth rate denoted $A1_{t,\%}$ as follows:

$$A1_{t,\%} = \frac{A1_t - A0_t}{|A0_t|}, \tag{1}$$

where $A0_t$ denotes the firm's earnings in the previous year. Similarly, an intermediate expected growth rate $A2_{t,\%}$ is inferred from $A2_t$ as

$$A2_{t,\%} = \sqrt{1 + \frac{A2_t - A0_t}{|A0_t|}} - 1. \tag{2}$$

[3] Hong and Kacperczyk (2008) report that analyst optimism is more prevalent when there is less competition among analysts. Their finding implies that the forecasts we utilize are less likely to manifest large biases since our sample contains firms with relatively high analyst coverage.

[4] As detailed in Diether, Malloy, and Scherbina (2002), earnings per share (EPS) after a share split is often a small number that IBES rounds to the nearest cent. This rounding procedure can distort certain properties of dollar-denominated analyst forecasts, such as their revisions and forecast errors.

[5] The book-to-market ratio in June of year t is book equity for the fiscal year ending in calendar year $t-1$, divided by market equity at the end of December in year $t-1$. Size is defined as market equity at the end of June in year t. To avoid potential data errors and extreme outliers, we exclude stocks whose book-to-market ratios exceed the 99th percentile or are below the 1st percentile.

Table 1
Firm and forecast characteristics.

This table summarizes the analyst earnings forecasts during our 1984–2005 sample period. The implied $A1_{t,\%}$ and $A2_{t,\%}$ growth forecasts are defined in Eqs. (1) and (2) as $(A1_t - A0_t)/|A0_t|$ and $\sqrt{1+(A2_t - A0_t)/|A0_t|} - 1$, respectively, using realized earnings from the previous year ($A0_t$) as well as consensus analyst forecasts for the current year ($A1_t$) and the subsequent year ($A2_t$). LTG_t denotes long-term analyst growth forecasts for the next three to five years. Book-to-market and size (in millions of dollars) are also reported in Panel A along with the percentage of stocks in our sample listed on the NYSE, Amex, and Nasdaq. At the end of June, stocks are also sorted into portfolios according to their book-to-market, size, and past return over the prior three years. Panel B then summarizes these firm characteristics and the analyst-forecasted earnings growth rates for the portfolios that define the value premium, size premium, and long-term return reversals.

Panel A: Average characteristics by year

Year	# of Stocks	Percent coverage	NYSE	Amex	Nasdaq	Book-to-market	Size	$A1_{t,\%}$	$A2_{t,\%}$	LTG_t
1984	886	53.5%	70.2%	6.2%	23.6%	0.83	1059.3	26.6%	22.3%	15.9%
1985	1047	63.6%	67.3%	6.5%	26.3%	0.83	1240.5	11.7%	13.0%	15.1%
1986	1201	69.7%	64.1%	6.2%	29.7%	0.78	1476.7	10.4%	13.0%	14.7%
1987	1310	71.5%	60.6%	6.1%	33.3%	0.72	1615.0	17.3%	19.4%	14.6%
1988	1384	72.2%	60.2%	6.4%	33.4%	0.78	1430.5	30.9%	21.0%	14.5%
1989	1544	75.6%	56.9%	7.3%	35.8%	0.77	1546.8	11.6%	11.6%	14.3%
1990	1766	80.6%	54.3%	6.8%	38.9%	0.71	1427.4	13.3%	14.6%	14.6%
1991	1824	82.4%	53.7%	6.2%	40.1%	0.83	1640.5	3.8%	13.6%	14.7%
1992	1994	82.3%	53.9%	5.8%	40.3%	0.79	1728.5	22.9%	23.0%	15.6%
1993	2230	80.3%	53.3%	5.1%	41.6%	0.65	1745.1	21.8%	20.7%	16.1%
1994	2483	78.3%	50.8%	4.3%	44.9%	0.59	1628.6	17.8%	18.0%	16.8%
1995	2573	77.9%	48.9%	3.1%	48.0%	0.62	1848.5	19.5%	17.8%	17.1%
1996	2882	76.9%	46.0%	2.7%	51.3%	0.60	2064.1	11.8%	13.6%	18.8%
1997	3133	77.7%	45.1%	2.8%	52.1%	0.55	2462.8	13.5%	15.1%	20.1%
1998	3113	76.6%	44.6%	2.9%	52.5%	0.50	3013.8	8.2%	13.5%	20.6%
1999	2909	76.0%	45.0%	2.5%	52.5%	0.55	3932.3	14.1%	16.8%	20.6%
2000	2609	71.7%	46.7%	2.1%	51.2%	0.61	4827.4	17.5%	18.1%	23.5%
2001	2239	68.0%	46.1%	1.6%	52.3%	0.72	4405.4	−6.9%	7.0%	22.6%
2002	2149	66.6%	43.3%	1.5%	55.3%	0.67	3892.0	15.6%	19.7%	19.0%
2003	2094	65.0%	44.5%	1.5%	54.0%	0.68	3973.2	15.7%	16.8%	16.2%
2004	2040	62.1%	44.5%	1.6%	53.9%	0.59	4748.6	21.3%	18.2%	15.8%
2005	2021	58.8%	44.1%	1.6%	54.3%	0.48	5001.9	15.6%	15.1%	16.1%
Average	2065	72.2%	52.0%	4.1%	43.9%	0.68	2577.7	15.2%	16.5%	17.1%

Panel B: Average characteristics by portfolio

	# of Stocks	Book-to-market	Size	Past return	$A1_{t,\%}$	$A2_{t,\%}$	LTG_t
Value	583.2	1.23	1326.3	31.4%	16.4%	17.5%	11.4%
Growth	583.3	0.27	4566.0	150.4%	18.2%	17.8%	21.3%
Small	694.4	0.87	94.6	92.2%	84.8%	80.7%	19.0%
Large	693.9	0.60	6571.9	60.5%	15.3%	15.4%	13.8%
Loser	527.0	0.91	1993.3	−18.0%	65.4%	118.3%	14.5%
Winner	526.6	0.48	3933.7	213.0%	13.0%	30.2%	17.2%

Although $A0_t$ may be negative, our empirical analysis is primarily conducted at the portfolio level when these instances are very rare.

The results in Table 1 sum across the earnings forecasts of individual stocks. According to Panel A, the market's analyst-forecasted earnings growth varies across time. This time series variation is complemented by cross-sectional variation across different portfolios, as reported in Panel B. For example, growth stocks are forecasted to experience higher long-term earnings growth than value stocks. Furthermore, small stocks and past long-term losers have higher forecasted short-term earnings growth than large stocks and past long-term winners, respectively. However, forecasted earnings growth between the extreme size portfolios and the extreme past return portfolios converges over the long-term.

In summary, we employ multiple analyst forecasts to derive our cashflow risk measure since a single analyst forecast cannot fully describe the time series and cross-sectional variation in forecasted earnings growth within our sample.

3. Analyst forecast revisions and cashflow risk

With stock prices equaling the discounted sum of expected cashflows, stock returns are partially driven by changes in investor expectations of future cashflows. Campbell and Shiller (1988) formalize this intuition by decomposing stock returns into a cashflow component ($N_{CF,t+1}$) and a discount rate component ($N_{DR,t+1}$)[6]:

$$r_{t+1} - E_t[r_{t+1}] = N_{CF,t+1} - N_{DR,t+1}. \tag{3}$$

The discount rate component equals

$$N_{DR,t+1} = (E_{t+1} - E_t)\sum_{j=1}^{\infty}\rho^j r_{t+j+1} \tag{4}$$

while this paper focuses on the cashflow component, which is defined as

$$N_{CF,t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j \Delta d_{t+j+1}, \tag{5}$$

where Δd_{t+j+1} and r_{t+j+1} denote a stock's log cashflow growth and log stock return, respectively, over a future $[t+j, t+j+1)$ time period, with ρ being a log-linearization constant (typically 0.95 at an annual frequency). The cashflow component is not identical to changes in expected earnings. Nonetheless, the expectations that comprise $N_{CF,t+1}$ are ascertained from analyst forecasts using a three-stage earnings growth model.

The cashflow component in Eq. (5) equals an investor's gain from holding a stock. However, this payoff represents an outflow of funds from the firm's perspective. Conversely, earnings represent an inflow of funds. Thus, cashflow and earnings are related to one another through the clean-surplus accounting identity

$$B_{t+1} = B_t + X_{t+1} - D_{t+1}, \tag{6}$$

where B_{t+1}, X_{t+1}, and D_{t+1} denote a firm's book value, earnings, and cashflow, respectively, with d_{t+j+1} in Eq. (5) being the log of D_{t+j+1}. The log return on book equity is defined as

$$e_{t+j+1} = \log\left(1 + \frac{X_{t+j+1}}{B_{t+j}}\right). \tag{7}$$

Vuolteenaho (2002) log-linearizes the clean-surplus identity to replace the Δd_{t+j+1} terms in Eq. (5) with log returns on book equity, which implies the cashflow component in Eq. (5) becomes

$$N_{CF,t+1} = (E_{t+1} - E_t)\sum_{j=0}^{\infty}\rho^j e_{t+j+1}. \tag{8}$$

The log return on book equity e_{t+j+1} involves earnings X_{t+j+1} over the $[t+j, t+j+1)$ time period and book values B_{t+j} at the beginning of this interval. Eq. (8) simply states that cashflow innovations and earnings revisions contain similar information when evaluated over an infinite horizon. This relationship arises naturally since cashflow eventually has to be financed by a firm's earnings.

Eq. (8) states that the cashflow component of stock returns requires earnings forecast revisions across *all* future horizons. However, analysts only issue earnings forecasts for the next five years. To estimate Eq. (8), the next subsection introduces a benchmark three-stage earnings growth model for estimating the cashflow component that imposes an assumption on earnings growth beyond five years.

