Aggregate Earnings and Asset Prices*

Ray Ball, Gil Sadka, and Ronnie Sadka†

September 28, 2007

Abstract

This paper applies a principal-components analysis to earnings and demonstrates that earnings factors explain a significant portion of firm-level earnings volatility, suggesting earnings shocks are not fully diversifiable. The earnings factors are correlated with macroeconomic indicators such as Industrial Production and Real GDP, suggesting they reflect real business conditions. We also show that aggregate earnings are positively correlated with lagged aggregate returns (consistent with investors' foresight of future changes in earnings) and negatively correlated with contemporaneous aggregate returns (consistent with investors' demand of low rates of returns upon the expectation of high earnings). Moreover, the return sensitivities to lead earnings factors explain a significant portion of the cross-sectional variation of some asset-pricing anomalies. The findings suggest that the information sets of returns and earnings are jointly determined, which amplifies the difficulty in separately identifying cash-flow risk and return risk.

JEL classification: E32, G12, G14, M41.

Keywords: Accounting valuation, expected-return variation, profitability, asset pricing

---

*We gratefully acknowledge the comments of Robert Korajczyk and workshop participants at Columbia University and University of Texas/Dallas, as well as participants in the 2006 CRSP Forum. Any errors are our own.

†Ray is from University of Chicago, Graduate School of Business; Gil is from Columbia University; Ronnie is from University of Washington (visiting University of Chicago/GSB).

1 Introduction

Asset prices are discounted expected cash flows, therefore variation in asset prices is due to variation either in expected returns (discount rates) or in expected future cash flows. The stock-price volatility literature generally finds that cash-flow variation is primarily idiosyncratic and diversifiable and does not affect aggregate stock prices.[1] Specifically, these studies find that aggregate returns cause most of the variation in aggregate prices (e.g., Campbell and Shiller, 1988a, 1988b; Campbell, 1991; and Campbell and Ammer, 1993). When the analysis is applied to the cross-section of firms (e.g. Vuolteenaho, 2002; Cohen, Polk and Vuolteenaho, 2003; Callen and Segal, 2004; and Easton, 2004), the results suggest that variation in expected profitability can explain much of the variation in firm-level returns, book-to-market ratios, and earnings-price ratios. These studies attribute the difference between the aggregate and firm-level results to the relative strength of the idiosyncratic components of cash-flow variation versus the systematic components of expected returns. The implication is that variation in expected returns explains most of the variation in the aggregate stock prices and aggregate stock returns.

This result is troublesome for a variety of reasons. First, it is counter-intuitive that price variation for such a large class of risky assets is independent of variation in their underlying income stream. Second, the cash flow variable employed in these studies typically is dividends which, for multiple reasons outlined in Section 2 below, we believe is a poor proxy relative to earnings for expected cash flows. Third, the existence of a substantial systematic component in earnings has been known since at least Brown and Ball (1967). Fourth, an extensive accounting literature beginning with Ball and Brown (1968) documents a positive contemporaneous correlation between idiosyncratic (firm-level) earnings and returns, a result that does not sit well with the opposite conclusion reached at the aggregate level. Fifth, the accounting literature concludes that the equity market largely anticipates earnings, which suggests the need to incorporate lags in the analysis.[2]

[1] Consistent with this conclusion, the literature generally finds that dividend yields predict returns but not dividends (see e.g., Fama and French, 1988, 1989; Keim and Stambaugh, 1986; Lettau and Ludvigson, 2001; Kothari and Shanken, 1997; Lamont, 1998; and Cochrane, 2001). Contrary evidence is in Fama (1990), Schwert (1990), Kothari and Shanken (1992), and Sadka (2007).

[2] This problem is even more severe for dividends, which lag earnings. Earnings evidence is provided as early as Ball and Brown (1968), who show that only 10-15 percent of the information in earnings is revealed during the month of announcement. The major use of accounting seems to be in confirming and hence disciplining prior management disclosures (Ball, 2001) and in contracting contexts such as debt and compensation (Watts and Zimmerman, 1986; Watts, 2003a, 2003b; Ball, Robin, and Sadka, 2007).

We report that there does exist a significant systematic component in earnings, that it is correlated with macroeconomic variables, and that it is priced (i.e., it partly explains the cross-section of asset returns). We use a principal-components analysis to extract five aggregate factors in earnings, and equivalent factors in returns. We then show that these factors explain similar fractions (approximately 60%) of firm-level volatility in both earnings and returns. These results suggest that variation in earnings is considerably systematic and is not fully diversifiable. In addition, we show that the earnings factors are correlated with macroeconomic indicators such as Industrial Production and Real GDP, suggesting the factors reflect real business conditions.

An important consideration in the relation between aggregate earnings and returns is timing: as an information variable, accounting earnings lags other information that is incorporated in stock prices. We show that aggregate earnings are positively correlated with lagged returns. This result is consistent with the firm-level accounting literature (e.g., Ball and Brown 1968; Beaver, Lambert, and Morse, 1980; Collins and Kothari, 1989; and Collins, Kothari, Shanken, and Sloan, 1994), which presents consistent evidence that the market anticipates most of the variation in earnings. The result is also consistent with accounting conservatism (e.g., Basu, 1997), under which economic income (returns) is not "recognized" as accounting income until it is "realized" in later periods.[3]

We also document that contemporaneous aggregate earnings and returns are negatively correlated, consistent with prior studies such as Kothari, Lewellen, and Warner (2006), and Sadka and Sadka (2007). We offer two alternative explanations. One possibility is that the same state variables cause variation in both earnings and returns, but with opposing signs. For example, during recessions expected returns are high because investors are more reluctant to hold risky securities and demand a high risk premium (e.g., Fama and French, 1989; and Cochrane, 2001); while at the same time expected profitability is low. Then, expected returns and expected earnings would be negatively correlated. This interpretation is supported by the high canonical correlation (approximately 70%) between our aggregate earnings factors and aggregate returns factors, suggesting that they are affected by similar underlying factors. The second possible explanation for a negative relation between earnings and returns arises from the fact that aggregate earnings is a real variable,

[3] The fact that economic income leads accounting income is also apparent in the relation between macro economic variables and our earnings factors. For example, real GDP growth and industrial production are strongly correlated with future profitability, because accounting rules only recognize the increase in GDP and industrial production when they are realized. The higher accounting hurdle for income recognition causes earnings to lag other measures of increases in market value, such as GDP growth and stock returns.

reflecting the net gain in corporate assets from their operating and trading activities during the period, and hence affecting the excess demand for capital in the corporate sector. Because profits represent realized gains, when aggregate profits increase firms demand less net capital from households (i.e., raise less new capital or return more in dividends, stock repurchases or debt repayment). This would imply a negative relation between earnings and expected returns at the aggregate level, though the effect would be weak at the individual-firm level.

Finally, because earnings variation has significant systematic components, these components can be used to test whether cash-flow risk is priced in the cross-section of stock returns. Employing covariance-risk models, we show that sensitivity to earnings factors explains a significant amount of the cross-sectional variation in some asset-pricing anomalies. This result is apparent when the lead earnings factors are used, which is consistent with the notion that current earnings were anticipated by investors during the previous period. Specifically, we apply the cross-sectional regression framework (see Fama and MacBeth, 1973), and for robustness we also use apply the stochastic discount factor approach (see Hansen and Jagannathan, 1997), to test whether our aggregate earnings factors can explain cross-sectional variation in returns on portfolios sorted according to some well-known anomalies, such as post-earnings-announcement drift (e.g., Ball and Brown 1968; Bernard and Thomas, 1989, 1990) and book-to-market (e.g., Basu, 1977). We use leading one-period-ahead earnings factors. Our results suggest that the leading earnings factors earn significant premiums, which are consistent with the hypothesis that cash-flow variation is not diversifiable and thus is priced in the market. These results are also consistent with the hypothesis that earnings do not provide timely information to the market, but rather reflect information perhaps already known to investors (e.g., Sadka and Sadka, 2007).

It is important to note some caveats concerning our cross-sectional analysis. First, since our study relies on a principal-components analysis which identifies factors up to a sign, it is difficult to determine the correct signs of the premiums of the earnings factors. We believe we are able to correctly sign the first principal component, because it usually is highly correlated with the market average, and therefore we sign the factor such that it obtains a high positive correlation with the market average return. The other principal components are similarly signed, to obtain a positive correlation with the macroeconomic variables. For robustness, we also include pricing tests for aggregate growth in free cash flow, a measure that does not utilize principal-components analysis, and find similar results. Second, our analysis only utilizes annual returns and earnings, which limits the time series to approximately 55 observations at best. The relatively short sample period poses limitations on the power of our tests. Despite these caveats, our results generally indicate that systematic earnings have an effect on the cross-sectional variation of stock returns in a way which is consistent with expectations.

Our pricing tests complement Campbell and Vuolteenaho (2004), who decompose the market return into cash-flow information and return information. Their results indicate that investors are quite sensitive to cash-flow risk. They reach the conclusion that most of the unexpected cash-flow variation is idiosyncratic, albeit the small systematic component is priced. Campbell and Vuolteenaho (2004) use an indirect method to extract cash-flow news, decomposing the market return into return news and then backing out the cash-flow news. In contrast, we use actual shocks to earnings to proxy for cash-flow news. We believe this is an important reason we find a significant systematic component for profitability, which is highly correlated with stock returns.

Our approach differs from most of the literature insofar as we impose very little structure and let the data "speak for itself." The factor analysis shows that both returns and earnings exhibit significant commonalities, and their common components are highly correlated. The findings suggest that the information sets of returns and earnings are jointly determined, which amplifies the difficulty in separately identifying cash-flow risk and return risk. In fact, the results raise the possibility that both cash-flow risk and return risk may capture the same underlying risk.Several recent studies, e.g., Bansal, Dittmar, and Lundblad (2005), Hansen, Heaton, and Li (2005), Santos and Veronesi (2006), Lettau and Watcher (2007), and Campbell, Polk, and Vuolteenaho (2007), attempt to separate cash-flow risk from return risk and test whether the two types of risk can explain the cross-section of stock returns. Our study suggests that cash-flow risk and return risk may not be easily separable and perhaps should not be studied separately.

The remainder of the paper is as follows. Section 2 outlines our reasons for believing dividends are a poor proxy relative to earnings for expected cash flows. Section 3 describes the data used for this study. Section 4 discusses the principal-components analyses of earnings and returns. In Section 5 we conduct asset-pricing tests showing aggregate earnings are priced. The robustness of our analysis is discussed in Section 6. Section 7 offers conclusions.

2 Dividends, Earnings, and Expected Cash Flows

The literature on determinants of stock-price volatility employs two general methodologies. The first is a "level" methodology that is based on the decomposition of dividend-price ratios into two components, expected returns and expected cash flows (e.g., Campbell and Shiller, 1988a, 1988b; and Vuolteenaho, 2000, who uses the book-to-market ratio). The second is a "flow" methodology that studies the volatility of stock returns rather than dividend-price ratios (e.g., Campbell, 1991; and Vuolteenaho, 2002). Both approaches conclude that aggregate expected cash flows do not generate significant aggregate price volatility. Nevertheless, the two methodologies might, in principle, yield different results because, as pointed out in Hecht and Vuolteenaho (2006), stock returns are not a function of expected cash flows and expected returns, but rather of changes in expected cash flows and changes in expected returns (see also Campbell, 1991).

Moreover, other studies that regress aggregate returns on cash-flow-based measures, such as dividend growth, earnings growth, and growth in industrial production (e.g., Fama, 1990; Schwert, 1990; Kothari and Shanken, 1992; and Collins, Kothari, Shanken and Sloan, 1994) conclude that cash flows do cause significant return variation. Here again, returns depend on changes in expectations of cash flows and returns, not on their expected values. Thus, using various expectation models, Hecht and Vuolteenaho (2006) suggest that the cash-flow proxies used by Kothari and Shanken (1992), Fama (1990), and Schwert (1990), may provide more information about changes in expected returns than about changes in expected cash flows. Hecht and Vuolteenaho (2006) conclude that cash flows are indeed diversifiable and that aggregate cash flows do not affect stock returns. In sum, the prevalent view in the literature is that aggregate cash flows do not affect aggregate prices.

Nevertheless, from a theoretical standpoint, one would expect that both cash-flow and return variation generate price variation. As Cochrane (2001) points out: "It is nonetheless an uncomfortable fact that almost all variation in price/dividend ratios is due to variation in expected excess returns. How nice it would be if high prices reflected expectations of higher future cash flows." We believe one contributor to the troublesome result is that dividends and cash flows are poor proxies relative to earnings for expected future cash flows. There are several reasons for this belief.

One reason for preferring earnings to dividends a priori is the Miller and Modigliani (1961) proof that (ignoring tax effects) dividends are irrelevant for asset prices given earnings. Another reason is the legal requirement that dividends can only be paid from realized earnings. Both of the above reasons share the common view that earnings are the primitive variable from which dividends and other distributions are derived. A third reason for preferring earnings is the fact that a large proportion of firms pay little or no dividends (Fama and French, 2001; DeAngelo, DeAngelo, and Skinner, 2004). Lorrain and Yogo (2007) estimate the net payout (the sum of dividends, interest, and net repurchases of equity and debt) and find that much of the net-payout yield can be explained by cash-flow variation. Fourth, the firm-level literature contains ample evidence that returns are more highly correlated with earnings than with cash flows and dividends, particularly when these variables are measured over horizons as short as a quarter or a year.[4] Fifth, research has shown that only a small percentage of equity analysts use cash-flow measures to justify their recommendations.[5] Finally, the much-misunderstood objective of accrual accounting is to make earnings a better predictor of future cash flow than cash flow itself. The Financial Accounting Standards Board (FASB, the US standard-setter) states this as follows:

> "Information about enterprise earnings based on accrual accounting generally provides a better indication of an enterprise's present and continuing ability to generate favorable cash flows than information limited to the financial effects of cash receipts and payments." (FASB 1978)
>
> "(Investors, creditors and others) interest in an enterprise's future cash flows and its ability to generate favorable cash flows leads primarily to an interest in information about its earnings rather than information directly about its cash flows." (FASB 1985, ¶ 43)

For the above reasons, we explore the possibility that a contributor to troublesome prior results is that dividends and cash flows are poor proxies relative to earnings for expected future cash flows.

[4] Kleidon (1986) points out that assesing the voaltility of cash flows using dividends is especially difficult in the presence of dividend smoothing. Kleidon further suggests that other measures, such as accounting earnings, may be more appropriate.

[5] From an analysis of 976 equity analyst reports, Govindajaran (1980) found that an overwhelming majority of analysts focus on earnings rather than cash flow measures. Bradshaw (2002) found that 76 percent of equity analysts use P/E multiples in making investment recommendations, and only 5 use cash-flow-based multiples.

3 Data

Return and earnings are both measured annually; return is measured as annual cumulative return (from the beginning of April of one year to end of March of the next year), and earnings growth is measured as return-on-assets (ROA), i.e. earnings at year t scaled by the average asset values at the end of years $t-1$ and t. Our data includes NYSE- and AMEX-listed stocks with December fiscal year-end for the period 1950-2005, from the CRSP and Compustat databases. Our sample consists of 71,622 firm-year observations of returns and earnings.

