Growth or Glamour?

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Abstract

We show that growth stocks' cash flows are particularly sensitive to temporary movements in aggregate stock prices (driven by movements in the equity risk premium), while value stocks' cash flows are particularly sensitive to permanent movements in aggregate stock prices (driven by market-wide shocks to cash flows.) Thus the high betas of growth stocks with the market's discount-rate shocks, and of value stocks with the market's cash-flow shocks, are determined by the cash-flow fundamentals of growth and value companies. Growth stocks are not merely "glamour stocks" whose systematic risks are purely driven by investor sentiment.

JEL classification: G12, G14, N22

1 Introduction

At least since the publication of Graham and Dodd's *Security Analysis* in 1934, it has been understood that value stocks, with low valuation ratios of market prices to accounting measures of cash flow, tend to outperform growth stocks with high valuation ratios. An enormous literature on this value-growth effect asks two main questions.

The first question, and the one that has attracted the most attention, is whether the value-growth effect represents an attractive investment opportunity for a rational investor, or whether it is merely appropriate compensation for some form of risk. Ball (1978), Basu (1977, 1983), Rosenberg, Reid, and Lanstein (1985), Fama and French (1992), and others show that value stocks earn higher returns than the Capital Asset Pricing Model (CAPM) would predict. Lakonishok, Shleifer, and Vishny (1994), La Porta (1996), and Lakonishok, La Porta, Shleifer, and Vishny (1997) argue that value stocks are underpriced and growth stocks overpriced because irrational investors inappropriately extrapolate earnings results, and thus offer an attractive investment opportunity for rational investors.

In constrast, others have suggested that using the CAPM to measure risk may understate the riskiness of value stocks and overstate that of growth stocks. Fama and French (1993) show that value stocks tend to move together, so that an investor who holds them (and/or shorts growth stocks) takes on a common source of risk. Identifying such common variation is necessary for a rational risk story. Fama and French's results, however, leave open the question of whether that common risk should be of concern to a rational investor.

Campbell (1996) and Campbell and Vuolteenaho (2003) propose a version of Merton's (1973) Intertemporal Capital Asset Pricing Model (ICAPM), in which investors care more about permanent cash-flow-driven movements than about temporary discount-rate-driven movements in the aggregate stock market. In their model, the required return on a stock is determined not by its overall beta with the market, but by its "bad" cash-flow beta that earns a high premium and its "good" discount-rate beta that earns a low premium. Campbell and Vuolteenaho find empirically that value stocks have relatively high bad betas while growth stocks have relatively high good betas. Therefore, rational long-horizon investors should be cautious about tilting their portfolios towards value stocks and away from growth stocks, despite value earning higher returns than growth on average.

A second question about the value-growth effect is what drives the realized price movements of growth and value stocks. One view is that the stock market simply prices value and growth stocks differently at different times. For example, Cornell (1999) argues that growth stock profits accrue further in the future than value stock profits, so growth stocks are longer-duration assets whose values are more sensitive to changes in the market discount rate. Barberis and Shleifer (2003) and Barberis, Shleifer, and Wurgler (2002) argue that value stocks lack common fundamentals but are merely those stocks that are currently out of favor with investors, while growth stocks are merely "glamour stocks" that are currently favored by investors. According to the pure-sentiment view, changes in the market's mood or sentiment will then cause a value stock to comove with other value stocks and a glamour stock to comove with other glamour stocks, simply because investor sentiment causes correlated movements in the pricing of certain types of stocks.