3.1. Estimation of cashflow innovations

Let $X_{t,t+j}$ denote the *expectation* of X_{t+j} in Eq. (7), with the additional subscript referring to an expectation at time t. A three-stage growth model that parallels the formulation in Frankel and Lee (1998), as well as Pástor, Sinha, and Swaminathan (2008), infers these earnings expectations from analyst forecasts. In the first stage, expected earnings are computed directly from analyst forecasts until year 5 as follows[7]:

$$\begin{aligned}
X_{t,t+1} &= A1_t,\\
X_{t,t+2} &= A2_t,\\
X_{t,t+3} &= A2_t,(1+LTG_t),\\
X_{t,t+4} &= X_{t,t+3}(1+LTG_t),\\
X_{t,t+5} &= X_{t,t+4}(1+LTG_t).
\end{aligned} \tag{9}$$

Given that LTG_t exceeds 30% for certain portfolios, it is unrealistic to assume that such high earnings growth will continue indefinitely. Therefore, we assume that expected earnings growth converges (linearly) to an economy-wide

[6] Firm-specific superscripts are occasionally suppressed in this section for notational simplicity.

[7] The $A3_t$ forecast is not used as a proxy for $X_{t,t+3}$ since few analysts issue this forecast during the early part of our sample period. At the portfolio level, a negative $A2_t$ is very rare (about 0.1% of the observations) and is limited to the smallest two size deciles. $A2_t$ is set to zero in these instances but this assumption does not affect the earnings beta estimates.

steady-state growth rate g_t from year 6 to year 10 in the second stage. Specifically, expected earnings are estimated as

$$X_{t,t+j+1} = X_{t,t+j}\left[1 + LTG_t + \frac{j-4}{5}(g_t - LTG_t)\right], \tag{10}$$

for $j = 5, \ldots, 9$. The steady-state growth rate g_t is computed as the cross-sectional average of LTG_t. We also assume the cashflow payout is equal to a fixed portion (ψ) of the ending-period book value. Under this assumption, Eq. (6) implies that the evolution of expected book value is $B_{t,t+j+1} = (B_{t,t+j} + X_{t,t+j+1})(1-\psi)$. The ψ parameter is initially set to 5% since this percentage is close to the average payout rate for the firms in our sample. In the third stage, expected earnings growth converges to g_t, which implies expected accounting returns converge to $g_t/1-\psi$ beyond year 10. After 10 years, the annualized discount factor $\rho = 0.95$ also results in the remaining cashflows exerting little influence on the earnings beta estimates.

In summary, the expected log accounting return $e_{t,t+j}$ is estimated at time t as[8]

$$e_{t,t+j+1} = \begin{cases} \log\left(1 + \dfrac{X_{t,t+j+1}}{B_{t,t+j}}\right) & \text{for } 0 \le j \le 9, \\ \log\left(1 + \dfrac{g_t}{1-\psi}\right) & \text{for } j \ge 10, \end{cases} \tag{11}$$

where the $X_{t,t+j+1}$ expectations are defined in Eqs. (9) and (10). Consequently, the three-stage growth model implies

$$E_t \sum_{j=0}^{\infty} \rho^j e_{t+j+1} = \sum_{j=0}^{9} \rho^j e_{t,t+j+1} + \frac{\rho^{10}}{1-\rho} \log\left(1 + \frac{g_t}{1-\psi}\right). \tag{12}$$

The cashflow innovations in Eq. (8) are the difference between Eq. (12) over consecutive months, that is,

$$N_{CF,t+\delta} = E_{t+\delta} \sum_{j=0}^{\infty} \rho^j e_{t+j+1} - E_t \sum_{j=0}^{\infty} \rho^j e_{t+j+1}. \tag{13}$$

Although earnings forecasts pertain to annual intervals, their revisions are computed over monthly horizons (δ). Monthly revisions increase the sample size and therefore improve the precision of our earnings beta estimates. Furthermore, monthly revisions mitigate analyst forecast biases that persist over this short horizon.[9]

Empirically, the cashflow innovations in Eq. (8) are computed for individual portfolios. The estimation of Eq. (8) equally weights the individual earnings forecasts (scaled by price) and book values (scaled by price) of stocks within each portfolio. Specifically, each month, the $A1_t$ forecasts are aggregated across individual firms as follows:

$$A1_t = \sum_{k=1}^{m} A1_t^k / P_t^k, \tag{14}$$

[8] Consistent with our notational convention, $e_{t,t+j}$ denotes the expectation of e_{t+j} at time t. The approximation $E[\log(1+X/B)] \approx \log(1 + E[X]/E[B])$ ignores a convexity term that is mitigated by computing the necessary innovations.

[9] At each annual portfolio rebalancing, firms enter and exit a particular portfolio. However, the cashflow innovations in Eq. (13) are computed using earnings forecasts for the same set of firms.

where m denotes the number of stocks in a portfolio and P_t^k denotes the stock price of firm k at time t. This aggregation is repeated for the $A2_t$ forecasts and future book values ($B_{t,t+j}$). The portfolio's LTG_t is computed as the simple average of these long-term forecasts within a portfolio. These aggregate quantities define portfolio-level $e_{t,t+j+1}$ terms in Eq. (11). The resulting portfolio-level cashflow innovations correspond to a trading strategy that invests one dollar in each stock within a portfolio. This trading strategy is consistent with the equally weighted returns that define the value premium, size premium, and long-term return reversals. As the true market portfolio is value weighted, we value weight individual firm-level earnings forecasts when computing market-level cashflow innovations. Specifically, Eq. (14) is modified by multiplying $A1_t^k$ by the number of shares outstanding for firm k. To remove the effect of outliers, we winsorize dollar-denominated earnings forecasts ($A1_t$ and $A2_t$ scaled by price), book values (scaled by price), and LTG_t at their 1st and 99th percentiles each month before aggregating them into portfolios.

Seasonality in earnings forecasts is alleviated by analyzing portfolios and the time series summation in Eq. (12). With firms having different fiscal year-ends, summing their earnings forecasts at the portfolio level may lead to a "non-synchronicity" problem whose impact on the cashflow component is alleviated by the time series summation in Eq. (12). In addition, at the annual horizon, earnings data may suffer from management's discretionary choices regarding the timing of accruals and other potential accounting manipulations, as shown in Teoh, Welch, and Wong (1998). However, earnings management exerts a negligible impact on the cashflow component since this aggregate sum operates over an (infinite) array of future cashflows.

Once changes in expected cashflow are determined, the earnings beta can be defined in a straightforward fashion. Observe that Eq. (13), in conjunction with Eq. (11), enables revisions in analyst forecasts to be converted into cashflow innovations. Thus, we refer to these changes in expectations interchangeably throughout the remainder of the paper.

3.2. *Definition of earnings beta*

Once the cashflow component $N_{CF,t+\delta}$ is defined, earnings betas are estimated using the following regression:

$$N^i_{CF,t+\delta} = \alpha^i_{CF} + \beta^i_{CF} N^M_{CF,t+\delta} + \varepsilon^i_{t+\delta}, \tag{15}$$

where the i and M superscripts denote portfolio i and the market, respectively. The earnings beta β_{CF} measures the covariance between changes in the expected cashflow of a portfolio and these changes for the market. A higher β^i_{CF} implies that portfolio i has a greater sensitivity to fluctuations in the market's expected cashflows, hence greater systematic risk.

To analyze the relative importance of revised earnings expectations across different time horizons, and to ensure that our results are not driven by the mean-reversion assumption, cashflow innovations from the three-stage earnings growth model are decomposed into three components. Each component corresponds to a particular stage of the earnings growth model. The decomposition is then utilized to estimate the contribution of revisions in expected earnings within the first five years as well as the subsequent five-year horizon to the composite earnings betas. We begin by decomposing the cashflow innovations into three components:

$$N^{i,1}_{CF,t+\delta} = \sum_{j=0}^{4} \rho^j e_{t+\delta,t+j+1} - \sum_{j=0}^{4} \rho^j e_{t,t+j+1},$$

$$N^{i,2}_{CF,t+\delta} = \sum_{j=5}^{9} \rho^j e_{t+\delta,t+j+1} - \sum_{j=5}^{9} \rho^j e_{t,t+j+1},$$

$$N^{i,3}_{CF,t+\delta} = \sum_{j=10}^{\infty} \rho^j e_{t+\delta,t+j+1} - \sum_{j=10}^{\infty} \rho^j e_{t,t+j+1}, \tag{16}$$

where $N^{i}_{CF,t+\delta} = N^{i,1}_{CF,t+\delta} + N^{i,2}_{CF,t+\delta} + N^{i,3}_{CF,t+\delta}$. Three corresponding earnings betas are then defined as the respective covariances between these components and the cashflow innovations of the market. The sum of these earnings betas, $\beta^i_1 + \beta^i_2 + \beta^i_3$, equals the composite earnings beta β^i_{CF} in Eq. (15). Recall that a firm's expected accounting return converges to an economy-wide steady-state growth rate in the third stage. Thus, β^i_3 is a constant in the cross-section, while β^i_1 is independent of the mean-reversion assumption.

4. Empirical results

Having derived earnings betas and described their estimation, this section focuses on the ability of our cashflow risk measure to explain the value premium, size premium, and long-term return reversals. We also examine whether our earnings beta reflects exposure to macroeconomic risk.

4.1. Earnings betas across portfolios

The average equally weighted monthly returns across 30 book-to-market, size, and long-term return reversal portfolios are reported in Panel A of Table 2. We observe a considerable value premium in our sample as average returns increase almost monotonically with a portfolio's book-to-market ratio. The return spread between the portfolio with the highest and lowest book-to-market ratio is 0.68% per month. The size premium is also present in our sample, with the smallest stocks earning an additional 0.29% per month.[10] Furthermore, the return spread between past long-term losers and past long-term winners averages 0.47% per month.

We also evaluate the stationarity of the monthly cashflow innovations using the Augmented Dickey-Fuller (ADF) test with a constant and one lag. The t-values from this test are reported in Panel A of Table 2. With a critical value of -3.99 at the 1% confidence level, a unit root in the portfolio-level cashflow innovations is overwhelmingly rejected. Using the Ljung-Box Q statistic, we also test for autocorrelation in the portfolio-level cashflow innovations. The associated p-values from this statistic are higher than 0.05 for all but one portfolio (29 out of 30). Thus, they reject the presence of autocorrelation in the portfolio-level cashflow innovations. Augmented Dickey-Fuller and Ljung-Box (LB) statistics also confirm that the market's cashflow innovations are stationary and serially uncorrelated. Overall, cashflow innovations computed using analyst forecast revisions are not predictable based on their lagged values.[11]

Fig. 1 records the cashflow innovations of the portfolios that define the value premium, size premium, and long-term return reversals during our sample period. For comparative purposes, the market's cashflow innovations are also graphed. The monthly cashflow innovations from Eq. (13) are averaged within rolling five-month windows for ease of interpretation. A simple visual inspection of Fig. 1 reveals that the cashflow innovations of value stocks, small stocks, and past long-term losers comove more with the market's cashflow innovations than the cashflow innovations of growth stocks, large stocks, and past long-term winners. Consequently, value stocks, small stocks, and past long-term losers are expected to have higher earnings betas that reflect their higher cashflow risk.