In contrast to other studies such as Vuolteenaho (2000, 2002) and Callen and Segal (2004), we use return-on-assets instead of return-on-equity as our earnings/profitability (or cash-flow) measure for several reasons. First, unlike return-on-equity, return-on-assets is unaffected by financing decisions. For example, different returns-on-equity can have the same return-on-assets because of different debt-to-equity ratios. Second, unlike the book value of equity, which can be negative, assets are always positive. Moreover, return-on-equity is more sensitive to accounting conservatism than return-on-assets insofar as conservatism can result in very low book values, and thus in very high values of return-on-equity. Finally, the earnings distribution is highly left-skewed, i.e. has many large negative values. These negative earnings are also associated with low book values, which suggest even higher negative return-on-equity. We therefore find it more appropriate to use return-on-assets rather than return-on-equity. Nevertheless, repeating the analyses presented below using return-on-equity yields similar, yet somewhat weaker, results due to the smaller sample of feasible observations.

4 The Systematic Components of Earnings and Returns

When checking for systematic components of earnings and returns, it is important to note that the two variables are fundamentally different. Stock returns represent the change in the economic value of the firm. Under the efficient market hypothesis, stock prices reflect all available information about both increases and declines in the firm value, and therefore, stock returns are expected to be fairly symmetrically distributed. However, due to limited liability the minimum stock return is bounded by -100%, i.e. one cannot lose more than the invested amount.

Unlike returns, which symmetrically reflect all information about increases and declines in firm value, accounting earnings are based on accounting recognition rules. These rules are guided by accounting principles, including conservatism. On the one hand, accounting conservatism allows gain recognition only when these gains are realized. For example, when a firm enters a contract to supply its product, the stock price will react immediately. However, accounting earnings will only realize this gain when the product has been delivered to the purchaser and the firm is entitled to the payments. On the other hand, accounting conservatism requires the immediate recognition of losses as soon as they are anticipated. For example, when the value of an asset declines below its book value the firm is required to recognize the decline in value immediately. In sum, accounting earnings are more sensitive to "bad" news than "good" news. This results in a relatively high frequency of large negative earnings figures.

Figure 1, Panels A and B, plot the distributions (pooled across firm and time) of stock returns and returns-on-assets. Since returns are bounded on the negative side but not on the positive, the return distribution exhibits some extreme positive observations, but not negative. In contrast, since earnings are asymmetrically sensitive to "bad" news as discussed above, the earnings figures exhibit a significant number of extreme negative observations (Figure 1, Panel B). In order to extract the systematic components of earnings and returns it is therefore necessary to exclude the extreme observations. For returns, we exclude the top 5% and bottom 1% of the distribution each year to obtain the distribution plotted in Figure 1, Panel C. However, the earnings distribution has a much larger left tail, and therefore we exclude the top 1% and bottom 5% of the distribution each year to obtain the distribution plotted in Figure 1, Panel D. Nevertheless, the return distribution remains more symmetric than the distribution of the earnings.

It is important to note that we exclude the extreme negative earnings observations because these observations reflect different accounting processes. In general, firms report their "regular" operating accounting results. However, in some extreme situations, where the value of their assets decline below their book value, firms are required to recognize the full loss immediately. Therefore, the obervartions of extreme negative earnings presumably represent firms that are subject to different accounting rules than the rest. For this reason, they should be excluded from our principal-component analysis, which attempts to extract common factors from firms that are in a "regular" situation.

4.1 Extracting Principal Components

To estimate the systematic risks of prices and earnings we use principal-component analysis. Specifically, we extract five principal components (PCs), separately for earnings and returns. We follow the methodology implemented in Connor and Korajczyk (1986, 1987), which allows the extraction of principal components of an unbalanced panel.

Define X to be the $n \times T$ matrix of observations on the variable considered (either return or ROA). We assume that the data generating process for $X_{j,t}$ is an approximate factor model:

$$X = B \cdot F + \varepsilon \tag{1}$$

where F is a $k \times T$ matrix of shocks to the variable that are common across the set of n assets, B is a $n \times k$ vector of factor sensitivities to the common shocks, and ε is an $n \times T$ matrix of asset-specific shocks. Systematic, or undiversifiable, shocks are those affecting most assets while diversifiable shocks are those which have weak commonality across assets. Define $V = E(\varepsilon\varepsilon')$. Chamberlain and Rothschild (1983) characterize an approximate factor model with k systematic factors as one for which the minimum eigenvalue of $B'B$ approaches infinity and the maximum eigenvalue of V remains bounded as n approaches infinity.

In an approximate factor-model setting for a balanced panel (complete data), Connor and Korajczyk (1986) show that n-consistent estimates (up to a linear transformation) of the latent factors, F, are obtained by calculating the eigenvectors, corresponding to the k largest eigenvalues, of

$$\Omega^i = \frac{X'X}{n}. \tag{2}$$

They refer to these estimates as Asymptotic Principal Components (APC). Note that Ω is a $T \times T$ matrix so that the computational burden of the eigenvector decomposition is independent of the cross-sectional sample size, n. This implies that factor estimates can be obtained for very large cross-sectional samples. Standard approaches to principal-component or factor analysis are often unimplementable on large cross-sections since they require eigenvector decompositions of $n \times n$ matrices.

To accommodate missing data we follow the approach in Connor and Korajczyk (1987), i.e. we estimate each element of Ω by averaging over the observed data. Let X be the data for the variable considered with missing data replaced by zeros. Define N to be an $n \times T$ matrix for which $N_{j,t}$ is equal to one if $X_{j,t}$ is observed and is equal to zero if $X_{j,t}$ is missing. Define

$$\Omega^u_{t,\tau} = \frac{(X'X)_{t,\tau}}{(N'N)_{t,\tau}}. \tag{3}$$

Ω^u is the unbalanced panel equivalent of Ω in which the (t, τ) element is defined over the cross-sectional averages over the observed data only. While Ω in a balanced panel is guaranteed to be positive semi-definite, Ω^u is not. However, in large cross-sections we have not encountered cases in which Ω^u is not positive definite. The estimates of the latent factors, $\widehat{F}$, are obtained by calculating the eigenvectors for the k largest eigenvalues of Ω^u.

For each variable, either return or ROA, we extract the first five principal components. To illustrate the amount of commonality, across assets, for each variable, we calculate the time-series regression for each stock on the five extracted factors, and record the p-values of the factor loadings, the R^2 value, and the adjusted-R^2 value. The regression estimated is:

$$X_{j,t} = B_j \cdot \widehat{F}_t + \widehat{\varepsilon}_{j,t} \tag{4}$$

where $\widehat{F}_t$ is the $k \times 1$ vector of factor estimates for year t.

Figure 2 plots cross-sectional averages of the R^2 of the firm-level regressions. The R^2 represents the percent of the variation in firm-level returns and earnings that can be attributed to systematic variations in returns and earnings, respectively. Figure 2 shows that a significant component of the firm-level variation in both earnings and returns can be attributed to systematic variations in these variables. The first PC of earnings and of returns explains as much as 17% and 33% of firm-level earnings and returns, respectively; using both the first and second PCs explains 28% and 42%, respectively; and using three PCs, the systematic components of earnings and returns explain as much as 42% and 48%, respectively. These results suggest that both earnings and returns have significant systematic components: Five PCs explain about 60% of the firm-level variations in both earnings and returns.

Table 2 reports the fraction of firms that exhibit statistically significant variations between their returns and ROAs to the corresponding principal component. For example, approximately 65% and 40% of the sample firms have a statistically significant relation (at the 20% level) between their returns and ROAs and the corresponding principal component. These results are consistent with the hypothesis that both returns and earnings have a significant systematic component.

An interesting question is the number of factors that determine the commonality in earnings and returns. Although the exact number is not the focus of this paper, but rather the existence of such commonality, our results using annual data complement some previous studies, which typically focus on monthly return observations (see, e.g., Trzcinka ,1986; Brown ,1989; Connor and Korajczyk, 1993). Figure 3 plots the eigenvalue corresponding to each principal component (a.k.a. a Scree plot). The first principal component of both returns and earnings exhibits a significant effect, as expected. Following a sharp decline, the remaining eigenvalues are leveled off at about 15% of the value of the first eigenvalue. Although the exact number of factors remains unclear (likely one or two), our evidence suggests that returns and earnings seem to share a similar number of significant factors.

The literature has provided conflicting evidence on whether cash flows are diversifiable. On the one hand, some volatility studies find evidence suggesting that cash-flow variation is mostly idiosyncratic and diversifiable (e.g., Campbell and Shiller, 1988a, 1988b; Campbell, 1991; and Vuolteenaho, 2002). On the other hand, other studies (e.g., Brown and Ball, 1967; Fama, 1990, Schwert, 1990; Kothari and Shanken, 1992; Lettau and Ludvigson, 2005; Sadka, 2007; and Ang and Bekaert, 2007) find that variations in aggregate measures of cash flow cause variation in aggregate prices. The results presented in Figure 2 support the results in the latter studies, because they suggest that both cash flows (earnings) and returns have significant systematic components and, therefore, are not diversifiable.

Our paper differs from prior studies that examine the role of aggregate cash-flow information on stock prices. Prior studies mostly examine the joint hypothesis of whether cash-flow news is both systematic and priced. In this paper, we separate the two questions. First, Figure 2 shows that cash-flow variation as reflected in accounting earnings is systematic. Then, the tests below examine two pricing questions: (1) the relation between the systematic components of earnings variation and systematic return variation, and (2) whether the systematic components of earnings are priced in the cross-section of stock returns.

4.2 From Principal Components to Risk Factors

It is important to discuss two necessary adjustments to the principal components: rotation and prewhitening. The first issue of rotation includes both signing the factors and orthogonalizing them. Notice that the extraction of principal components is only up to a sign change. Determining the correct sign of the principal components is crucial for the interpretation of their associated coefficients as positive risk premia later on in the paper. The first principal component of each variable is signed to have a positive correlation with the variable's cross-sectional (equal-weighted) average. The rest of the components are signed to have positive correlation with the macroeconomic indicators, Real GDP growth and Industrial Production (each PC typically exhibits the same correlation sign with both indicators). The correlations between the different principal components reported in Table 2 incorporate our signing approach. Table 2 also reports the time-series correlations between the principal components and the equal-weighted cross-sectional averages. The literature documents a high correlation between the first principal component of returns and the equal-weighted average (e.g., Connor and Korajczyk, 1988). Consistent with the observation for monthly stock returns, we also find such a high correlation (0.99) exists for annual returns. Similar to the first return PC, the first earnings PC is highly positively correlated with average ROA (0.96). In light of these high correlations, we believe that the first PC of ROA simply captures the average profitability. Similarly, the first return component likely represents the market factor.

Panel A of Table 2 reports high correlations between the first and second principal components (0.28 for return and 0.76 for ROA). Although the PCs span the same space regardless of whether or not they are correlated, it is important for us to obtain uncorrelated components to understand the effects of different facets of each variable. We therefore orthogonalize the components of each variable as follows: the second component is orthogonalized to the first, the third is orthogonalized to the first and second, as so on. The correlations between the orthogonalized components are reported in Table 2, Panel B.

Figure 4 plots the time series of the average return and ROA as well as the first three principal component of each variable (orthogonalized). As can be seen in Figure 4, the principal components of ROA are highly persistent. Most noticeable is the declining time trend of the average ROA and its first PC. Yet, this time trend is not entirely surprising. It is consistent with Basu (1997) that documents that accounting conservatism, more timely recognition of economic losses than gains, has increased over time. Accordingly, the frequency of losses has increased. Therefore, the average ROA, which over time includes more small firms with large negative earnings, should decline.In addition, research and development (R&D) costs are treated as expenses for accounting purposes, therefore, the decline in average ROA is partly due to the increase in R&D expenditures over our sample period.

Nevertheless, the persistence of the earnings components makes their direct use unreasonable in the context of our asset-pricing tests below. From an economic standpoint, it is appropriate to use innovations to aggregate time series because only unanticipated changes in aggregate variables could theoretically be priced. Therefore, in addition to signing the components and applying orthogonalization, we also prewhiten them. Specifically, we apply an AR(2) model to each component of ROA and use the estimated shocks to proxy for innovations. In our sample, this model seems to generate serially uncorrelated shocks.[6] We henchforth denote our earnings risk factors as the serially uncorrelated errors extracted from these time-series models. Since unreported tests confirm that returns do not exhibit significant serial correlation, we use the simple return components (orthogonalized) as the return risk factors. The first two factors of returns and earnings are plotted in Figure 5.

4.3 The Relation Between Earnings and Returns

Prior studies have shown that earnings and returns are not independent. In fact, contemporaneous aggregate returns are negatively correlated with aggregate earnings changes (e.g., Kothari, Lewellen, and Warner, 2006). Campbell (1991) provides a useful framework for understanding the implications of the relation between earnings and returns. Campbell (1991) decomposes returns into three components: expected returns, return news, and cash-flow news as follows:

$$r_t = E_{t-1}\left(r_t\right) + N_{cf} - N_r \tag{5}$$

where r_t denotes stock returns (lower case denotes logs) and $E(\cdot)$ is the expectation operator. News about cash flow, N_{cf}, is defined as $N_{cf} = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j}$, i.e. changes in expected cash flows, where Δd_t denotes dividend growth (in logs) at time t and ρ is a deflator (the inverse of 1 plus the dividend yield). Consistently, return news (changes in expected returns), N_r, is defined as $N_r = (E_t - E_{t-1}) \sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}$.

Table 3 reports the correlation between the first five earnings factors (prewhitened), the lead earnings factors, and the returns factors. Consistent with Kothari, Lewellen, and Warner (2006), the first returns and earnings factors are contemporaneously negatively correlated (-0.21). The

[6] We also apply a time-series model similar to the one used by Basu (1997) at the firm level, where earnings changes are regressed on their lag value with a dummy variable for negative lag value. Bsau finds that negative earnings changes are transitory while positive earnings changes are persistent. The earnings shocks we extract using this model are highly correlated with the AR(2)-generated shocks (correlation above 0.90).

negative relation between earnings and returns is also apparent in Figure 5, which plots the contemporaneous return and earnings factors. In contrast to the contemporaneous correlation between earnings and returns, returns are positively correlated with future profitability. The return factor is positively correlated (0.34) with the lead earnings factor. The latter result is quite intuitive. Higher expected profitability results in higher prices, and hence higher contemporaneous returns. This result indicates the extent to which markets are efficient in predicting future profitability. In addition, accounting conservatism suggests that economic income is not recognized for accounting purposes until they are realized. Therefore, higher economic income (returns) this period would result in higher profits next period.