We report the estimated earnings betas in Panel A of Table 2. The t-values are computed using the Newey-West formula with 12 lags to account for any possible autocorrelation in the errors. Consistent with Fig. 1, value stocks have significantly higher earnings beta estimates than growth stocks, 1.12 versus 0.43, with this difference being highly significant (t-value of 3.25). The difference across the earnings beta estimates of the size portfolios is also significant (t-value of 2.19), with the small stock portfolio having an earnings beta estimate of 1.14 in comparison to 0.83 for the large stock portfolio. Furthermore, past long-term losers have an earnings beta estimate of 1.20 while past long-term winners have a smaller earnings beta estimate of 0.42. Once again, this difference is highly significant (t-value of 5.65).

The first two components of our earnings betas are also reported. The β_1 and β_2 estimates correspond respectively to the first five-year stage and second five-year stage of our three-stage earnings growth model. These components exhibit a similar pattern to the composite earnings betas. Recall that β_1 is independent of the mean-reversion assumption since the first stage of our earnings growth model is defined directly by revisions in analyst forecasts. The β_1 estimates confirm that our composite earnings betas are not driven by the assumption of mean-reverting earnings growth. The β_2 components parallel the β_1 components with less dramatic variation across portfolios. By construction, β_3 cannot explain cross-sectional return variation and simply reflects the equity market's cashflow risk.

[10] Recall that our sample is orientated towards large firms, and these firms are also required to have $A1_t$, $A2_t$, and LTG_t forecasts.

[11] Although a small positive average cashflow innovation of 0.0050 is observed for the market, this translates into a one-period expected log accounting return below 0.025% ($0.0050 \times (1-\rho)$). A portion of this accounting return may originate from earnings forecasts having a positive mean if analysts are less likely to revise their earnings forecasts downwards.

Table 2
Earnings betas.

This table reports the earnings betas denoted β_{CF}^{i} across book-to-market, size, and long-term return reversal portfolios. These covariances are estimated using Eq. (15), $N_{CF,t+\delta}^{i}=\alpha_{CF}+\beta_{CF}^{i}N_{CF,t+\delta}^{M}+\varepsilon_{t+\delta}^{i}$, where N_{CF}^{i} and N_{CF}^{M} denote the cashflow innovations of portfolio i and the market, respectively. In Panel A, the earnings beta estimates are reported for each book-to-market, size, and past long-term return portfolio, along with their respective returns. The earnings beta denoted β_1 corresponds to the first five-year stage of our earnings growth model while β_2 corresponds to its second five-year stage. The t-values (in italics) associated with these estimates are computed using the Newey-West formula with 12 lags. ADF and LB denote the test statistic and p-value from applying the Augmented Dickey-Fuller and Ljung-Box procedures to a portfolio's cashflow innovations. The ADF critical value is −3.99 for the 1% confidence level. Panel B contains the results of the cross-sectional regression in Eq. (17), $r_{t+\delta}^{i}-rf_t=\lambda_0+\lambda_1\beta_{CF}^{i}+\varepsilon_{t+\delta}^{i}$, which is conducted on 30 book-to-market, size, and past long-term return portfolios. The dependent variable $r_{t+\delta}^{i}$ represents the realized return for a particular portfolio while rf_t denotes the risk-free rate over the same monthly horizon. The robust t-value in Panel B accounts for estimation error in the earnings betas.

Panel A: Portfolio returns and earnings betas

	Value	2	3	4	5	6	7	8	9	Growth	(1–10)
Monthly return	1.66%	1.41%	1.45%	1.49%	1.36%	1.30%	1.24%	1.22%	1.10%	0.98%	
ADF	−21.21	−22.25	−19.55	−21.95	−21.18	−20.76	−19.76	−19.96	−20.73	−21.71	
LB p-value	0.475	0.998	0.828	0.994	0.613	0.325	0.025	0.202	0.544	0.674	
β_1	0.24	0.13	0.17	0.10	0.12	0.07	−0.04	0.00	−0.10	−0.24	
β_2	0.23	0.13	0.14	0.09	0.10	0.08	0.03	0.07	0.04	0.04	
Earnings beta	1.12	0.90	0.95	0.83	0.86	0.79	0.63	0.71	0.58	0.43	0.68
Newey-West t-value	*9.24*	*13.19*	*8.00*	*13.70*	*17.08*	*14.44*	*12.87*	*12.13*	*7.33*	*3.15*	*3.25*

	Small	2	3	4	5	6	7	8	9	Large	(1–10)
Monthly return	1.43%	1.23%	1.24%	1.21%	1.13%	1.27%	1.20%	1.30%	1.27%	1.14%	
ADF	−20.99	−21.71	−21.39	−19.48	−19.45	−20.74	−20.23	−21.30	−20.20	−21.09	
LB p-value	0.656	0.880	0.792	0.176	0.198	0.853	0.407	0.747	0.291	0.740	
β_1	0.21	0.07	0.14	0.10	0.08	0.12	0.11	0.05	0.10	0.10	
β_2	0.29	0.16	0.21	0.19	0.16	0.17	0.15	0.10	0.10	0.09	
Earnings beta	1.14	0.86	0.99	0.93	0.88	0.92	0.90	0.78	0.84	0.83	0.31
Newey-West t-value	*7.89*	*12.02*	*13.34*	*13.91*	*10.91*	*12.88*	*11.85*	*13.14*	*17.06*	*23.29*	*2.19*

	Loser	2	3	4	5	6	7	8	9	Winner	(1–10)
Monthly return	1.50%	1.40%	1.37%	1.42%	1.39%	1.40%	1.37%	1.31%	1.18%	1.03%	
ADF	−22.74	−21.24	−21.66	−23.45	−22.37	−21.17	−21.66	−19.678	−22.55	−21.55	
LB p-value	0.990	0.897	0.987	0.749	0.917	0.653	0.975	0.242	0.946	0.305	
β_1	0.33	0.16	0.16	0.15	0.12	0.14	0.08	0.03	−0.05	−0.24	
β_2	0.23	0.13	0.12	0.11	0.09	0.10	0.09	0.05	0.05	0.02	
Earnings beta	1.20	0.94	0.93	0.91	0.86	0.89	0.81	0.73	0.64	0.42	0.78
Newey-West t-value	*12.77*	*11.95*	*12.81*	*12.35*	*13.14*	*16.08*	*10.11*	*12.70*	*6.49*	*3.63*	*5.65*

Panel B: Fama-MacBeth regression on 30 test portfolios

	λ_0	λ_1	Adj. R^2
Estimate	0.0037	0.0063	55.1%
Robust t-value	*0.84*	*2.05*	

To summarize, variation in our earnings beta across book-to-market, size, and long-term return reversal portfolios is consistent with their return variation. This finding suggests that cashflow risk, measured using earnings forecast revisions, provides a partial explanation for the value premium, size premium, and long-term return reversals. The next subsection conducts a cross-sectional regression to formalize the relationship between cashflow risk and average returns.

4.2. *Cross-sectional regression*

Cross-sectional regressions involving 30 book-to-market, size, and long-term reversal portfolios confirm the economic importance of our earnings betas. These cross-sectional regressions involve the β_{CF}^{i} coefficients estimated from Eq. (15),

$$r_{t+\delta}^{i}-rf_t=\lambda_0+\lambda_1\beta_{CF}^{i}+\varepsilon_{t+\delta}^{i}. \tag{17}$$

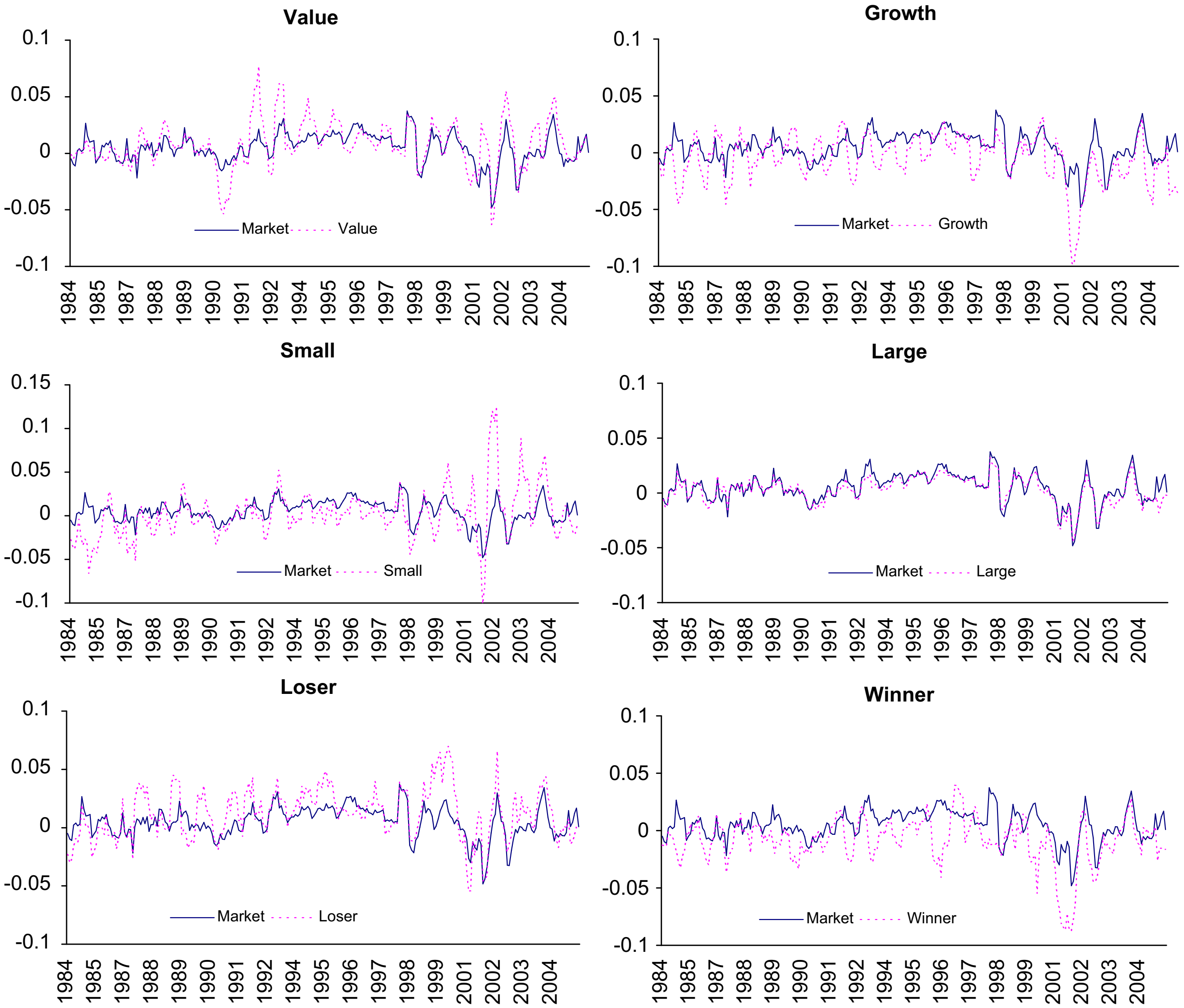

Fig. 1. This figure plots the cashflow innovations of each portfolio that define the value premium, size premium, and long-term return reversals. The cashflow innovations of the market are also reported for comparison. For ease of interpretation, the cashflow innovations are averaged within rolling five-month intervals, from 1984 until 2005. Cashflow innovations are computed each month as

$$N_{CF,t+\delta} = E_{t+\delta}\sum_{j=0}^{\infty}\rho^j e_{t+j+1} - E_t\sum_{j=0}^{\infty}\rho^j e_{t+j+1}$$

according to Eq. (13). A three-stage earnings growth model implies

$$E_t\sum_{j=0}^{\infty}\rho^j e_{t+j+1} \quad \text{equals} \quad \sum_{j=0}^{9}\rho^j e_{t,t+j+1} + \frac{\rho^{10}}{1-\rho}\log\left(1+\frac{g_t}{1-\psi}\right)$$

with the expected log accounting return $e_{t,t+j+1}$ being

$$\log\left(1+\frac{X_{t,t+j+1}}{B_{t,t+j}}\right) \quad \text{for } 0 \le j \le 9$$

and

$$\log\left(1+\frac{g_t}{1-\psi}\right) \quad \text{for } j \ge 10.$$

$X_{t,t+j+1}$ represent earnings expectations in year t for year $t+j+1$ and are defined using analyst forecasts for the current year, subsequent year, and long-term. $B_{t,t+j}$ denotes the expectation in year t of book value in year $t+j$ while g_t and ψ denote a steady-state growth rate and payout rate that are common to all stocks. Our sample of analyst earnings forecasts is obtained from the Institutional Broker's Estimate System (IBES) Summary unadjusted file. A total of 545,165 firm-month observations are available from 1984 to 2005.

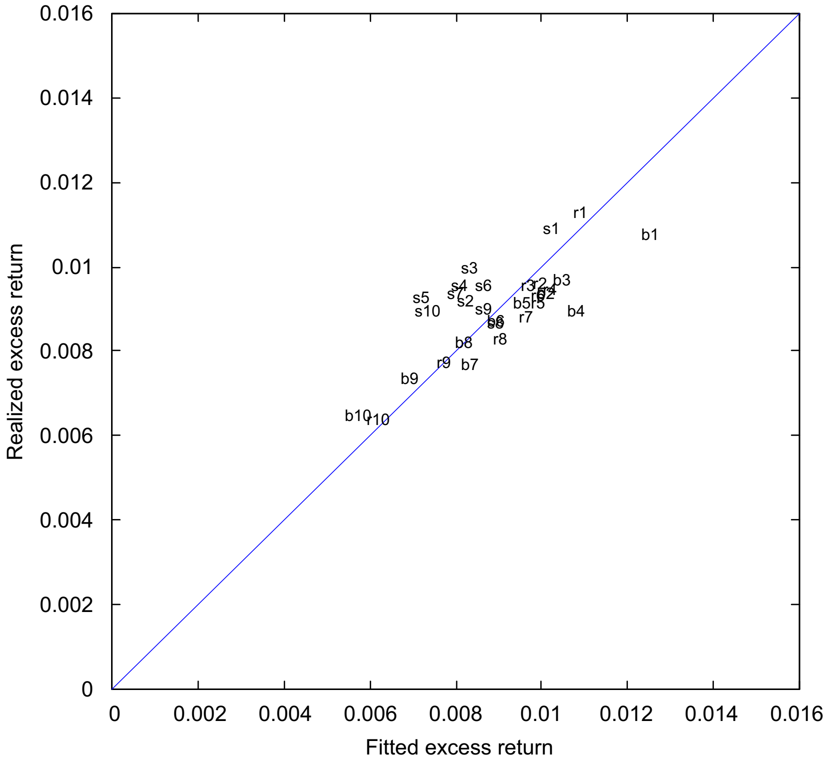

Fig. 2. This figure graphs the average realized monthly return for 10 book-to-market, 10 size, and 10 past long-term return portfolios against their predicted (fitted) returns. The predicted returns are computed using Eq. (17), $r^i_{t+\delta} - rf_t = \lambda_0 + \lambda_1 \beta^i_{CF} + \varepsilon^i_{t+\delta}$, where the dependent variable $r^i_{t+\delta}$ represents the realized return for a particular portfolio while rf_t denotes the risk-free rate over the same monthly horizon. The earnings beta β^i_{CF} captures the comovement between the cashflow innovations of portfolio i and those of the market. The predicted returns are computed using the earnings beta estimates from Table 2 for β^i_{CF}. b1 (b10) denotes the portfolio returns for stocks with the highest (lowest) book-to-market ratios, s1 (s10) denotes the portfolio returns for stocks with the smallest (largest) market capitalizations, and r1 (r10) denotes the portfolio returns for stocks with the lowest (highest) long-term past returns. The adjusted R^2 from this regression is 55.1%. The sample period is from 1984 to 2005.

The dependent variable $r^i_{t+\delta}$ represents the realized return for a particular portfolio while rf_t denotes the risk-free rate over the same monthly horizon.

The λ_1 estimate is positive (63 bp per month), with a t-value of 2.05, indicating that higher earnings betas imply higher returns. Robust t-values are computed using standard errors from a generalized method of moments (GMM) procedure to account for the estimation error in the earnings beta estimates. Moment conditions from both the time series and cross-sectional regressions are stacked into a one-stage GMM system. These moment conditions are chosen to ensure the resulting GMM system produces point estimates identical to those from an ordinary least squares (OLS) regression using average returns. The covariance matrix for the moment conditions is computed using a Newey-West adjustment with 12 lags. Thus, the resulting robust t-values account for estimation errors in the cross-section and across time.[12] Without accounting for estimation error in β^i_{CF}, the t-value for the λ_1 coefficient is more than twice as large.

The results from this cross-sectional regression in Panel B of Table 2 indicate that the R^2 from Eq. (17) equals 55.1%. Thus, over half of the cross-sectional variation in the value premium, size premium, and long-term return reversal is attributable to cashflow risk measured using analyst forecast revisions. In addition, the risk premium derived from exposure to our earnings betas is significant while the intercept term is insignificant. The unexplained return variation may be attributable to changes in expected discount rates that are not modeled in this paper. Fig. 2 plots the realized average monthly returns for the 30 book-to-market, size, and long-term return reversal portfolios against their predicted returns according to Eq. (17) and the estimates from Table 2. This plot illustrates the ability of our earnings betas to describe cross-sectional return variation.

Our empirical results indicate that cashflow risk is an important determinant of cross-sectional return variation when this risk is measured using revisions in analyst earnings forecasts. For risk-averse long-term investors who hold the market portfolio, small value stocks with low past returns are required to earn higher returns than large growth stocks with high past returns since changes in their expected cashflow have a higher covariance with marketwide fluctuations. Thus, our earnings beta implies that the value premium, size premium, and long-term return reversals are partially attributable to systematic cashflow risk.

[12] Details of this procedure are found on pages 240–243 of Cochrane (2001).

Finally, in unreported results, our earnings beta cannot explain momentum. This finding is not surprising for several reasons. First, Hong, Lim, and Stein (2000) report that this anomaly is weaker among stocks with analyst coverage, making our sample of firms less conducive to investigating momentum. Indeed, the return variation across portfolios formed according to returns over the prior year is very small in our sample. Second, as argued in Campbell and Vuolteenaho (2004), cashflow risk is important for long-term investors whose holding periods exceed those of momentum strategies. Third, extreme recent losers are often associated with negative earnings forecasts for the next two years, which complicates the computation of forecasted earnings growth and cashflow risk for these stocks.

4.3. Macroeconomic risk

Flannery and Protopapadakis (2002) conclude that changes in the real economy simultaneously affect the cashflows of many firms. This subsection provides evidence that exposure to the macroeconomy is captured by our earnings beta.

Our choice of macro state variables is motivated by the prior literature. Patelis (1997) and Sharpe (2002) report that inflation has important implications for cashflow expectations. Feldstein (1980) finds a negative relationship between inflation and aggregate stock returns due to the taxation of capital gains. Although Fama (1990) proxies for expected discount rates using the credit spread and term spread, fluctuations in these variables also alter the future earnings of levered firms. Indeed, the evidence in Chen (1991) shows that changing expectations of future economic activity are manifested in the credit spread and term spread.[13] Fama (1990) proxies for changes in expected cashflow directly using growth in industrial production. A survey compiled by the Chicago Federal Reserve provides a forward-looking indicator of national economic activity abbreviated CFNAI hereafter that generalizes industrial production. This normalized variable represents a weighted average of 85 different macroeconomic variables, with details in Stock and Watson (1999). For completeness, we also include personal consumption given Breeden's (1979) consumption-based capital asset pricing model and housing starts as a proxy for long-term consumer confidence. Finally, we examine an indicator variable denoted Recession for economic contractions defined by the National Bureau of Economic Research (NBER).