Sadka and Sadka (2007) provide an explanation for the negative contemporaneous correlation between earnings and returns at the aggregate level. To understand the correlation, one may study the correlation of earnings with each of the three components of returns, as depicted in Campbell's decomposition. Also, as aggregate earnings are predictable (the results above show at least one variable can predict earnings—returns), one should differentiate between the expected and the unexpected components of earnings. Since the correlation of unexpected earnings with N_{cf} is likely positive, and with N_r likely negative, it must be that the negative correlation between earnings and returns stem from a negative correlation between their expected values. For example, empirically it seems that returns vary with the business conditions, insofar as expected returns are high in recessions because investors demand a high risk premium. Yet, at the same time expected profitability is low in recessions. Hence, expected returns and expected earnings are negatively correlated. See Sadka and Sadka (2007) for a detailed development of this explanation.

In addition to the pairwise factor correlations, we also compute canonical correlations between earnings and returns. In particular, we compute the first canonical correlation between the first two factors of earnings and the first two factors of returns; the first canonical correlation between the first three factors of earnings and the first three factors of returns; and so on. Table 4 reports the results for both contemporaneous and lead-lag canonical correlations. The contemporaneous canonical correlations between earnings and returns is 0.36, 0.51, 0.58, and 0.62 with 2, 3, 4, and 5 factors, respectively. These results suggest that the return space contains some information about earnings of the same period. While contemporaneous earnings and returns seem highly correlated, it seems that returns are even more strongly correlated with lead earnings factors. When returns lead earnings, i.e. using the first lead of earnings factors with contemporaneous return factors, the correlations increase to the range of 0.57-0.72. The results suggest that contemporaneous returns are more correlated with future profitability than with contemporaneous profitability. This result is consistent with the conservative nature of accounting and with the efficiency of markets in foreseeing earnings. Notice, when earnings lead returns the correlations decrease to the range of 0.19-0.55 but they do not completely disappear. This result may be interpreted as a sign of market inefficiency, insofar as returns are predictable (by earnings), yet it is also consistent with our argument that earnings and returns are highly correlated and that it is difficult to completely distinguish between them.

The high canonical correlations between earnings and returns have significant implications. Theoretically, if cash-flow news and returns news are distinct, one can identify two different types of risk (such as performed in Campbell and Vuolteenaho, 2004): return risk, as measured by the sensitivity of a firm's stock returns to N_r, and cash-flow risk, as measured by the sensitivity of a firm's stock returns to N_{cf}. However, if N_r and N_{cf} are highly correlated, it is difficult to distinguish between cash-flow risk and return risk. Campbell and Vuolteenaho (2004) use a vector-autoregression (VAR) model to separately infer N_r and N_{cf}. In particular, their VAR model, which employs variables to predict returns, is used to estimate $E_{t-1}(r_t)$ and N_r; then, the variable N_{cf} is estimated as a "residual" term, i.e. the return variation that is not due to expected returns and return news. Yet, the results in Tables 2-4 of our study suggests that the two components of prices (cash flows and returns) are highly correlated, and therefore the residual term perhaps need not be interpreted as a component that represents cash-flow news. In particular, we document that expected earnings are negatively correlated with stock returns, which suggests that N_r and N_{cf} are negatively correlated. Since cash-flow news and return news are highly correlated, excluding return news from returns is essentially excluding cash-flow news. In fact, the high correlation suggests that the two components, returns and cash flows, may be jointly driven by common factors. In other words, it is difficult to determine whether stock returns are high because of high expected cash flows or low discount rates.

4.4 Macroeconomic Variables and the Earnings and Returns Factors

The advantage of using the principal component analysis is that it extracts common variation in the underlying variables, in this case earnings and returns. In the context of asset pricing, since systematic risk is priced, this analysis is very useful. The disadvantage of using the principal-component analysis to extract common factors is that these common factors lack economic intuition. It is difficult to identify the macroeconomic effects that generate common variation in firm profitability. To address this issue, Table 5 reports the correlations between the extracted common factors and macroeconomic variables. Specifically, the table reports the pairwise correlations of the earnings and returns factors with each of growth in Industrial Production, Real GDP growth, Unemployment rate, and Inflation, as well as the canonical correlations of each group of five factors (returns, ROA, and lead ROA) with the group of the four macroeconomic variables.

The correlation between the returns factors and the macroeconomic variables strengthens the hypothesis that returns vary with the business conditions (e.g., Fama and French, 1989). The return factors are correlated with Industrial Production and Real GDP growth. These latter macroeconomic variables are strong indicators for the business conditions. The correlation between these macroeconomic variables and returns is consistent with the hypothesis that investors' risk preferences vary with the business cycle.

Consistent with the results about returns, the earnings factors are also correlated with the macroeconomic variables. This result is not surprising; firm profitability is clearly a function of the business conditions. In fact, corporate earnings are a significant component of GDP. In a similar fashion, higher industrial production should indicate higher profits.

The pairwise correlations, reported in Table 5, are surprising in the sense that they suggest that the lead earnings factors, rather than the contemporaneous factors, are strongly related to macroeconomic variables. For example, Industrial production has a correlation of 0.25 with the first contemporaneous earnings factor compared with 0.58 correlation with the lead earnings factor. Note that the first earnings factor has a 0.96 correlation with average ROA (Table 2). Thus, the positive correlation between current industrial production and the lead earnings factor suggests that higher current industrial production results in higher future profitability. The same is true for real GDP growth, which has a correlation of 0.04 with the first contemporaneous earnings factor and a correlation of 0.67 with the lead earnings factor. The relation between real GDP growth and Industrial Production and future profitability is consistent with accounting conservatism. The profits from current production will be recognized for accounting purposes only when the profits are realized in the future.

The canonical correlations reported in Table 5 are all quite high, suggesting that the spaces of returns, ROAs, and lead ROAs are all correlated with the space of macroeconomic variables. This once again suggests these variables are related to business cycle effects.

5 Pricing Systematic Earnings

5.1 Contemporaneous versus Lead Earnings Factors

In previous sections, we provide evidence that prices lead earnings and that current economic income results in future accounting profits (consistent with prior accounting studies such as Collins and Kothari, 1989; Beaver, Lambert, and Morse, 1980). Sadka and Sadka (2007) finds that while firm-level earnings changes are informative, aggregate earnings changes are mostly predictable and provide little if no new information. Furthermore, the evidence suggest that contemporaneous aggregate cash-flow information is reflected mostly in future (one-period ahead) profits. In addition to the relation between contemporaneous stock returns and future profitability, we find that current aggregate industrial production and real GDP growth, results in higher future shocks to profitability. In fact, as noted above, both industrial production and GDP growth are more highly correlated with future shocks to profitability than they are to contemporaneous shocks. Since the factor model requires surprises in factor realizations, it may be more appropriate to use the lead earnings factors as the risk factors.[7] Therefore, for the pricing tests we study both the contemporaneous earnings factors and the lead factors.

It is important to note that Basu (1997) finds that earnings are more timely (are more highly correlated with returns) for negative returns than for positive returns. In unreported results, we find that this result does not hold at the aggregate level. In particular, we regress the shocks to the first earnings factor on contemporaneous first returns factor, a dummy variable that is equal to one if the first return factor is negative (and zero otherwise), and an interaction term of the dummy variable and the first returns factor. Basu (1997) finds that the interaction term is, on average, positive and statistically significant in the cross-section. At the aggregate, we find that the coefficient of the interaction term, while positive, is statistically insignificant.

[7] Similarly, Vassalou (2003) finds that a factor that includes information about future GDP growth explains some of the cross-sectional variation in stock returns.

In this study, we interpret the positive correlation between returns and future profits as evidence of earnings predictability, i.e. returns are high because investors predict higher earnings. In contrast, Dow and Gorton (1997) develop a model in which managers learn about their firms' growth options from their firms' stock prices, and, as a result, invest more when prices are high, and obtain higher profits in the future. Similarly, Hirshleifer, Subrahmanyam, and Titman (2006) suggest that higher stock prices can result in higher profits. For example, Hirshleifer et al. hypothesize that higher stock prices can help retain and hire more productive employees, and therefore result in higher future profits. Nevertheless, while the interpretation is somewhat different than ours, these studies suggest that contemporaneous stock returns would be positively correlated with future profits.

The ability of investors to predict future aggregate earnings is a key aspect in our pricing tests, because we use future earnings to proxy for expectations. However, as noted by Sadka and Sadka (2007) the post-2000 period is characterized by less predictability due to aggregate unexpected adverse shocks to the economy. This is particularly true for the year 2001 in wake of September 11; for example, the airline industry encountered a significant, unpredictable, economic cost. Therefore, in our pricing test we exclude the year 2001 from the analysis. In particular, we exclude the factors for the year 2000, i.e. the contemporaneous factors of year 2000 along with the lead earnings factors that contain information about the year 2001.

5.2 Test Portfolios

Three sets of portfolios are used test whether earnings variation is priced. The first two sets of portfolios we use are 25 book-to-market-sorted portfolios (both equal- and value-weighted). It is well documented that stocks with high book-to-market outperform stocks with low book-to-market. Prior studies, e.g., Kothari and Shanken (1997) and Vuolteenaho (2002), also document that the book-to-market ratio has two major components—expected returns and expected profitability. Therefore, book-to-market portfolios are a natural choice to test for pricing of aggregate shocks to profitability. The book-to-market portfolios are rebalanced in the beginning of April of each year (and held for one year); the portfolio weights for the value-weighted portfolios are the market values in the beginning of April. Book-to-market portfolio returns are recorded for the period April 1963 through March 2006.

In addition to book-to-market-sorted portfolios, we use post-earnings-announcement drift or earnings momentum portfolios. Since earnings momentum is an earnings based anomaly, it is also a natural choice to test the pricing of systematic earnings risk. To investigate the post-earnings-announcement drift, we sort stocks into portfolios according to their standardized unexpected earnings (SUE). This measure is based on a model of seasonal random walk with a drift. More specifically, SUE for stock i in month t is defined as

$$SUE_{i,t} = \frac{E_{i,q} - E_{i,q-4} - C_{i,t}}{\sigma_{i,t}} \tag{6}$$

where $E_{i,q}$ is the most recent quarterly earnings announced as of month t for stock i (not including announcements in month t), $E_{i,q-4}$ is earnings four quarters ago, and $\sigma_{i,t}$ and $C_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. This measure has been used by Chan, Jegadeesh, and Lakonishok (1996), Chordia and Shivakumar (2002), and by Chordia et al. (2007) except that they do not include a drift term, i.e. they assume $C_{i,t} = 0$. The drift term is added here to comply with Bernard and Thomas (1989, 1990) and Ball and Bartov (1996), who use a seasonal random walk with a trend. The portfolios are rebalanced every month while holding each stock up to four months after the announcement date. We then use cumulative annual return for the SUE-sorted portfolios. Since we use quarterly data, the sample is restricted to the period April 1974 through March 2006.

5.3 Cross-Sectional Regressions

The portfolios are used to test linear asset-pricing models of the form

$$E\left[R_i\right] = \gamma_0 + \gamma' \beta_i \tag{7}$$

where $E\left[R_i\right]$ denotes the expected return of portfolio i (excess of risk-free rate), β_i are factor loadings and γ is a vector of premiums. Since loadings are unobservable, they are pre-estimated through a multiple time-series regression

$$R_{i,t} = \alpha_i + \beta_i \cdot f_t + \varepsilon_{i,t} \tag{8}$$

where f_t is a vector of factors. Model (7) may be consistently estimated using the cross-sectional regression method proposed by Black, Jensen, and Scholes (1972), and Fama and MacBeth (1973). First, the regression in (8) is estimated using the full sample. Then, (7) is estimated every year resulting in a time series γ_t. The time-series mean and standard error are finally calculated. Last, the adjusted R^2 of the cross-sectional regression is calculated as an intuitive measure that expresses the fraction of the cross-sectional variation of average excess returns captured by the model. Note, as our factors are extracted using principal-components analysis they are identified upto a scale. Thus, prior to running the regression in (7), we normalize the cross-section of β by scaling each β_i by the its respective cross-sectional standard deviation. This has no impact on the calculated standard errors, but it allows us to interpret each estimated factor premium as the percent return per unit standard deviation of sensitivity to that factor and zero to all other factors.

We use these models to test whether the extracted factors can explain the cross-section of returns of some well known portfolios and profitable trading strategies. These models will allow us to test whether the first earnings and first returns factors are priced, i.e., carry a positive premium. Also, these tests would show whether the earnings factors contribute to the understanding of the cross-sectional variation of expected portfolio returns.[8] To facilitate further understanding of the economic significance of the factor premiums reported below, it is noteworthy to report that the cross-sectional variations of expected portfolio returns are 4.06, 2.92, and 7.83 percent annually for the equal- and value-weighted book-to-market portfolios, and the SUE portfolios, respectively.

5.4 Results

Before we discuss the results of the cross-sectional regressions, we first show that the sensitivities of portfolio returns to the ROA factors are indeed significant, to alleviate potential concerns of spurious results of our pricing tests. Table 6 reports the factor loadings of each portfolio using a model that includes both contemporaneous and lead ROA factors. Overall, the results of all three portfolio sets indicate that very few loadings on contemporaneous ROA are statistically significant, while most of the loadings on lead ROA are significant. This is consistent with our notion that lead ROA is more important than contemporaneous ROA insofar as pricing implications.

For the equal-weighted 25 book-to-market portfolios, the evidence in Table 7, Panel A, suggests that the first return factor, which is in essence the market factor, is priced. The premium varies

[8] Note that our goal is not to offer the "best" model for expected returns, but rather to emphasize the important role of earnings risk. Nevertheless, our research design, based on 25 portfolios separately sorted by book-to-market and SUE rather than the commonly used 25 portfolios double sorted by size and book-to-market, alleviates some of the concerns outlined in Daniel and Titman (2005) and Lewellen, Nagel, and Shanken (2007).

from 1.67 to 3.00 percent annually and the t-statistic varies from 2.18 to 3.36 for different models. Thus, the premium is statistically significant for all model specifications.[9] The pricing of the market factor is also apparent by the high adjusted-R^2 when the first returns factor is included on its own (53%). Unlike the first returns factor, the second returns factor, which is the second principal component, does not appear to be priced.

The results in Table 7, Panel A, suggests that systematic earnings variation is priced. The first earnings factor, which is similar in essence to a market ROA, is priced. The premium varies from 1.38 to 2.95 for the different asset-pricing models and the premium is statistically significant in all models. The t-statistic varies from 2.80 to 3.68. The tables shows that the lead earnings factor is priced as well. Its premium varies from 1.17 to 2.44 and its premium is statistically significant in all models. The t-statistic varies from 2.43 to 3.96.

Figure 6, Panel A, plots the excess returns and the loadings, β_i, for the shocks to the lead of the first principal component of ROAs. The figure shows that the loading on our earnings risk factor is increasing with expected returns. These results suggest that high book-to-market portfolios earn higher returns because they are more sensitive to variation in aggregate earnings. As shown in the figure, this result generally holds with the exception of the 2 bottom book-to-market portfolios, which earn low returns but have high loadings on our earnings risk factor. Figure 7 complements Figure 6 as it plots the realized average returns with the fitted expected returns. The fitted values are calculated using Equation (7), where the loading are computed through a time-series regression of portfolio excess returns on the lead shock to the first principal component of ROAs. Note that apart from the bottom book-to-market portfolios, the realized returns are fairly similar to the model's fitted returns.