To summarize, the macro variables in our analysis include the national activity indicator constructed by the Chicago Federal Reserve (CFNAI), inflation (yield on Treasury bills), credit spread (Credit, Baa yield minus Aaa yield), term spread (Term, 10-year Treasury bond yield minus short-term Treasury yield), housing starts (Housing), personal consumption (Consumption), and a recession indicator (Recession). Monthly data are obtained from the Federal Reserve (Inflation, Credit, Term), US Census (Housing), and the Bureau of Economic Analysis (Consumption). We then compute changes in the macro variables.[14] The correlations among these variables are low, which mitigates the influence of multicollinearity. Fama (1990) highlights the empirical complications arising from multicollinearity when studying the real economy's influence on stock returns.

Proxies for economic activity are predicted to be positively related with market-level cashflow expectations. In contrast, higher credit and term spreads as well as inflation are expected to reduce aggregate expected cashflow. After regressing market-level cashflow innovations on the set of macro variables, the results in Panel A of Table 3 confirm that CFNAI is positively related to market-level cashflow innovations while the regression coefficients for inflation and the credit spread are negative. The NBER indicator variable for a recession is also negative, which is consistent with reductions in expected cashflow during economic contractions. The macro variables explain about 10% of the variation in market-level cashflow innovations.

To examine which macro variables are responsible for cross-sectional variation in the earnings betas, we also regress portfolio-level cashflow innovations on the set of macro variables. These regressions capture cross-sectional variation across the sensitivity of portfolio-level cashflow innovations to the macroeconomy. As reported in Panel B of Table 3, the cashflow innovations of value stocks, small stocks, and past losers are negatively correlated with inflation while the cashflow innovations of growth stocks, large stocks, and past winners are positively correlated with inflation. The differences between these sensitivities are significant. Intuitively, inflation appears to be detrimental to the expected cashflow of value stocks, small stocks, and past losers. Conversely, the expected (nominal) cashflows from growth firms, large firms, and past winners increase with inflation, which suggests that these firms are in a better position to protect their margins. Feldstein (1980) also demonstrates that inflation lowers after-tax earnings under historical-cost accounting by reducing the value of depreciation. With value firms having proportionately larger book values, they experience greater reductions in after-tax cashflow as a consequence of inflation. Overall, when combined with the negative sensitivity of market-level cashflow innovations to inflation, cross-sectional differences in the inflation sensitivities are consistent with cross-sectional variation in the earnings betas reported in Table 2.

Panel B of Table 3 also indicates that the cashflow innovations of past losers are more negatively correlated with the credit spread than the cashflow innovations of past winners. The difference in their sensitivities is significant (t-value of −2.10). Intuitively, consistent with an increase in leverage, stocks with poor past returns suffer greater reductions in expected cashflow as a result of higher credit spreads. In addition, the expected cash-

[13] Chan, Chen, and Hsieh (1985) relate the size premium directly to the credit spread.

[14] Our results are robust to using macro innovations computed from AR(p) and ARMA(p,q) models.

Table 3
Macroeconomic risk.

This table reports on the importance of macroeconomic state variables to cashflow risk. Panel A reports the results from regressing market-level cashflow innovations on the national economic activity index from the Chicago Federal Reserve (CFNAI), Treasury bill yield (Inflation), credit spread (Credit), term spread (Term), housing starts (Housing), personal consumption (Consumption), and an indicator variable (Recession) for economic contractions as defined by the National Bureau of Economic Research (NBER). This regression is then repeated for the portfolio-level cashflow innovations. The *t*-value (in italics) for each regression coefficient is computed using the Newey-West formula with 12 lags. For brevity, Panel B only reports the cashflow sensitivity coefficients of the six portfolios that define the value premium, size premium, and long-term return reversals along with the difference between the cashflow sensitivities of these portfolios.

Panel A: Market-level cashflow innovations

	CFNAI	Inflation	Credit	Term	Housing	Consumption	Recession
Coefficient	0.0091	−0.0791	−0.0186	−0.0006	0.0106	−0.0022	−0.0237
t-value	*2.84*	*−2.32*	*−3.37*	*−1.13*	*0.93*	*−0.67*	*−3.35*

Panel B: Portfolio-level cashflow innovations

	CFNAI	Inflation	Credit	Term	Housing	Consumption	Recession
Value	0.0131	−3.0346	−0.0227	−0.0002	0.0294	−0.0001	−0.0322
	2.55	*−2.27*	*−2.52*	*−0.50*	*1.95*	*−0.04*	*−2.77*
Growth	0.0119	1.9328	−0.0161	0.0000	0.0251	0.0024	−0.0338
	1.74	*1.75*	*−2.13*	*−0.01*	*1.80*	*0.48*	*−1.30*
Value–growth	0.0012	−4.9674	−0.0066	−0.0002	0.0042	−0.0025	0.0015
	0.13	*−3.71*	*−0.57*	*−0.24*	*0.29*	*−0.43*	*0.04*
Small	0.0017	−5.8584	−0.0155	−0.0002	0.0705	−0.0046	−0.0283
	0.39	*−3.08*	*−0.82*	*−0.26*	*2.41*	*−0.88*	*−2.11*
Large	0.0086	0.7124	−0.0168	−0.0005	−0.0003	−0.0017	−0.0226
	2.72	*0.85*	*−3.04*	*−1.00*	*−0.03*	*−0.52*	*−3.07*
Small–large	−0.0070	−6.5708	0.0013	0.0003	0.0708	−0.0030	−0.0057
	−0.91	*−3.37*	*0.07*	*0.43*	*2.76*	*−0.73*	*−0.42*
Loser	0.0100	−2.7151	−0.0282	−0.0009	−0.0049	−0.0043	−0.0320
	2.03	*−2.02*	*−3.34*	*−1.08*	*−0.23*	*−0.79*	*−2.98*
Winner	0.0142	0.1013	−0.0073	−0.0008	−0.0084	−0.0035	−0.0402
	2.01	*0.09*	*−0.90*	*−1.17*	*−0.55*	*−0.86*	*−1.67*
Loser–winner	−0.0043	−2.8164	−0.0209	−0.0001	0.0036	−0.0008	0.0082
	−0.71	*−1.94*	*−2.10*	*−0.14*	*0.17*	*−0.15*	*0.43*

flows from small stocks are more sensitive to housing starts than the expected cashflows from large stocks, with the difference having a t-value of 2.76. As housing starts proxy for long-term consumer confidence, this result suggests that the expected cashflows from small stocks are more sensitive to consumer confidence.

While changing expectations of future economic activity are critically important to time series variation in the market-level cashflow innovations, CFNAI cannot explain cross-sectional variation among the portfolio-level cashflow innovations. The inability of the recession dummy variable to explain cross-sectional differences in cashflow risk is not surprising as the US economy only experienced two minor economic contractions during our sample period, each lasting eight months. Interestingly, unreported results show that value stocks experience a greater decline in expected cashflow than growth stocks in the six-to nine-month periods before these recessions.

In summary, the ability of our earnings beta to explain the value premium, size premium, and long-term return reversals appears to originate from different portfolio-level exposures to the real economy.

5. Robustness checks and additional results

This section presents the results from a battery of robustness tests. These tests confirm that our conclusions regarding cashflow risk are not driven by poor statistical inferences associated with a small sample, a specific sample period, a specific weighting scheme, assumptions regarding firm-level cashflow payout rates, nor analyst forecast biases that are predictable using firm characteristics. In addition, we also compare our approach to an alternative methodology that estimates cashflow risk using a vector autoregression (VAR) for expected returns.

5.1. Bootstrap simulation

The robust t-values estimated in our cross-sectional analysis are derived using asymptotic statistics and could be imprecise due to a small sample size. Lewellen, Nagel, and Shanken (2007) emphasize the importance of simulation to determine the power (confidence interval) of test statistics such as R^2. To examine the finite-sample empirical distribution for the intercept λ_0, the risk premiums λ_1 on the earnings beta, and the cross-sectional regression R^2, we implement two simulations that parallel the experiments in Bansal, Dittmar, and Lundblad (2005). These simulations bootstrap the cashflow innovations from their empirical distributions, which are often non-normal, and confirm that our empirical results reflect economic content rather than random chance.

The first bootstrap simulation is conducted under the alternative hypothesis that the one-factor earnings beta model in Eq. (17) is incorrect by bootstrapping market-level cashflow innovations ($N^M_{CF,t+\delta}$). We then regress observed portfolio-level cashflow innovations ($N^i_{CF,t+\delta}$) on each of the 10,000 bootstrapped market-level cashflow innovations to estimate an earnings beta for each portfolio. Next, observed average excess returns for the 30 portfolios are regressed on these earnings beta estimates. This procedure is repeated 10,000 times. By construction, the distribution of the earnings betas is centered at zero since the bootstrapped cashflow innovations of the market are uncorrelated with those of the 30 portfolios. Consequently, the risk premium on the earnings betas should equal zero, the regression intercept term should equal the average excess return in the cross-section (0.0090 per month), and the R^2 of the cross-sectional regression should also equal zero.

The result of the first bootstrap simulation is presented in Panel A of Table 4. The risk premium of our earnings beta is estimated with considerable error, but its distribution is centered at zero. The point estimate of 0.0063 in Panel B of Table 2 for λ_1 is close to the 95th percentile of the simulated distribution. Furthermore, the cross-sectional R^2 and adjusted R^2 both exceed their 97.5th percentiles. Conversely, the point estimate on the regression intercept equals 0.0037, and is below the 5th percentile of its simulated distribution. These results indicate that the magnitude of the regression intercept, risk premium, and cross-sectional R^2 we extract from the data are extremely unlikely if the one-factor earnings beta model is incorrect. Thus, the relationship we report between our earnings betas and portfolio returns is unlikely to result from chance.

The second bootstrap simulation is conducted under the null hypothesis that the one-factor earnings beta model is correct. To simulate the earnings betas, we consider the relationship

$$N^i_{CF,t+\delta} = \alpha^i_{CF} + \beta^i_{CF} N^M_{CF,t+\delta} + \varepsilon^i_{t+\delta}. \tag{18}$$

Once again, we bootstrap market-level cashflow innovations ($N^M_{CF,t+\delta}$) from their empirical distribution. We also block-bootstrap error terms ($\varepsilon^i_{t+\delta}$) from the empirical distribution of each portfolio's residuals. Each time series of bootstrapped $\varepsilon^i_{t+\delta}$, when combined with the estimated intercept terms (α^i_{CF}) and the estimated earnings betas β^i_{CF} along with the bootstrapped market cashflow innovations, yields a time series of bootstrapped cashflow innovations for portfolio i according to Eq. (18). These bootstrapped portfolio-level cashflow innovations are then regressed on the original bootstrapped market-level cashflow innovations to estimate bootstrapped earnings betas. Finally, average excess returns are computed from the one-factor earnings beta model whose error term is bootstrapped from its empirical distribution. This procedure is repeated 10,000 times.

The result of the second bootstrap simulation is presented in Panel B of Table 4. Due to the estimation error in the earnings betas, the corresponding risk premium estimates are biased towards zero. Consequently, the R^2 estimates are also biased below their population value of one. The fact that these statistics are biased towards zero, even under the null hypothesis, suggests that our previously reported cashflow risk premium λ_1 and R^2 estimates are understated. Finally, the estimated risk premiums are generally positive, which indicates that the relationship between cashflow risk and

Table 4
Bootstrap simulations.

This table reports the empirical distributions of our parameter estimates. Panel A reports these distributions under the alternative hypothesis that the one-factor earnings beta model is incorrect. In particular, market-level cashflow innovations are obtained from a bootstrap procedure that randomly draws them from their empirical distribution. Observed portfolio-level cashflow innovations are then regressed on the bootstrapped market-level cashflow innovations, as in Eq. (17), $r^i_{t+\delta} - rf_t = \lambda_0 + \lambda_1 \beta^i_{CF} + \varepsilon^i_{t+\delta}$. The dependent variable $r^i_{t+\delta}$ represents the realized return for portfolio i while rf_t denotes the risk-free rate over the same monthly horizon. The λ_1 estimate and R^2 of this regression are identically zero under the alternative hypothesis since the bootstrapped market-level cashflow innovations are uncorrelated with the observed portfolio-level cashflow innovations, while λ_0 equals the average monthly return (0.0090) of the portfolios. Panel B reports the parameter distributions under the null hypothesis that the one-factor earnings beta model is correct. Under the null hypothesis, bootstrapped market-level cashflow innovations are combined with bootstrapped error terms $\varepsilon^i_{t+\delta}$ along with our original cashflow beta estimates and intercept estimates to form bootstrapped portfolio-level cashflow innovations, $N^i_{CF,t+\delta} = \alpha^i_{CF} + \beta^i_{CF} N^M_{CF,t+\delta} + \varepsilon^i_{t+\delta}$, as in Eq. (18). The $\varepsilon^i_{t+\delta}$ errors are block-bootstrapped from their empirical distribution. These bootstrapped portfolio-level cashflow innovations are then regressed on the bootstrapped market-level cashflow innovations to obtain earnings beta estimates. Under the null hypothesis, λ_1 and λ_0 equal their values in Panel B of Table 2, while the regression R^2 equals one. Both bootstrap experiments consist of 10,000 runs.

	Alternative hypothesis	Percentiles						
		2.5%	5.0%	10.0%	50.0%	90.0%	95.0%	97.5%
Regression intercepts (λ_0)	0.0090	0.0054	0.0058	0.0063	0.0079	0.0097	0.0103	0.0108
Risk premiums on earnings beta (λ_1)	0.0000	−0.0070	−0.0062	−0.0053	0.0002	0.0056	0.0064	0.0071
R^2	0.000	0.000	0.001	0.005	0.113	0.387	0.451	0.505
Adj R^2	*−0.036*	*−0.035*	*−0.035*	*−0.031*	*0.081*	*0.365*	*0.432*	*0.487*
	Null hypothesis	Percentiles						
		2.5%	5.0%	10.0%	50.0%	90.0%	95.0%	97.5%
Regression intercepts (λ_0)	0.0037	−0.0010	−0.0005	0.0001	0.0024	0.0049	0.0056	0.0062
Risk premiums on earnings beta (λ_1)	0.0063	0.0038	0.0041	0.0045	0.0060	0.0077	0.0084	0.0089
R^2	1.000	0.343	0.381	0.422	0.558	0.677	0.710	0.741
Adj R^2	*1.000*	*0.320*	*0.359*	*0.401*	*0.542*	*0.665*	*0.700*	*0.731*

returns can be recovered from the data despite its imprecision.

5.2. Alternative implementations and subperiods

To ensure that our results are not limited to equally weighted cashflows, we also value weight the cashflow forecasts within the portfolios. Value weighting is achieved by modifying Eq. (14) as follows:

$$A1_t = \sum_{k=1}^{m} A1_t^k N_t^k, \tag{19}$$

where m denotes the number of stocks in a portfolio and N_t^k denotes the number of shares outstanding at time t for firm k. We also examine our earnings betas over two subperiods: 1984–1994 and 1995–2005. In the interest of brevity, Panels A1 and A2 of Table 5 only contain the earnings betas for the portfolios that define the value premium, size premium, and long-term return reversals. For both weighting schemes and during both subperiods, value stocks, small stocks, and past long-term losers have higher earnings betas than growth stocks, large stocks, and past long-term winners, with slightly smaller spreads in the second subperiod. These differences are all significant. In general, value weighting produces earnings betas with less variation across the book-to-market, size, and long-term return reversal portfolios.

To ensure that our results are not driven by our assumed payout rate, different ψ values are also studied. Panel A3 of Table 5 reports that ψ values of 2% and 10% yield almost identical earnings betas. We also examine an alternative payout assumption in which firms retain a fixed fraction (retention rate) of their current earnings and pay out the remainder. As shown in Panel A4 of Table 5, the earnings beta estimates are qualitatively very similar under this alternative payout assumption. Increasing the retention rate from 20% to 80% leads to a slight increase in the earnings beta of the growth and past loser portfolios, from 0.26 to 0.39 and from 1.08 to 1.17, respectively, but produces nearly identical cashflow beta estimates for the other portfolios. In unreported results, the earnings betas of the intermediate portfolios are also insensitive to different payout assumptions.

Book-to-market and size double-sorted portfolios often appear in empirical asset pricing tests. As a robustness check, we form 4-by-4 book-to-market and size double-sorted portfolios and estimate their earnings betas. Comparing Panel B1 to B2 in Table 5, cross-sectional variation in the earnings betas matches cross-sectional variation in average returns across these 16 portfolios. More formally, a cross-sectional regression of each double-sorted portfolio's average return on its respective earnings beta produces an adjusted R^2 of 74.1% and a positive cashflow risk premium.

5.3. Forecast biases

Our earnings beta is estimated using monthly revisions in analyst forecasts. Although analyst forecasts may be biased, computing monthly forecast revisions mitigates the impact of persistent forecast biases on the earnings betas. Nonetheless, analyst forecast biases can induce predictable forecast revisions. For example, Richardson, Teoh, and Wysocki (2004) report that analysts tend to revise their forecasts downward over time to mitigate the optimism in their initial forecasts. The results in Table 2 demonstrate that our cashflow innovations are not predictable using their own lags. This subsection uses a comprehensive list of firm characteristics associated with analyst forecast biases to further examine the predictability in our cashflow innovations.

Specifically, monthly portfolio-level cashflow innovations are regressed on firm characteristics (averaged within each portfolio to reduce noise) using a balanced panel regression:

$$N^i_{CF,t+\delta} = \gamma_0 + \gamma_1' X_{i,t} + \varepsilon_{i,t+\delta}, \tag{20}$$

where $X_{i,t}$ denotes the vector of firm characteristics for portfolio i in month t. These characteristics include *LTG* (long-term growth rate forecast); *FREV* (revisions in annual consensus forecast over the past six months normalized by price); *EP* (earnings-to-price ratios); *BP* (book-to-price ratios); *CAPEX* (capital expenditures to total assets); *TA* (total accruals to total assets); *SG* (prior sales growth); *SUE* (the most recent standardized earnings surprise); *RETP* (returns over the prior six months); *RET2P* (returns over the prior 12-to-six month horizon); *Size* (log market capitalization); *Cover* (analyst coverage); and *Disp* (dispersion in analyst forecasts). These characteristics are shown to be related to forecast biases in previous literature (LaPorta, 1996; Frankel and Lee, 1998; Jegadeesh, Kim, Krische, and Lee, 2004; Scherbina, 2004 and Hughes, Liu, and Su, 2008). *Cover* is defined as the number of analysts issuing an earnings forecast for the firm. *Disp* equals the standard deviation of earnings forecasts ($A1_t$) scaled by the absolute value of the mean earnings forecast, as in Diether, Malloy, and Scherbina (2002). Details of the remaining characteristics are in Appendix A of Jegadeesh, Kim, Krische, and Lee (2004).

The panel regression results are presented in Panel A of Table 6 with t-values computed using standard errors that are clustered by portfolio. *LTG*, *FREV*, *EP*, *CAPEX*, *SUE*, *RET2P*, *Size*, and *Cover* are significant in predicting cashflow innovations. Specifically, downward forecast revisions are more likely for small stocks and those with high *LTG* forecasts and high earnings-to-price ratios. Downward revisions are also more likely for stocks with prior downward revisions, poor returns, and negative earnings surprises. Thus, analysts appear to slowly incorporate past performance into their forecasts. However, the adjusted R^2 of the regression is small (4.5%), suggesting that our portfolio-level cashflow innovations are difficult to predict.

With the "true" revision in expected cashflow being unpredictable due to the law of iterated expectations, predictability in the cashflow innovations ($\gamma_1' X_{i,t}$) is likely induced by forecast biases rather than cashflow risk. This distinction allows us to decompose our earnings betas into predictable and unpredictable components. To examine whether the earnings betas are unduly influenced

Table 5

Robustness tests.

This table demonstrates the robustness of our earnings betas, which continue to be estimated from Eq. (15) as $N^i_{CF,t+\delta} = \alpha^i_{CF} + \beta^i_{CF} N^M_{CF,t+\delta} + \varepsilon^i_{t+\delta}$, where N^i_{CF} and N^M_{CF} denote the cashflow innovations of portfolio i and the market, respectively, while β^i_{CF} denotes the portfoio's earnings beta. Panel A reports the earnings beta estimates using cashflow innovations during two separate subperiods; from 1984 to 1994 and from 1995 to 2005, using equally weighted and value weighted portfolio-level cashflow innovations. Panel A also records earnings beta estimates under different book value payout rates that define the dividends underlying the return on equity in Eq. (7), and when dividends are defined by different earnings retention rates. Panel B reports the returns and earnings beta estimates for double-sorted portfolios formed from book-to-market and size quartiles. In addition, Panel B reports on the cross-sectional regression in Eq. (17), $r^i_{t+\delta} - rf_t = \lambda_0 + \lambda_1 \beta^i_{CF} + \varepsilon^i_{t+\delta}$, where the dependent variable $r^i_{t+\delta}$ represents the realized return from a double-sorted portfolio and rf_t denotes the risk-free rate over the same monthly horizon. The t-values (in italics) associated with the earnings beta estimates are computed using the Newey-West formula with 12 lags, while the robust t-value in Panel B accounts for their estimation error.