The relation between returns and profitability is also apparent in Table 7, Panel A. Note that when the earnings factors are included in the pricing model the premium on the returns factor declines significantly. For example, the premium on the first returns factor declines from 3.00, when included alone, to 1.67, when the contemporaneous and lead of the first earnings factors are added.

Table 7, Panel B, reports pricing tests results using value-weighted returns for 25 book-to-

[9] This result differs from many other studies that do not find the market return to be priced. Our results may stem from the use of annual betas versus the commonly used monthly betas; for example, Handa, Kothari, and Wasley (1989) show market betas may vary substantially with the frequency of the returns used for their calculation.

market-sorted portfolios.The results are quite similar to those reported in Table 7, Panel A, using equal-weighted portfolio returns. The first return factor appears to be priced, as are the contemporaneous and lead first earnings factor. However, the statistical significance of the results decline, particularly when the earnings and returns factors are included together. When included together, the risk premiums for returns and earnings decline as well. These results support not only the hypothesis that systematic earnings variation is priced, but also that it is difficult to distinguish between earnings risk and returns risk.

The plot in Figure 6, Panel B, is consistent with the results in Table 7, Panel B. The loadings on the shocks to the lead earnings factor, which is the first principal component of ROAs is increasing with expected excess returns. However, as is apparent from the difference between Panels A and B, the value-weighted book-to-market portfolios generate less of a spread in excess returns, compared with the equal-weighted returns. This difference in the spread can explain the lower statistical significance for the pricing results for value-weighted versus equal-weighted portfolio returns. The lower spread in excess returns is also observable in Figure 7, Panel B, where the realized returns are plotted against the fitted returns, as described above.

The results for the SUE-sorted portfolios are reported in Table 7, Panel C. The results suggest that earnings risk, and in particular the lead of the shocks to the first principal component of ROAs is priced and is significant. The premium varies from 1.68 to 6.22. The t-statistic varies from 3.80 to 10.87. When included on its own, the shocks to the lead of the first principal component of ROAs explains as much as 61% of the cross-section of expected portfolio returns. Note that this high explanatory power is not due to a small spread in excess returns as Figure 6, Panel C, shows that the post-earnings-announcement-drift portfolios generate high excess returns.

Figure 6, Panel C, plots the excess returns for the SUE portfolios and their loadings on the lead of the shock to the first principal component of ROAs. The figure clearly demonstrates that expected returns increases with the loading, suggesting that the excess returns obtained using earnings momentum can be in part explained by earnings risk. Figure 7, Panel C, provides additional support for the latter hypothesis. The realized returns align quite well with the fitted (expected) returns generated by an asset pricing model using only the lead of the shocks to the first principal component of ROAs.

Overall, the results reported in Table 7 and Figures 6-7 are consistent with our hypothesis that earnings risk is priced. More specifically, it seems that since aggregate earnings shocks are highly predictable (e.g., Sadka and Sadka, 2007), the lead earnings factor seems to be a more significant risk factor than the contemporaneous factor. However, the high correlation between earnings and returns factors limits our ability to clearly identify whether earnings risk or return risk is priced, or alternatively whether an unobservable factor, e.g. business conditions, is driving both the pricing of returns and earnings.

6 Robustness Tests

6.1 Free-Cash-Flow Factor

In addition to principal components approach, we study aggregate growth in free cash flow as a robustness check.[10] Aggregate growth in free cash flow is calculated as the growth in the sum of free-cash flow in the market, which is similar to the growth in the free cash flows of a value-weighted market portfolio. To obtain fairly accurate data on free cash flow, it is necessary to have some data from the statement of cash flows. Unfortunately these are not available until 1971. Therefore, we employ a measure of free cash flow used by Lehn and Poulson (1989) and by Lang, Stulz, and Walking (1991), where free cash flow is defined as operating income before depreciation minus interest expenses and taxes.[11] As Lang et al. point out, this measure may be more a measure of performance than a measure of free cash flow, nevertheless it provides some diagnostic of the robustness of our findings.The results are summarized in Table 8.

The results using our measure of free cash flow are similar to those reported in Table 7 using our principal component factors. The results indicate that the lead growth in free cash flow, rather than the contemporaneous growth is priced. For example, the lead growth in free cash flow explains as much as 32%, 35%, and 21% of the cross-section of expected portfolio returns for equal- and value-weighted book-to-market portfolios, and post-earnings-announcement-drift portfolios, respectively. Consistent with our principal component factors, the premium declines significantly when the returns factors are included.

[10] We also use aggregate growth in earnings and arrive at similar results.

[11] Lehn and Poulson (1989) also exclude dividends in the calculation of free cash flow. The results in Table 8 are robust to this definition of free cash flow.

6.2 Pricing Systematic Earnings with the SDF approach

The stochastic discount factor (SDF) approach is another method used to test different asset-pricing models. The idea is that the tested factors represent some underlying state variables that affect investors' utility functions. This method utilizes the General Method of Moments (GMM; Hansen, 1982) and is added to the analysis for robustness purposes.

It is well known that as long as the law of one price holds in the economy, there exists some random variable, a stochastic discount factor d_t, which prices all assets. That is, for any (excess) return $R_{i,t}$, the following is satisfied

$$E\left[R_{i,t}d_t\right] = 0. \tag{9}$$

If the factor-based asset-pricing model explains returns, the stochastic discount factor can be expressed as

$$d_t\left(\delta\right) = 1 - \delta' f_t. \tag{10}$$

(Because excess returns of the portfolios are used, the constant term is normalized to a value of one.) The universe contains 25 portfolios, which translates to 25 moment conditions over roughly 40 years. The asset-pricing models tested here have four factors at most. Therefore, an overidentified system is left. The moment conditions are constructed as follows. Define R_t as the $25{\times}1$ vector of portfolio returns at time t. Define the sample analogs

$$R_T = \frac{1}{T}\sum_{t=1}^{T} R_t \ ; \ D_T = \frac{1}{T}\sum_{t=1}^{T} R_t f_t'. \tag{11}$$

The sample analog of the moment conditions is given by

$$w_T = R_T - D_T\delta \tag{12}$$

For a given weighting matrix Ψ, the estimates of δ are those that minimize $J\left(\delta\right)$ such that

$$J\left(\delta\right) = w_T'\Psi^{-1}w_T. \tag{13}$$

Because the system is linear, the solution is analytically solved as

$$\delta_T = \left(D_T'\Psi^{-1}D_T\right)^{-1} D_T'\Psi^{-1}R_T, \tag{14}$$

and the risk premiums can be calculated through $E[ff']\delta$ (where f are demeaned factors).

For the weighting matix, we follow Hansen and Jagannathan (1997), who develop a method that helps to evaluate the different asset-pricing models on a common scale. They propose a common weighting matrix for all models:

$$\Psi = E\left[R_t R_t'\right]. \tag{15}$$

They show that the resulting $J(\delta)$ can be interpreted as the least-square distance between the given estimated stochastic discount factor and the nearest point to it in the set of all discount factors that price assets correctly. However, because Ψ^{-1} perhaps is not optimal, $T \times J(\delta_T)$ does not generally converge to a χ^2 distribution. Therefore, to calculate the p-values, we follow the correction presented in Jagannathan and Wang (1996). To adjust for serial correlation of the moment conditions, a Bartlett kernel with two lags is applied.

The results of this analysis are presented in Table 9. The results are quite similar to those reported in Table 7 using cross-sectional regressions: both return and lead ROA factors seem to be priced (while contemporaneous ROA is not) when they are considered separately (although in Table 9 the premium on return is higher and on lead ROA lower). Yet, when they are included together, return seems to dominate lead ROA. This results is consistent with the notion that returns and earnings proxy for a similar information set. As for the p-values of the different models, it is difficult to draw a clear conclusion. Some models that lead ROA are not rejected at the 5% confidence level, while others are rejected. Nevertheless, the models that include lead ROA seems to have higher p-values than those that include return. Overall, the evidence seem to support the notion that lead ROA represents a priced risk factor and that it is highly correlated with the return factor.

7 Conclusion

This paper shows that there exists a significant systematic component to earnings variation and that this systematic component affects asset prices. In particular, we extract three aggregate factors of earnings and of returns and show that these factors explain about 60% of firm-level volatility in earnings and returns, respectively. In contrast to several prior studies that suggest that cash flows are diversifiable, these results suggest that the variations in earnings are largely systematic and are not diversifiable. We also find the factors to be correlated with macroeconomic indicators. In particular, real GDP growth and growth in Industrial Production are highly correlated with the following period's variation in our earnings factors.

We then employ covariance-risk models to show that the sensitivity to the earnings factors can explain a significant portion of the cross-sectional variation of some well-known asset-pricing anomalies: book-to-market and post-earnings-announcement drift. The pricing of our earnings factors are mostly apparent when the lead earnings factors are used, which is consistent with the notion that current earnings are anticipated by investors during the previous period. These results strengthen recent accounting studies, such as Watts and Zimmerman (1986), Watts (2003a, 2003b), and Ball, Robin, and Sadka (2007), suggesting that the main role of accounting is not to provide timely information to the market, but rather to serve as contractible financial outcomes. Most importantly, we also find that the common factors of earnings and returns are highly correlated, which suggests that the information sets of returns and earnings are jointly determined. This amplifies the difficulty in separately identifying cash-flow risk and return risk.

References

Ang, Andrew, and Geert Bekaert, 2007, Stock return predictability: Is it there? *Review of Financial Studies*, forthcoming.

Ball, Ray, 2001, Infrastructure requirements for an economically efficient system of public financial reporting and disclosure, Brookings-Wharton Papers on Financial Services, 127-169.

Ball, Ray, and Eli Bartov, 1996, How naive is the stock market's use of earning information, *Journal of Accounting and Economics* 21, 319-337.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159-178.

Ball, Ray, Ashok Robin, and Gil Sadka, 2007, Is accounting conservatism due to debt or share markets? A test of "Contracting" versus "Value Relevance" theories of accounting, working paper, University of Chicago.

Bansal, Ravi, Robert F. Dittmar, and Christian T. Lundblad, 2005, Consumption, dividends, and the cross-section of equity returns, *Journal of Finance* 60, 1639-1672.

Basu, S., 1977, Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis, *Journal of Finance* 32, 663-682.

Basu, Sudipta., 1997, The conservatism principle and the asymmetric timeliness of earnings, *Journal of Accounting and Economics*, 24, 3-37.

Beaver, William H, Richard Lambert, and Dale Morse, 1980,The information content of security prices, *Journal of Accounting and Economics*, 2, 3-28.

Bernard, Victor and Jacob Thomas, 1989, Post-earnings announcement drift and: Delayed price response or risk premium? *Journal of Accounting Research*, 27, 1-36.

Bernard, Victor, and Jacob Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics*, 13, 305-340.

Black, Fischer, Michael C. Jensen, and Myron Scholes, 1972, The capital asset pricing model: some empirical tests, in Michael Jensen, Ed.: Studies in the theory of capital markets (Praeger, New York), pp. 79-121.

Bradshaw, Mark T., 2002, The use of target prices to justify sell side analysts' stock recommendations, *Accounting Horizons* 16, 27-41.

Brown, Philip, and Ray Ball, 1967, Some preliminary findings on the association between the earnings of a firm, its industry, and the economy, *Journal of Accounting Research* 5, 55-77.

Brown, Stephen J., 1989, The number of factors in security returns, *Journal of Finance* 44, 1247-1262.

Callen, Jeffrey L., and Dan Segal, 2004, Do accruals drive stock returns? A variance decomposition analysis, *Journal of Accounting Research*, 42(3), 527-560

Campbell, John Y., 1991, A variance decomposition for stock returns, *Economic Journal*, 101, 157-179.

Campbell, John Y., and John Ammer, 1993, What moves the stock and bond markets? A variance decomposition for long-term asset returns, *Journal of Finance* 48, 3–37.

Campbell, John Y., Christopher Polk, and Tuomo Vuolteenaho, 2007, Growth or glamour? Fundamentals and systematic risk in stock returns, working paper.

Campbell, John Y., and Robert J. Shiller, 1988a, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies*, 1, 195-227.

Campbell, John Y., and Robert J. Shiller, 1988b, Stock prices, earnings, and expected dividends, *The Journal of Finance*, 43, 661-676.

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249-1275.

Chamberlain, Gary, and Michael Rothschild, 1983, Arbitrage, factor structure, and mean variance analysis on large asset markets, *Econometrica* 51, 1281-1304.

Chan, Louis K.C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681-1713.

Chordia, Tarun, Amit Goyal, Gil Sadka, Ronnie Sadka, and Lakshmanan Shivakumar, 2007, Liquidity and the post-earnings-announcement drift, working paper - Columbia University.

Chordia Tarun, Lakshmanan Shivakumar, 2002, Earnings, business cycle and stock returns Working Paper.

Cochrane, John H., 2001, Asset Pricing. Princeton, N.J.: Princeton University Press.

Collins, Daniel W., S.P. Kothari, 1989, An analysis of intertemporal and cross-sectional determinants of earnings response coefficients, *Journal of Accounting and Economics*, 11, 143-181.

Collins, Daniel W., S.P. Kothari, Jay Shanken, Richard G. Sloan, 1994, Lack of timeliness and noise as explanations for the low contemporaneous return-earnings association, *Journal of Accounting and Economics*, 18, 289-324.

Cohen, Randolph, Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609-641.

Connor, Gregory, and Robert A. Korajczyk, 1986, Performance Measurement with the Arbitrage Pricing Theory: A New Framework for Analysis, *Journal of Financial Economics*, 15(3), 373–394.

Connor, Gregory, and Robert A. Korajczyk, 1987, Estimating pervasive economic factors with missing observations, Working paper #34, Department of Finance, Northwestern University.

Connor, Gregory, and Robert A. Korajczyk, 1988, Risk and return in an equilibrium APT: Application of a new test methodology, *Journal of Financial Economics* 21, 255-289.

Connor, Gregory, and Robert A. Korajczyk, 1993, A test for the number of factors in an approximate factor model, *Journal of Finance* 48, 1263-1291.

Daniel, Kent, and Sheridan Titman, 2005, Testing factor-model explanations of market anomalies, working paper.

DeAngelo, Harry, Linda DeAngelo, and Douglas J. Skinner, 2004, Are dividends disappearing? Dividend concentration and the consolidation of earnings, *Journal of Financial Economics* 72, 425–456.

Dow, James, and Gary Gorton, 1997, Stock market efficiency and economic efficiency: Is there a connection? *The Journal of Finance*, 52, 1087-1129.

Easton, Peter D., 2004, PE ratios, PEG ratios, and estimating the implied expected rate of return on equity capital, *Accounting Review* 79, 73-95.

Fama, Eugene F., 1990, Stock returns, expected returns, and real activity, *Journal of Finance*, 45, 1089-1108.

Fama, Eugene F., and Kenneth R. French, 1988, Dividend yields and expected stock returns, *Journal of Financial Economics*, 22, 3-25.

Fama, Eugene F., and Kenneth R. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics*, 25, 23-49.

Fama, Eugene F., and Kenneth R. French, 2001, Disappearing dividends: changing firm characteristics or lower propensity to pay? *Journal of Financial Economics* 60, 3–43.

Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: empirical tests, *Journal of Political Economy* 81, 607-636.

Financial Accounting Standards Board, 1978, Statement of Financial Accounting Concepts No.1: Objectives of Financial Reporting by Business Enterprises. Stamford, Connecticut: Financial Accounting

Standards Board.

Financial Accounting Standards Board, 1985, Statement of Financial Accounting Concepts No. 6: Elements of Financial Statements. Stamford, Connecticut: Financial Accounting Standards Board.

Govindajaran, Vijayaraghavan, 1980, The objectives of financial statements: An empirical study of the use of cash flow and earnings by security analysts, *Accounting, Organizations and Society* 5, 383-392.

Handa, Puneet, S.P. Kothari, and Charles Wasley, 1989, The relation between the return interval and betas, *Journal of Financial Economics* 23, 79-100.

Hansen, Lars P., 1982, Large sample properties of generalized method of moments estimators, *Econometrica* 50, 1029-1054.

Hansen, Lars P., John C. Heaton, and Nan Li, 2005, Consumption strikes back?: Measuring long-run risk, working paper.

Hansen, Lars P., and Ravi Jagannathan, 1997, Assessing specification errors in stochastic discount factor models. *Journal of Finance* 62, 557-590.

Hecht, Peter, and Tuomo Vuolteenaho, 2006, Explaining returns with cash-flow proxies, *Review of Financial Studies,* 19, 159-194.

Hirshleifer, David, Avanidhar Subrahmanyam, and Sheridan Titman, 2006, Feedback and the success of irrational investors, *Journal of Financial Economics*, 81, 311–338.

Jagannathan, Ravi, and Zhenyu Wang, 1996, The conditional CAPM and the cross-section of expected returns, *Journal of Finance* 51, 3-53.

Kleidon, Allan W., 1986, Variance bounds tests and stock price valuation models, *Journal of Political Economy* 94, 953-1001.

Keim, Donald B., and Robert F. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357–390.

Kothari, S.P., Jonathan W. Lewellen, and Jerold B. Warner, 2006, Stock returns, aggregate earnings surprises, and behavioral finance, *Journal of Financial Economics*, 79, 537-568.

Kothari, S.P. and Jay Shanken, 1992, Stock return variation and expected dividends, *Journal of Financial Economics*, 31, 177-210.

Kothari, S.P., and Jay Shanken, 1997, Book-to-market, dividend yield, and expected market returns: A time-series analysis, *Journal of Financial Economics* 44, 169-203.

Lamont, Owen, 1998, Earnings and expected returns, *Journal of Finance*, 53, 1563-1587.

Lang, Larry H.P., René M. Stulz, and Ralph A. Walking, 1991, A test of the free cash flow hypothesis: The case of bidder returns, *Journal of Financial Economics*, 29, 315-335.

Lehn, Kenneth, and Annette Poulsen, 1989, Free cash flow and stockholder gains in going private transactions, *Journal of Finance* 44, 771-787.

Lettau, Martin, and Sydney C. Ludvigson, 2001, Resurrecting the (C) CAPM: a cross-sectional test when risk premia are time-varying, *Journal of Political Economy*, 109, 1238-1287.

Lettau, Martin, and Sydney C. Ludvigson, 2005, Expected returns and expected dividend growth, *Journal of Financial Economics*, 76, 583-626.

Lettau, Martin, and Jessica A. Watcher, 2007, Why is long-horizon equity less risky? A duration-based explanation of the value premium, *Journal of Finance* 62, 55-92.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2007, A skeptical appraisal of asset-pricing tests, working paper.

Lorrain, borja, and Motohiro Yogo, 2007, Does firm value move too much to be justified by subsequent changes in cash flow? *Journal of Financial Economics*, forthcoming.

Miller, Meron H., and Franco Modigliani, 1961, Dividend policy, growth, and the valuation of shares, *Journal of Business* 34, 235-64.

Sadka, Gil, 2007, Understanding stock price volatility: The role of earnings, *Journal of Accounting Research*, 45, 1, 199-228.

Sadka, Gil, and Ronnie Sadka, 2007, Predictability and the earnings-returns relation, working paper.

Santos, Tano, and Pietro Veronesi, 2006, Habit formation, the cross section of stock returns and the cash-flow risk puzzle, working paper.

Schwert, William G., 1990, Stock returns and real activity: A century of evidence, *Journal of Finance* 45, 1237-1257.

Trzcinka, Charles, 1986, On the number of factors in the Arbitrage Pricing Model, *Journal of Finance* 41, 347-368.

Vassalou, Maria, 2003, News related to future GDP growth as a risk factor in equity returns, *Journal of Financial Economics*, 68, 47-73.

Vuolteenaho, Tuomo, 2000, Understanding the aggregate book-to-market ratio and its implications to current equity-premium expectations, working paper, Harvard University.

Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns? *Journal of Finance*, 57, 233-264.

Watts, Ross L., 2003a, Conservatism in accounting part I: Explanations and implications, *Accounting Horizons* 17, 207-221.

Watts, Ross L., 2003b, Conservatism in accounting part II: Evidence and research opportunities, *Accounting Horizons* 17, 287-301.

Watts, Ross L., and Jerold L. Zimmerman, 1986, Positive accounting theory, Englewood Cliffs, N.J.: Prentice-Hall.

Table 1
Diagnostics of commonality in stock returns and returns-on-assets

This table reports distribution statistics of time-series regressions. Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The principal components are orthogonalized in the following fashion: the second component is orthogonalized to the first, the third is orthogonalized to the first and second, as so on. Then, for each variable (return and ROA) and each stock, a time-series regression of the variable on its (orthogonalized) common factors is executed. The table reports the percentage of firms in the sample that exhibit significant coefficients at the 1%, 2%, 5%, 10%, and 20% statistical significance levels. The average R^2 and the average adjusted-R^2 of these regressions are also reported below. Prior to the extraction of principal components, each year the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

Panel A. Stock returns						Panel B. Returns-on-assets					
Significance	1 factor	2 factors	3 factors	4 factors	5 factors	Significance	1 factor	2 factors	3 factors	4 factors	5 factors
20	65.30	24.25	22.94	15.03	24.63	20	40.36	23.09	24.87	23.55	25.40
10	57.56	19.43	16.42	9.75	17.85	10	31.30	17.96	19.16	18.35	19.47
5	49.42	15.42	11.10	6.44	13.11	5	24.79	13.53	15.11	13.57	15.00
2	40.05	11.37	6.78	3.97	9.14	2	17.73	8.52	10.87	9.98	11.33
1	34.43	9.41	4.93	2.58	6.36	1	13.76	6.48	8.83	7.71	9.10
Avg R2	0.33	0.42	0.48	0.53	0.59	Avg R2	0.17	0.28	0.42	0.50	0.58
Avg AdjR2	0.28	0.34	0.36	0.37	0.41	Avg AdjR2	0.12	0.18	0.29	0.34	0.40

Table 2
Correlation of principal components of stock returns and returns-on-assets

Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. Panel A presented the time-series correlation matrix of the first five principal components and returns and ROAs, as well as the cross-sectional average of returns and ROAs. For Panel B, the principal components are orthogonalized in the following fashion: the second component is orthogonalized to the first, the third is orthogonalized to the first and second, as so on. Prior to the extraction of principal components, each year, the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

Panel A. Before orthogonalizatoin

	PC1 RET	PC2 RET	PC3 RET	PC4 RET	PC5 RET	PC1 ROA	PC2 ROA	PC3 ROA	PC4 ROA	PC5 ROA	Avg RET	Avg ROA
PC1 RET	1											
PC2 RET	0.28	1										
PC3 RET	0.09	-0.05	1									
PC4 RET	0.02	-0.01	0.00	1								
PC5 RET	0.18	-0.09	-0.03	-0.01	1							
PC1 ROA	0.08	0.21	-0.10	0.39	-0.05	1						
PC2 ROA	-0.02	0.08	-0.23	0.33	0.01	0.76	1					
PC3 ROA	-0.09	0.09	0.27	0.16	0.10	0.16	-0.01	1				
PC4 ROA	-0.02	-0.26	-0.27	0.24	0.20	-0.09	0.00	0.00	1			
PC5 ROA	-0.09	-0.02	-0.01	0.01	-0.06	-0.09	0.00	0.00	0.00	1		
Avg RET	0.99	0.37	0.11	0.00	0.16	0.13	0.01	-0.08	-0.07	-0.10	1	
Avg ROA	0.09	0.19	-0.06	0.37	0.05	0.96	0.75	0.30	-0.11	-0.11	0.14	1

Panel B. After orthogonalization

	PC1 RET	PC2 RET	PC3 RET	PC4 RET	PC5 RET	PC1 ROA	PC2 ROA	PC3 ROA	PC4 ROA	PC5 ROA	Avg RET	Avg ROA
PC1 RET	1											
PC2 RET	0	1										
PC3 RET	0	0	1									
PC4 RET	0	0	0	1								
PC5 RET	0	0	0	0	1							
PC1 ROA	0.08	0.20	-0.09	0.39	-0.04	1						
PC2 ROA	-0.13	-0.10	-0.23	0.05	0.07	0	1					
PC3 ROA	-0.14	0.07	0.26	0.12	0.18	0	0	1				
PC4 ROA	0.00	-0.24	-0.29	0.26	0.13	0	0	0	1			
PC5 ROA	-0.06	0.02	0.00	0.05	-0.06	0	0	0	0	1		
Avg RET	0.99	0.09	0.02	-0.02	-0.01	0.13	-0.14	-0.13	-0.04	-0.07	1	
Avg ROA	0.09	0.17	-0.05	0.37	0.07	0.96	0.02	0.16	-0.04	-0.03	0.14	1

Table 3

Correlation of principal components of stock returns and AR(2)-adjusted principal components of returns-on-assets

Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The principal components of returns and ROAs are separately orthogonalized in the following fashion: the second component is orthogonalized to the first, the third is orthogonalized to the first and second, as so on. A second order autocorrelation model is applied to each principal component of ROAs whose time-series shocks are used to proxy for factor innovations. The table reports the time-series correlation matrix of five components of returns and five components of ROAs (contemporaneous and lead). Prior to the extraction of principal components, each year the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

	PC1 RET	PC2 RET	PC3 RET	PC4 RET	PC5 RET	PC1 ROA	PC2 ROA	PC3 ROA	PC4 ROA	PC5 ROA	LPC1 ROA	LPC2 ROA	LPC4 ROA	LPC5 ROA
PC1 RET	1													
PC2 RET	-0.02	1												
PC3 RET	0.03	0.03	1											
PC4 RET	-0.07	-0.01	0.04	1										
PC5 RET	0.01	0.02	-0.02	-0.01	1									
PC1 ROA	-0.21	0.28	-0.29	0.20	-0.27	1								
PC2 ROA	0.13	-0.07	-0.28	0.11	0.07	-0.10	1							
PC3 ROA	-0.12	0.25	-0.10	0.20	0.10	0.17	0.14	1						
PC4 ROA	-0.12	-0.13	-0.03	0.17	0.32	0.05	-0.22	0.14	1					
PC5 ROA	-0.10	-0.02	-0.13	0.03	-0.07	0.17	-0.40	0.16	0.03	1				
LPC1 ROA	0.34	0.39	-0.10	0.38	0.15	0.02	0.04	0.30	0.07	-0.02	1			
LPC2 ROA	-0.20	-0.16	-0.13	0.09	-0.13	0.34	-0.06	0.04	0.12	0.23	-0.10	1		
LPC3 ROA	-0.02	0.14	-0.13	0.10	0.33	0.06	0.14	0.06	-0.01	0.04	0.17	0.16		
LPC4 ROA	0.13	-0.30	0.16	0.23	0.21	-0.19	0.19	-0.04	0.01	-0.12	0.05	-0.20	1	
LPC5 ROA	0.13	0.14	-0.24	-0.09	0.14	-0.19	0.22	0.05	-0.20	0.04	0.17	-0.42	0.02	1

Table 4

Canonical correlations stock returns and returns-on-assets

Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The principal components of returns and ROAs are separately orthogonalized in the following fashion: the second component is orthogonalized to the first, the third is orthogonalized to the first and second, as so on. A second order autocorrelation model is applied to each principal component of ROAs whose time-series shocks are used to proxy for factor innovations. The table reports the first canonical correlation between each two groups of common factors for different lags and for different number of factors in each group. The first column on the left indicates the number of lags that ROA components lead return components. For example, lead 0 is contemporaneous, lead 1 is the correlation of return at time t with ROA at time t+1, and lead -1 is the correlation of return at time t with ROA at time t-1. Prior to the extraction of principal components, each year the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

lead ROA	2 factors	3 factors	4 factors	5 factors
-5	0.28	0.34	0.34	0.64
-4	0.31	0.35	0.38	0.44
-3	0.23	0.43	0.45	0.52
-2	0.19	0.41	0.51	0.55
-1	0.35	0.42	0.57	0.57
0	0.36	0.51	0.58	0.62
1	0.57	0.57	0.70	0.72
2	0.38	0.42	0.50	0.60
3	0.40	0.56	0.64	0.68
4	0.31	0.31	0.55	0.58
5	0.20	0.37	0.39	0.49

Table 5

Correlations with macroeconomic variables

Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The principal components of returns and ROAs are separately orthogonalized in the following fashion: the second component is orthogonalized to the first, the third is orthogonalized to the first and second, as so on. A second order autocorrelation model is applied to each principal component of ROAs whose time-series shocks are used to proxy for factor innovations. The table reports the time-series pairwise correlations of five components of returns and five components of ROAs (contemporaneous and lead) with growth in industrial production, real GDP growth, unemployment rate, and inflation. The table also reports the first canonical correlation between each group of five factors (returns, ROA, and lead ROA) and the group of four macroeconomic variables. Prior to the extraction of principal components, each year the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

	Pairwise correlations				Canonical correlations
	Industrial production	Real GDP	Unemployment	Inflation	
PC1 RET	0.23	0.38	0.40	-0.19	0.68
PC2 RET	0.15	0.15	-0.15	0.33	
PC3 RET	-0.09	0.07	0.21	0.16	
PC4 RET	0.37	0.28	-0.04	-0.02	
PC5 RET	-0.01	0.14	0.14	-0.26	
PC1 ROA	0.25	0.04	-0.71	0.08	0.76
PC2 ROA	-0.11	-0.08	0.06	-0.18	
PC3 ROA	0.12	0.13	0.03	0.12	
PC4 ROA	0.12	0.15	-0.12	-0.13	
PC5 ROA	0.21	0.06	-0.15	-0.11	
LPC1 ROA	0.58	0.67	0.14	-0.25	0.75
LPC2 ROA	0.01	-0.09	-0.42	-0.16	
LPC3 ROA	-0.01	-0.02	0.04	0.11	
LPC4 ROA	0.10	0.19	0.12	-0.21	
LPC5 ROA	0.03	0.06	0.16	-0.12	

Table 6
Earnings factor loadings

Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. A second order autocorrelation model is applied to each principal component of ROAs whose time-series shocks are used to proxy for factor innovations. Three different sets of portfolios are analyzed: 25 book-to-market portfolios (both equal- and value-weighted) and 25 portfolios sorted by standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$, where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The book-to-market portfolios are rebalanced at the beginning of April of each year (and held for one year); the portfolio weights for the value-weighted portfolios are the market values at the beginning of April. The SUE portfolios are rebalanced every month while holding each stock up to four months after the announcement date. The returns of all portfolios are the cumulative annual return from April of a given year through March of the following year. The table reports factor loadings, which are calculated using time-series regressions of portfolio returns (excess of the risk-free rate) on the innovations of the first principal component of ROA and their lead values (*t*-statistics in square brackets). Prior to the extraction of principal components, each year the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The year 2001 was excluded from the analysis due to the adverse nature of that year. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1963 through March 2006 (SUE portfolio returns are available from March 1974).