Panel A: Alternative weighting schemes and payout assumption in different subperiods

A1: Equally weighted earnings betas

1984 to 1994

	Value	Growth	Small	Large	Loser	Winner
Earnings beta	1.21	0.24	1.23	0.83	1.38	0.25
Newey-West t-value	*4.42*	*1.00*	*5.71*	*19.00*	*9.07*	1.48

1995 to 2005

	Value	Growth	Small	Large	Loser	Winner
Earnings beta	1.06	0.54	1.08	0.82	1.10	0.51
Newey-West t-value	*8.71*	*3.08*	*5.56*	*16.75*	*9.23*	*3.71*

A2: Value weighted earnings betas

1984 to 1994

	Value	Growth	Small	Large	Loser	Winner
Earnings beta	1.27	0.55	1.07	0.87	1.18	0.38
Newey-West t-value	*5.46*	*2.62*	*6.36*	*14.35*	*8.70*	*2.18*

1995 to 2005

	Value	Growth	Small	Large	Loser	Winner
Earnings beta	0.80	0.39	0.84	0.65	0.86	0.52
Newey-West t-value	*7.80*	*2.55*	*5.33*	*10.24*	*8.81*	*3.64*

A3: Alternative book value payout rates

$\psi = 2\%$

	Value	Growth	Small	Large	Loser	Winner
Earnings beta	1.10	0.43	1.12	0.83	1.19	0.42
Newey-West t-value	*9.42*	*3.06*	*8.10*	*23.30*	*12.86*	*3.56*

$\psi = 10\%$

	Value	Growth	Small	Large	Loser	Winner
Earnings beta	1.15	0.43	1.17	0.82	1.21	0.42
Newey-West t-value	*8.97*	*3.26*	*7.53*	*23.24*	*12.65*	*3.73*

A4: Alternative earnings retention rates

Retention rate = 20%

	Value	Growth	Small	Large	Loser	Winner
Earnings beta	1.02	0.26	1.08	0.84	1.08	0.38
Newey-West t-value	*16.31*	*2.17*	*12.75*	*21.81*	*15.73*	*4.70*

Retention rate = 80%

	Value	Growth	Small	Large	Loser	Winner
Earnings beta	1.07	0.39	1.10	0.83	1.17	0.40
Newey-West t-value	*10.48*	*2.84*	*8.94*	*22.95*	*13.32*	*3.57*

Panel B: BM/size double-sorted portfolios

Panel Bl: Portfolio returns

	Large	2	3	Small
Value	1.41%	1.55%	1.52%	1.62%
2	1.40%	1.36%	1.44%	1.50%
3	1.27%	1.31%	1.12%	1.34%
Growth	1.13%	1.23%	1.01%	0.93%

Panel B2: Earnings betas

	Large	2	3	Small
Value	1.02	0.97	1.00	1.13
2	0.84	0.87	0.77	0.80
3	0.72	0.67	0.57	0.70
Growth	0.55	0.39	0.40	0.49

Panel B3: Fama-MacBeth regression

	λ_0	λ_i	Adj R^2
Estimate	0.0036	0.0076	74.1%
Robust t-value	*0.67*	*1.95*	

Table 6
Analyst forecast biases.

This table reports on the decomposition of portfolio-level cashflow innovations into predictable and unpredictable components, with predictability attributable to analyst forecast biases. Panel A summarizes the results from the pooled regression in Eq. (20), $N^i_{CF,t+\delta} = \gamma_0 + \gamma_1' X_{i,t} + \varepsilon_{i,t+\delta}$ where N^i_{CF} denotes the cashflow innovations of portfolio i. The independent variables in $X_{i,t}$ include long-term analyst forecasts (*LTG*), revisions in the annual consensus forecast over the past six months normalized by price (FREV), earnings-to-price ratios (EP), book-to-price ratios (BP), capital expenditures to total assets (CAPEX), total accruals to total assets (TA), prior sales growth (SG), the most recent standardized earnings surprise (SUE), returns over the prior six months (RETP), returns over the prior 12-to-six month horizon (RET2P), size, analyst coverage (Cover), and analyst forecast dispersion (DISP). Panel B reports the earnings beta estimates in Eq. (21) for the predictable and unpredictable components of the portfolio-level cashflow innovations, $Cov(\gamma_1' X_{i,t}, N^M_{CF,t+\delta})/Var(N^M_{CF,t+\delta})$ and $Cov(\varepsilon_{i,t+\delta}, N^M_{CF,t+\delta})/Var(N^M_{CF,t+\delta})$, respectively. These components are defined relative to market-level cashflow innovations, N^M_{CF}. Panel C contains the results from a cross-sectional regression involving these two beta components and the average returns from 30 book-to-market, size, and past long-term return portfolios. These cross-sectional regressions parallel those in Eq. (17), $r^i_{t+\delta} - rf_t = \lambda_0 + \lambda_1 \beta^i_{CF} + \varepsilon^i_{t+\delta}$, where the dependent variable $r^i_{t+\delta}$ represents the realized return of portfolio i and rf_t denotes the risk-free rate over the same monthly horizon. The t-values (in italics) associated with the earnings beta estimates are Newey-West adjusted with 12 lags, while the robust t-values in Panel C account for their estimation error.

Panel A: Pooled regression for estimating the predictability in portfolio-level cashflow innovations

	Intercept	LTG	FREV	EP	BP	CAPEX	TA	SG	SUE	RETP	RET2P	Size	Cover	Disp	Adj R^2
Coefficient	−0.0065	−0.0024	0.2290	−0.0290	0.0054	0.2598	0.0710	0.0050	0.0090	−0.0002	0.0151	0.0051	−0.0225	0.0181	4.5%
t-value	*−0.58*	*−10.35*	*5.53*	*−2.23*	*1.27*	*6.57*	*1.64*	*0.78*	*7.15*	*−0.04*	*2.51*	*5.79*	*−9.02*	*1.54*	

Panel B: Earnings betas from unpredictable and predictable components

	Panel B1: Unpredictable component			Panel B2: Predictable component		
	Value	Growth	Difference	Value	Growth	Difference
Analyst earnings beta	1.05	0.38	0.67	0.07	0.05	0.02
Newey-West t-value	*8.71*	*2.59*	*2.96*	*2.81*	*1.93*	*0.43*
	Small	Large	Difference	Small	Large	Difference
Analyst earnings beta	1.10	0.80	0.29	0.04	0.02	0.02
Newey-West t-value	*7.94*	*22.88*	*2.19*	*2.41*	*2.09*	*0.96*
	Loser	Winner	Difference	Loser	Winner	Difference
Analyst earnings beta	1.12	0.34	0.78	0.07	0.08	0.00
Newey-West t-value	*11.91*	*3.21*	*5.83*	*4.54*	*2.71*	*−0.10*

Panel C: Fama-MacBeth regression on 30 portfolios

	Panel C1: Unpredictable component			Panel C2: Predictable component		
	λ_0	λ_1	*Adj* R^2	λ_0	λ_1	*Adj* R^2
Estimate	0.0042	0.0061	52.4%	0.0078	0.0237	0.2%
Robust t-value	*0.97*	*2.05*		*2.71*	*0.93*	

by forecast biases, we decompose the earnings betas as follows:

$$\beta^i_{CF} = \frac{Cov(N^i_{CF,t+\delta}, N^M_{CF,t+\delta})}{Var(N^M_{CF,t+\delta})} = \frac{Cov(\gamma'_1 X_{i,t}, N^M_{CF,t+\delta})}{Var(N^M_{CF,t+\delta})} + \frac{Cov(\varepsilon_{i,t+\delta}, N^M_{CF,t+\delta})}{Var(N^M_{CF,t+\delta})}. \quad (21)$$

These two components are reported for the 30 test portfolios separately in Panel B of Table 6. Panel B confirms that the unpredictable component of the cashflow innovations produces earnings betas that continue to explain the value premium, size premium, and long-term return reversals. In contrast, the predictable component of the cashflow innovations produces earnings betas that are insignificantly different across the book-to-market, size, and long-term return reversal portfolios. With the predictable component of the cashflow innovations reflecting time-varying forecast biases, the results in Panel B suggest that variation in forecast biases is not responsible for our earnings beta's ability to explain cross-sectional return variation. The cross-sectional regression results in Panel C of Table 6 verify this assertion as the earnings beta computed using unpredictable cashflow innovations continues to explain more than 52% of the variation in average returns across the 30 portfolios. Furthermore, the λ_1 regression coefficients are very similar to those reported in Panel B of Table 2. In contrast, earnings betas computed from the predictable component of cashflow innovations cannot explain cross-sectional returns as they yield an adjusted R^2 of only 0.2%. We also examine earnings betas computed using both unpredictable portfolio-level cashflow innovations and unpredictable market-level cashflow innovations. These earnings betas are very similar to the original earnings betas since predictability in the market's cashflow innovations is extremely weak.

Although portfolio-level cashflow innovations may be influenced by unpredictable changes in forecast biases, investors cannot distinguish between these changes and revisions in true expected earnings, even expost. Indeed, this distinction would require a firm's true expected earnings to be available every month. Therefore, unpredictable changes in analyst forecast biases that are systematic can induce systematic price adjustments. Consequently, unpredictable fluctuations in earnings forecast biases are a source of cashflow risk. However, unpredictable changes in forecast biases are unlikely to be systematic for two reasons. First, individual analysts focus on a subset of stocks, usually within a single industry. Second, according to Lim (2001), analyst incentives to issue biased forecasts arise from their private information regarding a firm's future cashflows, and this private information is usually firm-specific.