Portfolio	Book-to-market (equal-weighted)				Book-to-market (value-weighted)				SUE (equal-weighted)			
ranking	ROA	T-statistic	Lead ROA	T-statistic	ROA	T-statistic	Lead ROA	T-statistic	ROA	T-statistic	Lead ROA	T-statistic
1	-4.01	[-1.14]	10.54	[2.76]	-5.49	[-2.10]	6.58	[2.32]	-1.81	[-0.67]	7.46	[2.54]
2	-3.84	[-1.20]	8.69	[2.49]	-6.13	[-2.53]	3.44	[1.31]	-2.30	[-0.85]	7.08	[2.38]
3	-2.98	[-0.89]	6.34	[1.74]	-3.82	[-1.93]	3.11	[1.44]	-2.00	[-0.73]	5.56	[1.87]
4	-4.23	[-1.44]	5.98	[1.87]	-3.91	[-1.84]	1.70	[0.74]	-2.38	[-0.83]	5.75	[1.83]
5	-5.25	[-1.93]	7.07	[2.39]	-3.02	[-1.52]	5.64	[2.61]	-3.47	[-1.23]	6.37	[2.07]
6	-4.23	[-1.42]	5.71	[1.76]	-3.40	[-1.55]	3.71	[1.56]	-3.43	[-1.16]	6.15	[1.91]
7	-4.61	[-1.77]	6.46	[2.28]	-3.17	[-1.55]	4.06	[1.83]	-3.68	[-1.10]	6.82	[1.86]
8	-3.09	[-1.01]	5.00	[1.50]	-2.29	[-1.17]	1.80	[0.85]	-3.70	[-1.23]	6.00	[1.83]
9	-3.99	[-1.57]	6.03	[2.18]	-2.90	[-1.37]	1.02	[0.44]	-2.37	[-0.76]	7.04	[2.06]
10	-3.97	[-1.60]	5.04	[1.88]	-2.87	[-1.48]	1.96	[0.93]	-3.56	[-1.20]	7.44	[2.31]
11	-4.36	[-1.87]	4.92	[1.94]	-3.12	[-1.48]	3.80	[1.66]	-2.80	[-0.83]	8.17	[2.21]
12	-2.51	[-1.06]	4.27	[1.66]	-0.81	[-0.39]	3.88	[1.71]	-3.00	[-0.92]	7.12	[1.99]
13	-2.59	[-1.05]	6.83	[2.56]	-0.28	[-0.15]	1.74	[0.85]	-3.20	[-1.05]	7.58	[2.27]
14	-5.13	[-2.09]	6.62	[2.48]	-1.20	[-0.59]	3.91	[1.77]	-3.34	[-1.00]	8.25	[2.26]
15	-2.50	[-1.04]	6.25	[2.39]	-2.66	[-1.27]	4.32	[1.90]	-3.66	[-1.09]	8.31	[2.26]
16	-4.27	[-1.52]	6.64	[2.18]	-3.02	[-1.55]	4.78	[2.25]	-3.83	[-1.13]	8.17	[2.21]
17	-3.29	[-1.17]	6.40	[2.08]	-3.12	[-1.67]	3.99	[1.96]	-4.80	[-1.62]	7.74	[2.40]
18	-1.97	[-0.67]	6.75	[2.12]	-2.90	[-1.26]	4.07	[1.63]	-3.62	[-0.99]	7.75	[1.95]
19	-3.32	[-1.12]	7.21	[2.23]	-1.11	[-0.48]	3.51	[1.39]	-5.11	[-1.59]	8.68	[2.47]
20	-3.44	[-1.22]	7.78	[2.54]	-0.16	[-0.06]	5.37	[1.98]	-4.63	[-1.32]	7.43	[1.95]
21	-2.19	[-0.65]	7.30	[1.98]	-3.37	[-1.32]	3.07	[1.10]	-3.78	[-1.08]	8.04	[2.11]
22	-1.83	[-0.51]	8.89	[2.28]	-0.74	[-0.30]	3.75	[1.42]	-6.39	[-1.77]	8.43	[2.15]
23	-1.53	[-0.39]	10.40	[2.45]	-0.44	[-0.16]	7.00	[2.40]	-5.07	[-1.34]	8.44	[2.05]
24	-3.76	[-1.06]	10.34	[2.69]	-0.98	[-0.37]	8.12	[2.78]	-5.61	[-1.53]	8.75	[2.19]
25	-2.57	[-0.98]	10.46	[3.68]	-1.14	[-0.51]	6.56	[2.72]	-4.62	[-1.25]	8.47	[2.10]

Table 7

Pricing systematic earnings using cross-sectional regressions

Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The second principal components of returns and ROAs are orthogonalized to the first components, respectively. A second order autocorrelation model is applied to each principal component of ROAs whose time-series shocks are used to proxy for factor innovations. Three different sets of portfolios are analyzed: 25 book-to-market portfolios (both equal- and value-weighted) and 25 portfolios sorted by standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$, where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The book-to-market portfolios are rebalanced at the beginning of April of each year (and held for one year); the portfolio weights for the value-weighted portfolios are the market values at the beginning of April. The SUE portfolios are rebalanced every month while holding each stock up to four months after the announcement date. The returns of all portfolios are the cumulative annual return from April of a given year through March of the following year. Factor loadings are calculated using time-series regressions of portfolio returns (excess of the risk-free rate) on various risk factors. The factors considered are the first two principal components of returns (orthogonalized) and the innovations to the first two principal components of ROAs (contemporaneous and lead). The table reports the results of Fama and MacBeth (1973) regressions of portfolio returns (excess of the risk-free rate) on the (normalized) factor loadings for different models (premiums are reported in percent; *t*-statistics in square brackets). For each model, the adjusted R^2 computed from a single cross-sectional regression of average excess portfolio returns on their factor loadings is reported. Prior to the extraction of principal components, each year the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The year 2001 was excluded from the analysis due to the adverse nature of that year. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1963 through March 2006 (SUE portfolio returns are available from March 1974).

Panel A. 25 book-to-market portfolios (equal-weighted)

Int.	RET PC1	ROA PC1	ROA LPC1	RET PC2	ROA PC2	ROA LPC2	Adj. R^2
-17.31	3.00						0.53
[-2.36]	[3.36]						
17.78		2.62					0.39
[3.72]		[3.63]					
2.08			2.44				0.33
[0.65]			[3.74]				
10.12		1.92	1.86				0.50
[2.64]		[3.08]	[3.31]				
-5.94	1.67	1.38	1.17				0.62
[-1.08]	[2.18]	[2.80]	[2.43]				
-18.83	3.17			-0.26			0.52
[-2.16]	[2.93]			[-0.32]			
19.26		2.95			-0.70		0.39
[4.23]		[3.68]			[-1.10]		
7.32			2.43			1.18	0.38
[2.06]			[3.73]			[2.09]	
13.83		2.54	2.28		-0.96	1.32	0.52
[3.09]		[3.18]	[3.90]		[-1.74]	[2.25]	
-8.98	2.19	1.67	1.81	1.32	-1.03	0.36	0.77
[-1.35]	[2.43]	[3.06]	[3.96]	[1.87]	[-2.03]	[1.28]	

Panel B. 25 book-to-market portfolios (value-weighted)

Int.	RET PC1	ROA PC1	ROA LPC1	RET PC2	ROA PC2	ROA LPC2	Adj. R^2
-9.05	2.33						0.62
[-1.67]	[2.99]						
10.10		1.62					0.28
[3.44]		[2.09]					
4.08			1.85				0.38
[1.62]			[3.11]				
6.35		1.19	1.53				0.48
[2.20]		[1.57]	[2.77]				
-4.71	1.84	0.36	0.84				0.65
[-1.08]	[2.57]	[0.51]	[1.68]				
-2.61	1.41			1.23			0.68
[-0.42]	[1.71]			[1.84]			
11.33		1.28			-1.02		0.36
[3.55]		[1.87]			[-2.01]		
4.13			2.00			0.38	0.35
[1.65]			[3.10]			[1.06]	
8.11		1.05	1.30		-0.84	-0.20	0.52
[2.33]		[1.41]	[2.10]		[-1.82]	[-0.51]	
0.95	1.22	0.25	0.51	1.26	-0.47	0.05	0.65
[0.17]	[1.43]	[0.34]	[1.01]	[1.82]	[-1.08]	[0.14]	

Panel C. 25 SUE portfolios (equal-weighted)

Int.	RET PC1	ROA PC1	ROA LPC1	RET PC2	ROA PC2	ROA LPC2	Adj. R^2
-50.98	6.92						0.77
[-13.49]	[11.35]						
-4.72		-6.39					0.65
[-1.25]		[-10.81]					
-33.25			6.22				0.61
[-9.15]			[10.87]				
-26.40		-4.13	3.67				0.78
[-7.62]		[-9.13]	[8.97]				
-42.21	4.80	-2.87	1.68				0.86
[-13.02]	[10.02]	[-7.60]	[5.20]				
-51.72	4.92			3.16			0.86
[-13.59]	[9.29]			[6.80]			
-8.42		-6.47			0.85		0.65
[-2.51]		[-10.89]			[2.68]		
-39.49			4.55			-3.13	0.78
[-10.47]			[9.18]			[-8.02]	
-33.37		-2.98	3.74		0.05	-1.82	0.80
[-10.49]		[-7.66]	[8.59]		[0.16]	[-5.78]	
-40.95	3.83	-2.81	2.02	3.92	-0.51	-1.00	0.92
[-12.38]	[8.24]	[-5.36]	[3.80]	[5.30]	[-1.54]	[-3.12]	

Table 8

Pricing tests using aggregate free cash flow

Stock returns are compounded annually from April of a given year through March of the following year. Common factors are extracted for returns using the asymptotic principal components (APC) method. The second principal component of returns is orthogonalized to the first components. Three different sets of portfolios are used: 25 book-to-market portfolios (both equal- and value-weighed) and 25 SUE portfolios. The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$, where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The book-to-market portfolios are rebalanced at the beginning of April of each year (and held for one year); the portfolio weights for the value-weighted portfolios are the market values at the beginning of April. The SUE portfolios are rebalanced every month while holding each stock up to four months after the announcement date. The returns of all portfolios are the cumulative annual return from April of a given year through March of the following year. Factor loadings are calculated using time-series regressions of portfolio returns on various risk factors. The factors considered are the first two principal components of returns (orthogonalized) and aggregate free cash flow (contemporaneous and lead). Free cash flow is defined as operating income before depreciation minus interest expenses and taxes. The table reports the results of Fama and MacBeth (1973) regressions of portfolio returns (excess of risk-free rate) on the (normalized) factor loadings for different models (premiums are reported in percent; *t*-statistics in square brackets). For each model two adjusted R^2 figures are reported: the top figure is computed from a single cross-sectional regression of average excess portfolio returns on their factor loadings, while the bottom figure is the average of the adjusted R^2s computed from a cross-sectional regression of excess portfolio returns on their factor loadings each year. Prior to the extraction of principal components, each year the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The year 2001 was excluded from the analysis due to the adverse nature of that year. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1963 through March 2006 (SUE portfolio returns are available from March 1974).

Panel A. 25 book-to-market portfolios (equal-weighted)

Intercept	FCF	LFCF	PC1 RET	PC2 RET	Adj-R^2
11.60	1.73				0.15
[2.97]	[2.77]				
7.68		2.39			0.32
[2.24]		[3.90]			
7.58	0.54	2.18			0.29
[2.01]	[1.09]	[4.37]			
-17.24	-0.75	1.24	2.88		0.59
[-2.07]	[-1.28]	[3.06]	[2.80]		
-17.46	-0.42	1.32	2.94	0.05	0.62
[-2.07]	[-1.00]	[3.21]	[2.74]	[0.06]	

Panel B. 25 book-to-market portfolios (value-weighted)

Intercept	FCF	LFCF	PC1 RET	PC2 RET	Adj-R^2
9.18	1.80				0.35
[3.33]	[2.42]				
7.86		1.80			0.35
[3.03]		[2.59]			
8.62	1.32	1.25			0.40
[3.21]	[2.12]	[2.39]			
-5.41	0.33	0.34	1.94		0.62
[-1.29]	[0.57]	[0.86]	[2.92]		
-2.15	0.12	0.46	1.40	1.35	0.65
[-0.40]	[0.22]	[1.13]	[1.92]	[1.97]	

Panel C. 25 SUE portfolios (equal-weighted)

Intercept	FCF	LFCF	PC1 RET	PC2 RET	Adj-R^2
23.97	-3.33				0.15
[4.65]	[-8.47]				
-12.03		3.86			0.21
[-3.68]		[9.72]			
-6.42	-2.66	3.76			0.44
[-1.90]	[-7.18]	[9.33]			
-43.49	-2.04	0.66	5.75		0.84
[-12.97]	[-5.68]	[2.30]	[10.62]		
-43.06	-1.42	0.28	4.58	2.70	0.91
[-12.84]	[-2.82]	[0.88]	[8.81]	[4.08]	

Table 9

Pricing systematic earnings using the stochastic discount factor approach

Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The second principal components of returns and ROAs are orthogonalized to the first components, respectively. A second order autocorrelation model is applied to each principal component of ROAs whose time-series shocks are used to proxy for factor innovations. Three different sets of portfolios are analyzed: 25 book-to-market portfolios (both equal- and value-weighted) and 25 portfolios sorted by standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q\text{-}4}) - c_{i,t}]/\sigma_{i,t}$, where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q\text{-}4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q\text{-}4})$ over the preceding eight quarters. The book-to-market portfolios are rebalanced at the beginning of April of each year (and held for one year); the portfolio weights for the value-weighted portfolios are the market values at the beginning of April. The SUE portfolios are rebalanced every month while holding each stock up to four months after the announcement date. The returns of all portfolios are the cumulative annual return from April of a given year through March of the following year. The returns (excess of risk-free rate) of the 25 portfolios in each set are used to estimate the following model for the moments $E[R_{i,t}(1-\delta' f_t)]=0$, where $R_{i,t}$ are the returns of portfolio *i*, and f_i is a vector of factors. The factors considered are the first two principal components of returns (orthogonalized) and the innovations to the first two principal components of ROAs (contemporaneous and lead). The models are estimated with the Generalized Method of Moments, using the weighting matrix proposed in Hansen and Jagannathan (1997). Premiums (reported in percent) are calculated as $E[ff']\delta$ (using demeaned factors). The *t*-statistic of δ (below each premium) tests whether the factor has additional pricing power given the other factors. *P*-values of Chi-Squared tests of the different models are also reported (in percent). Prior to the extraction of principal components, each year the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The year 2001 was excluded from the analysis due to the adverse nature of that year. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1963 through March 2006 (SUE portfolio returns are available from March 1974).

Panel A. 25 book-to-market portfolios (equal-weighted)

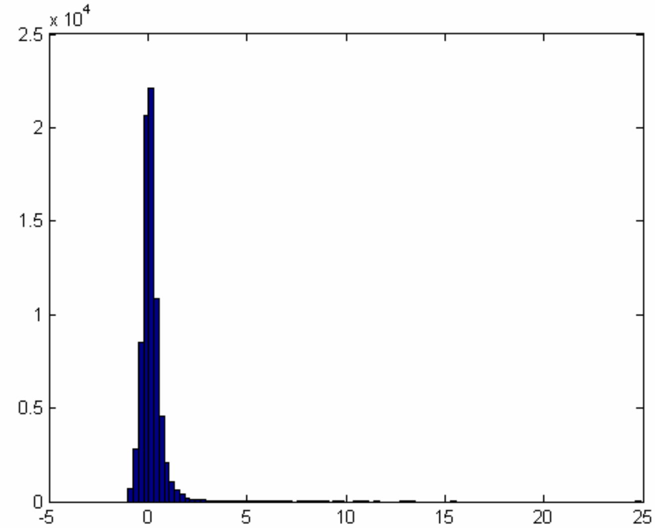
RET PC1	ROA PC1	ROA LPC1	RET PC2	ROA PC2	ROA LPC2	*P*-value
4.49						1.70
[5.33]						
	-2.17					0.00
	[-2.69]					
		1.61				6.04
		[2.93]				
	0.14	1.59				2.12
	[-0.04]	[3.97]				
3.89	1.05	0.17				0.74
[4.38]	[3.14]	[-0.19]				
4.48			0.24			0.35
[3.26]			[0.01]			
	-2.19			2.15		0.13
	[-2.03]			[0.56]		
		1.15			-2.03	1.66
		[2.75]			[-0.94]	
	0.86	1.42		-6.06	-4.01	0.24
	[2.24]	[3.87]		[-2.49]	[-3.24]	
3.66	1.27	0.44	3.76	-3.17	3.82	6.73
[3.16]	[2.28]	[0.02]	[-0.08]	[-1.45]	[0.90]	

Panel B. 25 book-to-market portfolios (value-weighted)

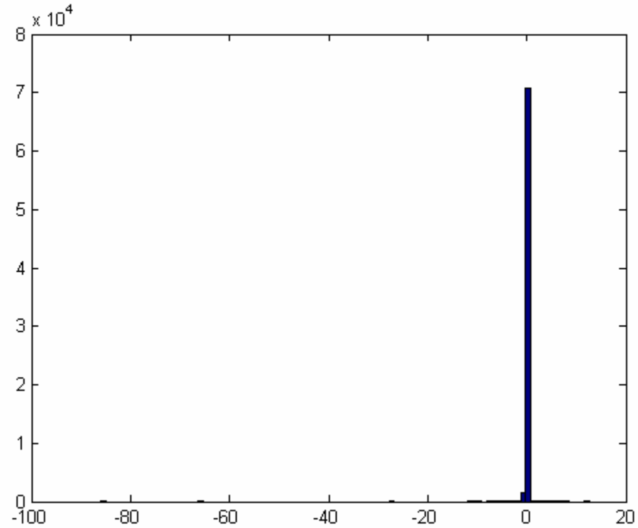
RET PC1	ROA PC1	ROA LPC1	RET PC2	ROA PC2	ROA LPC2	*P*-value
4.32						26.47
[2.91]						
	-1.60					0.00
	[-3.27]					
		1.88				47.67
		[2.07]				
	-0.24	1.63				2.06
	[-0.70]	[4.26]				
4.05	0.37	0.28				27.12
[2.12]	[0.72]	[0.35]				
4.16			4.71			69.25
[1.68]			[1.47]			
	-1.76			-1.63		0.42
	[-2.21]			[-0.64]		
		1.45			-3.09	38.61
		[2.40]			[-1.58]	
	-0.39	1.51		-2.09	-1.74	1.86
	[-0.60]	[2.84]		[-0.58]	[-0.73]	
4.04	-0.02	0.04	3.51	-0.95	-0.32	22.47
[3.39]	[-0.25]	[-1.14]	[2.54]	[-0.99]	[0.36]	

Panel C. 25 SUE portfolios (equal-weighted)

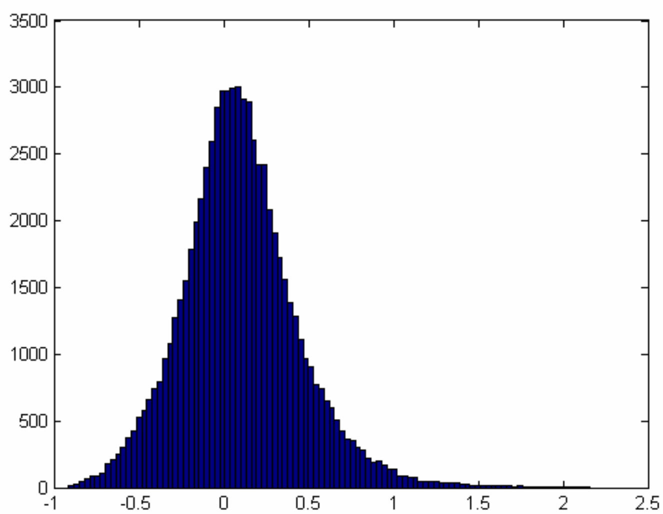
RET PC1	ROA PC1	ROA LPC1	RET PC2	ROA PC2	ROA LPC2	*P*-value
5.90						0.00
[2.86]						
	-2.63					3.15
	[-3.73]					
		2.11				0.00
		[3.06]				
	-3.11	-0.68				2.28
	[-4.13]	[-0.75]				
5.53	-1.11	-1.85				0.32
[6.23]	[-3.39]	[-5.84]				
11.24			-22.76			0.00
[9.08]			[-4.36]			
	-2.70			-5.13		0.23
	[-3.27]			[-0.75]		
		-1.89			-15.28	0.12
		[-2.04]			[-4.59]	
	-2.10	-0.69		-4.18	-8.29	0.26
	[-2.44]	[-1.12]		[-2.54]	[-2.95]	
4.26	-0.66	-1.29	-8.61	-3.21	-0.18	4.78
[5.22]	[-1.71]	[-3.39]	[1.21]	[-3.54]	[2.46]	



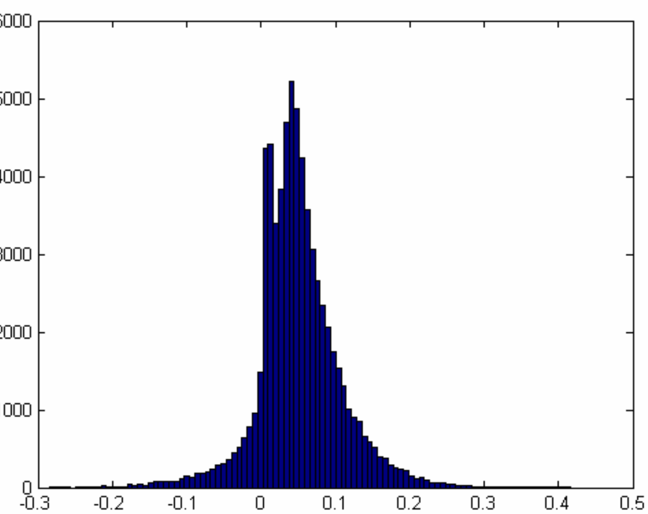
Panel A. Raw return distribution



Panel B. Raw ROA distribution

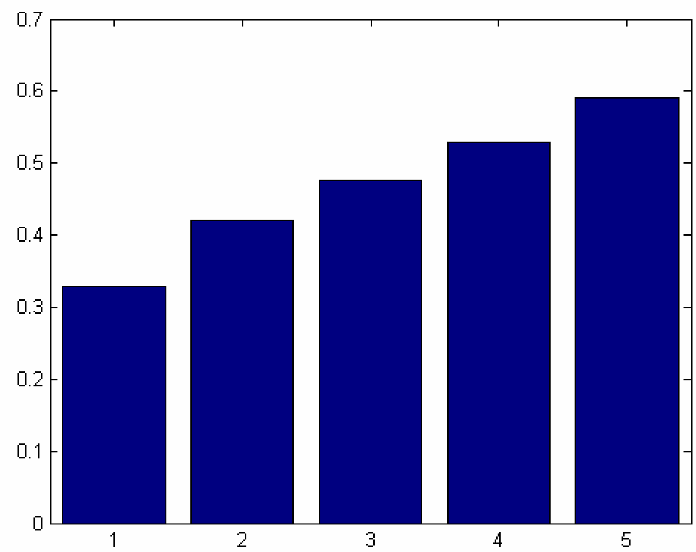


Panel C. Truncated return distribution

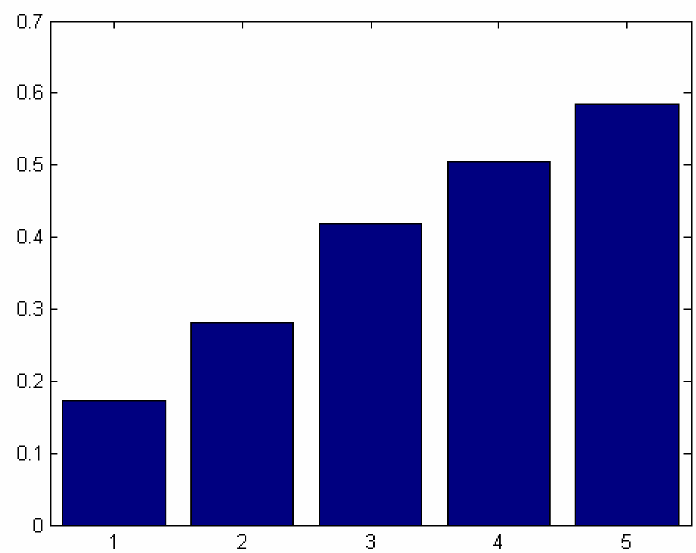


Panel D. Truncated ROA distribution

Figure 1. The distribution of stock return and return-on-assets (ROA). This figure presents histograms of stock returns and returns-on-assets of individual firms. Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Panels A and B include all observations pooled across the sample period. In Panel C, the bottom 1% and top 5% of the distribution of returns each year are truncated, while in Panel D, the bottom 5% and top 1% of ROAs are truncated. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.



Panel A. The average R^2 using principal components of return



Panel B. The average R^2 using principal components of ROA

Figure 2. Commonality diagnostics of stock returns and returns-on-assets. Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. Then, for each variable (return and ROA) and each stock, a time-series regression of the variable on its common factors is executed. The figure reports the average R^2 of these regressions using one, two, three, four, and five factors. Each year, the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

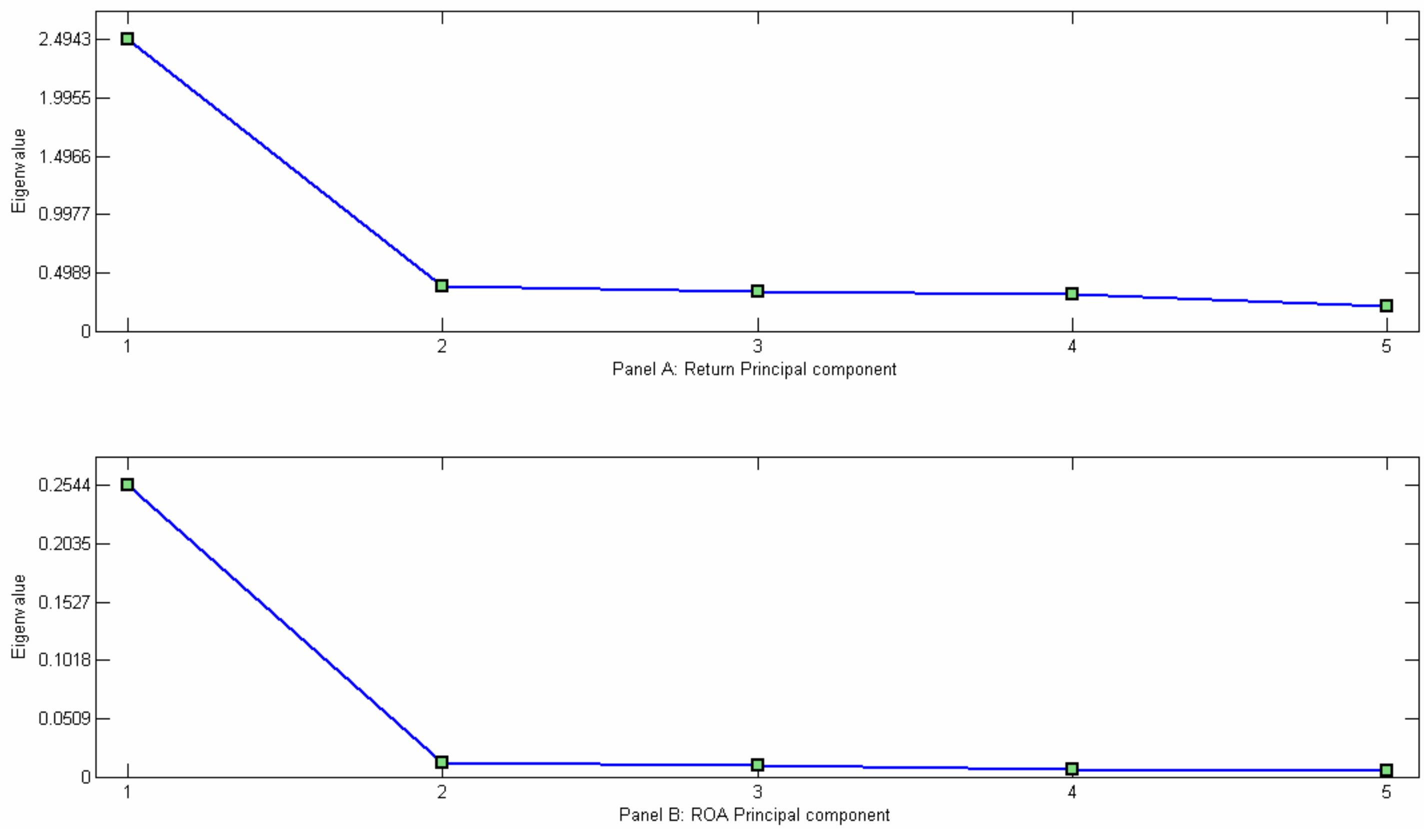


Figure 3. Scree plot. Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The eigenvalues corresponding to the eigenvectors resulting from this procedure are plotted above for the first five factors. Each year, the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