5.4. *Alternative cashflow risk measure*

A popular method of implementing Campbell and Shiller's (1988) return decomposition in Eq. (3) is to use a vector autoregression (VAR). Campbell and Vuolteenaho (2004) and Campbell, Polk, and Vuolteenaho (2008) implement such a VAR by assuming expected returns and the state variables that define their evolution are described by the process[15]

$$z_{t+\delta} = a + \Gamma z_t + u_{t+\delta}, \quad (22)$$

where $z_{t+\delta}$ is a column vector whose first element is $r_{t+\delta}$. The second through fifth elements consist of the market's log excess return (CRSP value weighted index minus risk-free rate), the log of the smoothed Standard and Poors (S&P) 500 price–earnings ratio from the prior 10 years, the term yield spread, and a small-stock value spread. The $u_{t+\delta}$ column vector represents the random innovations associated with each element of $z_{t+\delta}$. The VAR parameters a and Γ denote a column vector and matrix, respectively.

After estimating the VAR in Eq. (22), the cashflow innovations in Eq. (5) are computed as

$$N_{CF,t+\delta} = (e1^T + e1^T \Psi) u_{t+\delta}, \quad (23)$$

where $e1$ is a column vector whose first element is one and remaining elements are zero. The Ψ matrix equals $\rho\Gamma(I - \rho\Gamma)^{-1}$ and is responsible for translating the $u_{t+\delta}$ innovations of the state variables into cashflow innovations.[16] Persistent $u_{t+\delta}$ innovations are assigned a larger impact according to the $(I - \rho\Gamma)^{-1}$ component of Ψ.

The VAR approach is an indirect way of estimating the cashflow innovations since they are computed as residuals. Specifically, cashflow innovations are defined as the return variation that is not attributable to discount rate innovations. We implement Eq. (22) on the monthly returns of the 30 book-to-market, size, and long-term reversal portfolios as well as the market using the same four state variables in Campbell and Vuolteenaho (2004).[17] As with our earnings beta, a cashflow beta is then estimated for each portfolio by regressing its cashflow innovations on those of the market.

Panel A of Table 7 reports the estimated cashflow betas across the 30 portfolios. In general, the cashflow betas for value stocks, small stocks, and past long-term losers are larger than those of growth stocks, large stocks, and past long-term winners, respectively. These disparities are consistent with the value premium, size premium, and long-term return reversal. However, the cashflow betas explain only 3.1% of the return variation across the 30 portfolios. In addition, the cashflow beta's risk premium is insignificant while the intercept term is significantly positive. Therefore, the cashflow beta from a popular VAR specification explains less cross-sectional return variation than our earnings beta, despite the VAR methodology's economic intuitiveness and ability to incorporate time-varying discount rates.

[15] For notational simplicity, we suppress the i subscripts and superscripts that denote individual portfolios throughout this subsection.

[16] The discount rate innovations $N_{DR,t+\delta}$ equal $e1^T \Psi u_{t+\delta}$.

[17] Campbell, Polk, and Vuolteenaho (2008) compute portfolio cashflow innovations using a firm-level VAR at an annual frequency with accounting-based state variables that are not available on a monthly basis. The monthly time series of the four state variables until 2001 are obtained from John Campbell's Web site, and then extended to 2005. We thank John Campbell for sharing the data.

Table 7
VAR cashflow betas.

This table reports the cashflow betas from an alternative definition for the cashflow innovations in Eq. (23), $N_{CF,t+\delta} = (e1^T + e1^T\Psi)u_{t+\delta}$, where $e1$ is a column vector whose first element is one and remaining elements are zero. The Ψ matrix equals $\rho\Gamma(I-\rho\Gamma)^{-1}$ and translates the $u_{t+\delta}$ innovations of the state variables into cashflow innovations. The state variables evolve over time according to the following vector autoregression (VAR): $z_{t+\delta} = a + \Gamma z_t + u_{t+\delta}$, where a and Γ denote a column vector and matrix, respectively. The state variables underlying this VAR include the market's excess return along with its smoothed price–earnings ratio, a term yield spread, and a small-stock value spread. This VAR is applied to portfolio returns and market returns to obtain their corresponding cashflow innovations. These alternative cashflow innovations represent return variation that is unexplained by expected return innovations from the VAR specification in Campbell and Vuolteenaho (2004). Portfolio-specific cashflow betas are then estimated by regressing the cashflow innovations of each portfolio on the cashflow innovations of the market, as in Eq. (15), $N^i_{CF,t+\delta} = \alpha_{CF} + \beta^i_{CF} N^M_{CF,t+\delta} + \varepsilon^i_{t+\delta}$. These cashflow beta estimates are recorded in Panel A, while Panel C reports cashflow betas computed after removing the price–earnings ratio from the VAR specification. Panels B and D contain the results from the cross-sectional regression in Eq. (17), $r^i_{t+\delta} - rf_t = \lambda_0 + \lambda_1\,\beta^i_{CF} + \varepsilon^i_{t+\delta}$, using the earnings betas in Panels A and C, respectively. The dependent variable $r^i_{t+\delta}$ in these regressions is the realized return of portfolio i while rf_t denotes the risk-free rate over the same monthly horizon. The t-values (in italics) associated with the cashflow beta estimates are Newey-West adjusted with 12 lags, while the robust t-values account for their estimation error.

Panel A: Cashflow betas estimated from VAR cashflow innovations

	Value	2	3	4	5	6	7	8	9	Growth
Cashflow beta	2.01	1.28	1.37	1.52	1.48	1.55	1.46	1.61	1.73	1.60
Newey-West t-value	*15.57*	*12.48*	*14.66*	*16.87*	*16.91*	*18.20*	*16.21*	*18.54*	*17.92*	*14.77*

	Small	2	3	4	5	6	7	8	9	Large
Cashflow beta	3.10	2.32	1.99	1.72	1.52	1.37	1.16	1.19	1.16	0.79
Newey-West t-value	*16.43*	*15.46*	*16.62*	*16.47*	*13.92*	*14.88*	*12.90*	*18.75*	*21.76*	*28.14*

	Loser	2	3	4	5	6	7	8	9	Winner
Cashflow beta	2.98	1.84	1.59	1.30	1.13	0.97	1.08	0.99	1.10	1.39
Newey-West t-value	*17.34*	*16.40*	*18.02*	*17.96*	*15.04*	*13.00*	*14.59*	*12.95*	*12.57*	*13.08*

Panel B: Fama-MacBeth regression on 30 test portfolios

	λ_0	λ_1	*Adj* R^2
Estimate	0.0079	0.0007	3.1%
Robust t-value	*2.65*	*0.50*	

Panel C: Cashflow betas estimated from VAR cashflow innovations without price–earnings ratio

	Value	2	3	4	5	6	7	8	9	Growth
Cashflow beta	1.34	1.06	1.06	1.10	1.15	1.22	1.26	1.33	1.29	1.27
Newey-West t-value	*19.04*	*19.75*	*21.90*	*22.89*	*25.63*	*26.75*	*25.14*	*28.34*	*23.78*	*21.00*

	Small	2	3	4	5	6	7	8	9	Large
Cashflow beta	1.64	1.47	1.41	1.34	1.31	1.24	1.15	1.09	1.09	0.99
Newey-West t-value	*15.73*	*17.40*	*22.36*	*23.92*	*21.31*	*23.77*	*22.56*	*31.50*	*36.27*	*58.12*

	Loser	2	3	4	5	6	7	8	9	Winner
Cashflow beta	1.40	1.24	1.12	1.01	1.04	0.99	0.99	1.06	1.23	1.34
Newey-West t-value	*16.04*	*19.92*	*23.03*	*26.35*	*24.71*	*25.32*	*25.10*	*24.97*	*25.78*	*21.77*

Panel D: Fama-MacBeth regression on 30 test portfolios (without price–earnings ratio in VAR)

	λ_0	λ_1	*Adj* R^2
Estimate	0.0108	−0.0014	−1.1%
Robust t-value	*2.32*	*−0.30*	

Chen and Zhao (2008) argue that discount rate innovations cannot be accurately measured using a VAR due to weak predictability in the time series of stock returns. Moreover, these authors illustrate that the VAR methodology is not robust to the choice of state variables by omitting the price–earnings ratio. After excluding the price–earnings ratio, the results in Panels C and D of Table 7 indicate that the cashflow betas for value stocks and past long-term losers are no longer significantly higher than those for growth stocks and past long-term winners, respectively. Moreover, the cross-sectional regression involving realized average returns has a negative adjusted R^2.

In summary, our results are not driven by imprecise statistical inferences associated with a small sample, a specific sampling period, a particular weighting scheme, assumptions regarding firm-level cashflow payout rates, nor biases in analyst forecasts that are predictable using firm characteristics. In addition, our earnings beta performs favorably against an alternative cashflow risk measure that is derived from a vector autoregression for expected returns.

6. Conclusions

Stock returns are partially driven by changes in expected cashflow. We measure these changes using revisions in analyst earnings forecasts over a range of future maturities to investigate the systematic risk attributable to marketwide fluctuations in expected cashflow. As a consequence, we link the extensive literature on analyst earnings forecasts with the fundamental risk-return relationship. However, unlike past research on analyst forecasts, we focus on the *covariance* between revisions in the consensus earnings forecasts of analysts when deriving and estimating our analyst earnings beta. This cashflow risk measure involves analyst earnings forecasts over multiple future horizons.

Our earnings beta coefficients represent the comovement (sensitivity) between changes in portfolio-level expected cashflow and changes in the market's expected cashflow. These earnings betas are higher for value stocks and small stocks than for growth stocks and large stocks, respectively. In addition, past long-term losers have higher earnings betas than past long-term winners. Overall, our earnings beta simultaneously explains more than 55% of the cross-sectional return variation across book-to-market, size, and long-term reversal portfolios. The estimated market price of cashflow risk is also positive, which highlights the importance of fundamental cashflow risk in determining an asset's risk exposure. Furthermore, the systematic risk captured by our earnings beta originates from exposure to the macroeconomy as the real economy affects a wide cross-section of analyst earnings forecasts. We also demonstrate that the cross-sectional return variation attributable to our earnings beta compares favorably against an alternative cashflow risk measure derived from a common vector autoregression.

By introducing a novel cashflow risk measure derived from analyst forecast revisions, and empirically demonstrating its importance to cross-sectional return variation, we provide a new methodology for estimating systematic risk. Our methodology can provide cost-of-capital estimates even when prices (returns) are unavailable or unreliable. The cashflow innovations constructed in this paper facilitate future research involving discount rate innovations. Indeed, the estimation of cashflow risk using analyst forecasts also enables us to examine the importance of discount rate risk.

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