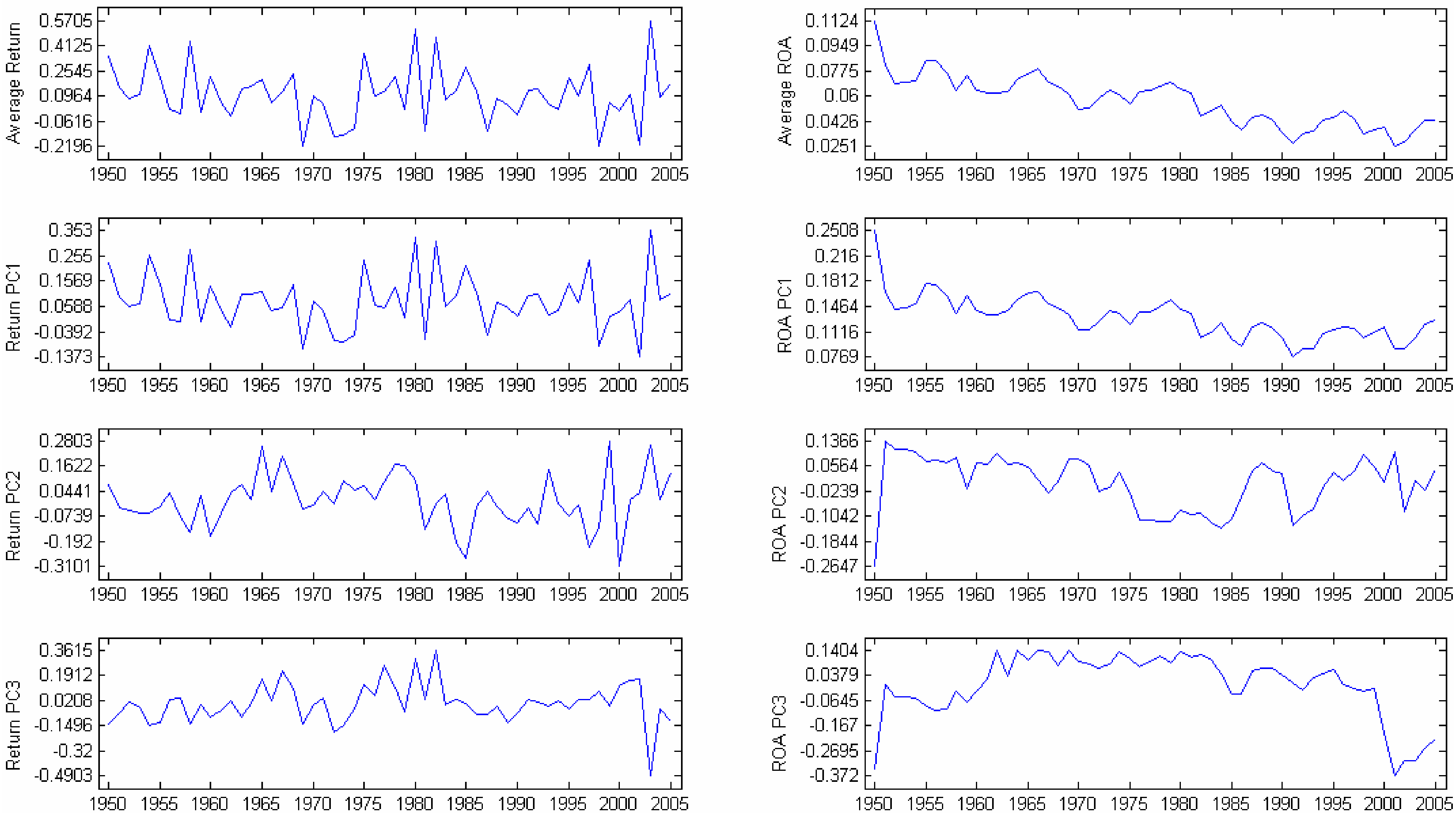


Figure 4. Time series averages and principal components of returns and returns-on-assets. Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The principal components of each variable are orthogonalized in the following fashion: the second component is orthogonalized to the first, the third is orthogonalized to the first and second, as so on. The figure plots the time series of the cross-sectional average of return and ROA as well as the first three principal components of each variable. Each year, the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

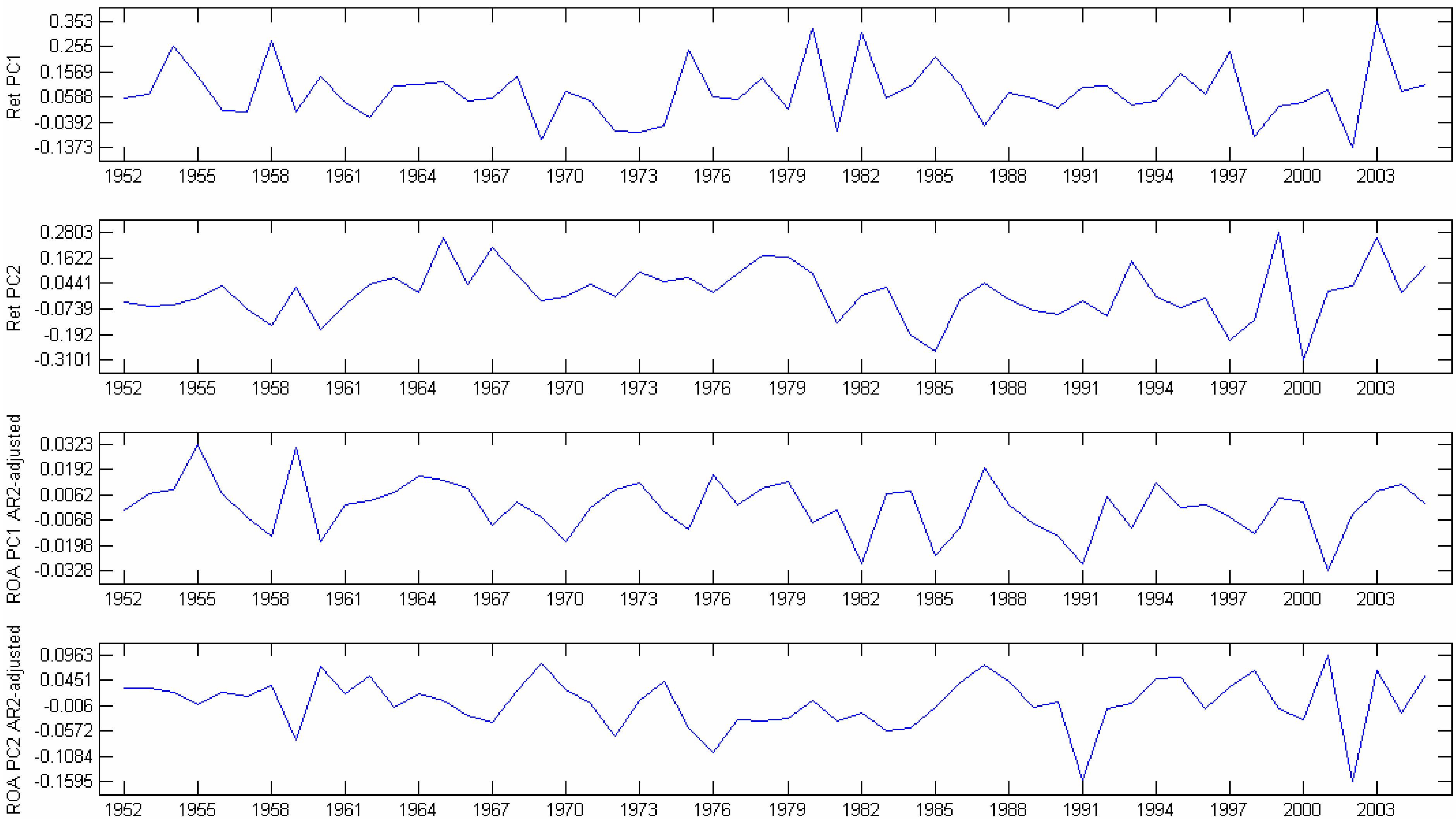


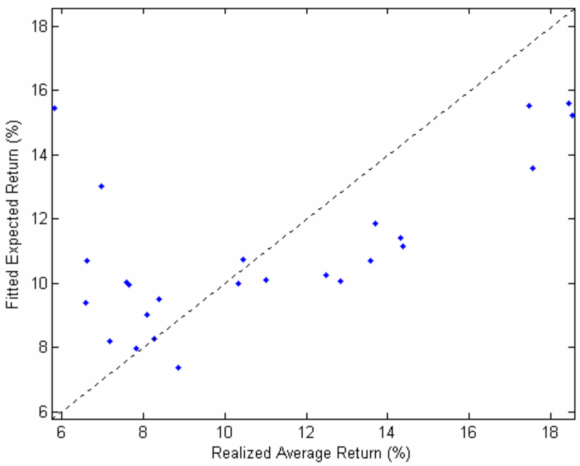
Figure 5. Time series of return principal components and return-on-assets AR(2)-adjusted principal components. Stock returns are compounded annually from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted separately for returns and ROAs using the asymptotic principal components (APC) method. The first two panels plot the time series of the first two principal components of returns. The second principal component is orthogonalized with respect to the first component. For ROAs, shocks to both time series are proxied by the residuals of a second order autocorrelation model applied to each component. The second two figures plot the time series shocks for the first two principal components of ROAs (orthogonalized). Each year, the return sample is truncated at the bottom 1% and the top 5%, while the ROA sample is truncated at the bottom 5% and the top 1%. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1950 through March 2006.

Panel A. 25 Book-to-market portfolios
(equal-weighted)

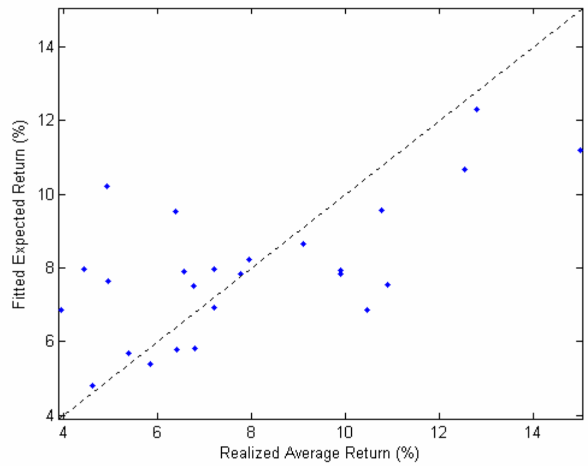
Panel B. 25 Book-to-market portfolios
(value-weighted)

Panel C. 25 SUE portfolios
(equal-weighted)

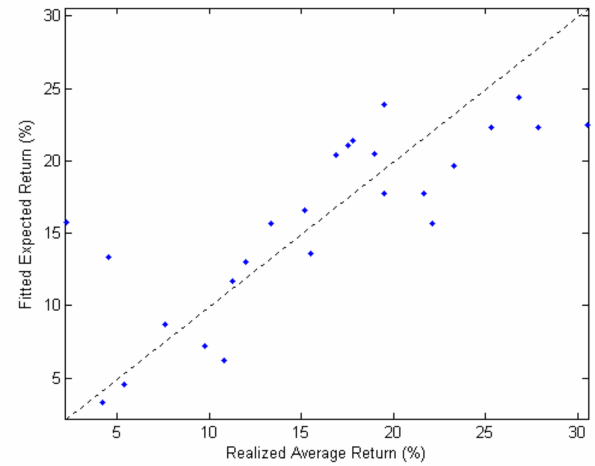
Figure 6. Excess returns and lead earnings loadings of book-to-market and earnings-momentum portfolios. Three different sets of portfolios are analyzed: 25 book-to-market portfolios (both equal- and value-weighted) and 25 portfolios sorted by standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$, where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The book-to-market portfolios are rebalanced at the beginning of April of each year (and held for one year); the portfolio weights for the value-weighted portfolios are the market values at the beginning of April. The SUE portfolios are rebalanced every month while holding each stock up to four months after the announcement date. The returns of all portfolios are the cumulative annual return from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted for ROAs using the asymptotic principal components (APC) method. Shocks to the first principal component of ROAs are proxied by the residuals of a second order autocorrelation model. The earnings loadings (points on the graphs) are calculated using time-series regressions of portfolio returns on the lead shock to the first principal component of ROAs. The time-series average of annual portfolio returns (excess of the risk-free rate) are shown as bars on the graphs. Prior to the extraction of principal components, each year the ROA sample is truncated at the bottom 5% and the top 1%. The year 2001 was excluded from the analysis due to the adverse nature of that year. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1963 through March 2006 (SUE portfolio returns are available from March 1974).



Panel A. 25 Book-to-market portfolios
(equal-weighted)



Panel B. 25 Book-to-market portfolios
(value-weighted)



Panel C. 25 SUE portfolios
(equal-weighted)

Figure 7. The cross-section of book-to-market and earnings-momentum portfolio returns and aggregate earnings. Three different sets of portfolios are analyzed: 25 book-to-market portfolios (both equal- and value-weighted) and 25 portfolios sorted by standardized unexpected earnings (SUE). The variable SUE for stock *i* in month *t* is defined as $[(E_{i,q} - E_{i,q-4}) - c_{i,t}]/\sigma_{i,t}$, where $E_{i,q}$ is the quarterly earnings most recently announced as of month *t* for firm *i* (not including announcements in month *t*); $E_{i,q-4}$ is earnings four quarters ago; and $\sigma_{i,t}$ and $c_{i,t}$ are the standard deviation and average, respectively, of $(E_{i,q} - E_{i,q-4})$ over the preceding eight quarters. The book-to-market portfolios are rebalanced at the beginning of April of each year (and held for one year); the portfolio weights for the value-weighted portfolios are the market values at the beginning of April. The SUE portfolios are rebalanced every month while holding each stock up to four months after the announcement date. The returns of all portfolios are the cumulative annual return from April of a given year through March of the following year. Return-on-assets (ROA) is defined as earnings in a given year scaled by the average of asset value during that year and the previous year. Common factors are extracted for ROAs using the asymptotic principal components (APC) method. Shocks to the first principal component of ROAs are proxied by the residuals of a second order autocorrelation model. Each scatter point in each of the graphs represents one of the 25 portfolios, with the realized average return (excess of risk-free rate) on the horizontal axis, and the fitted expected return on the vertical axis. The realized average return is the time-series average return, and the fitted expected return is calculated as the fitted value from $E(R_{i,t}) = \gamma_0 + \gamma`\beta_{i,}$, where $R_{i,t}$ are the returns of portfolio *i*, β_i is a factor loading, and γ is the estimated risk premium. The loadings are computed through a time-series regression of portfolio excess returns on the lead shock to the first principal component of ROAs over the entire sample period. The straight line in each graph is the 45° line from the origin. Prior to the extraction of principal components, each year the ROA sample is truncated at the bottom 5% and the top 1%. The year 2001 was excluded from the analysis due to the adverse nature of that year. The sample includes NYSE- and AMEX-listed stocks, with December fiscal year-end, over the period April 1963 through March 2006 (SUE portfolio returns are available from March 1974).