Another view is that value and growth stocks are exposed to different cash-flow risks. Fama and French (1996), for example, argue that value stocks are companies that are in financial distress and vulnerable to bankruptcy. Campbell and Vuolteenaho (2003) speculate that growth stocks might have speculative investment opportunities that will be profitable only if equity financing is available on sufficiently good terms; thus they are equity-dependent companies of the sort modeled by Baker, Stein, and Wurgler (2003). Cohen, Polk, and Vuolteenaho (2002) find that value stocks' profitability covaries more with the market-wide profitability than growth stocks', and Liew and Vassalou (2000) show that value-minus-growth returns covary with future macroeconomic fundamentals. According to this fundamentals view, growth stocks move together with other growth stocks and value stocks with other value stocks because of the fundamental characteristics of their cash flows, as would be implied by a simple model of stock valuation in which discount rates are constant.

In this paper we try to connect these two strands of the literature, on the average level of value and growth stock returns and the volatility of these returns. We focus on the systematic volatility of value and growth stocks, that is, on their covariances with permanent and temporary movements in the aggregate stock market. In particular, we ask whether the high "bad beta" of value stocks' returns with the market-wide cash-flow shocks, and the high "good beta" of growth stocks' return with market-wide discount-rate shocks, are driven by the cash-flow fundamentals of value and growth stocks or by their discount rates.

Our results from two sets of tests are easily summarized. In the first set of tests, we estimate a VAR in the manner of Campbell (1991), Campbell and Mei (1993), and Vuolteenaho (2002) to break firm-level stock returns of value and growth stocks into components driven by cash-flow shocks and discount-rate shocks. We then regress the firm level cash-flow and discount-rate news on the market's cash-flow and discount-rate news to find out whether sentiment or cash-flow fundamentals drives the systematic risks of value and growth stocks. According to our results, the bad beta of value stocks and the good beta of growth stocks are both determined primarily by their cash-flow characteristics.

In a second set of tests, we regress value and growth stocks' accounting profitability, measured by return on equity (ROE), on the two components of the market return estimated by Campbell and Vuolteenaho (2003), lengthening the horizon to emphasize longer-term trends rather than short-term fluctuations in profitability. We find that value stocks' ROE is more sensitive to market's cash-flow news than that of growth stocks, which is consistent with Cohen, Polk, and Vuolteenaho's (2002) results. More importantly, we are able to refute the pure-sentiment story by showing that growth stocks' ROE is more sensitive to the market's discount-rate news than that of value stocks. These simple ROE regressions are consistent with the perhaps more elegant VAR-based results.

Our results have important implications for our understanding of the value-growth effect. While formal models are notably lacking in this area, any structural model of the value-growth effect must relate to the underlying cash-flow risks of value and growth companies. Growth stocks are not merely glamour stocks whose comovement is driven purely by correlated sentiment. Our results show that there's more to growth than just "glamour."

Of course, our tests do not provide insight into why the expected equity premium varies over time. Our claim is only that the large part of growth stocks' sensitivity to the expected equity premium comes from the sensitivity of growth stocks' cash flows to the equity premium. Whether the movements in the equity premium are caused by time-varying risk aversion, investor sentiment, or some unmodelled change in the riskiness of equities remains an unanswered question.

The reminder of the paper is organized as follows. Section 2 motivates our empirical tests. Section 3 describes the data. Section 4 presents our empirical results. Section 5 concludes.

2 A Decomposition of Stock Returns

2.1 Two components of the stock return

The price of any asset can be written as a sum of its expected future cash flows, discounted to the present using a set of discount rates. The price of the asset changes when expected cash flows change, or when discount rates change. This holds true for any expectations about cash flows, whether or not those expectations are rational, but financial economists are particularly interested in rationally expected cash flows and the associated discount rates. Even if some investors have irrational expectations, there should be other investors with rational expectations, and it is important to understand asset price behavior from the perspective of these investors.

There are at least two reasons why it is interesting to distinguish between asset price movements driven by rationally expected cash flows, and movements driven by discount rates. First, investor sentiment can directly affect discount rates, but cannot directly affect cash flows. Price movements that are associated with changing rational forecasts of cash flows may ultimately be driven by investor sentiment, but the mechanism must be an indirect one, for example working through the availability of new financing for firms' investment projects. (See Subrahmanyam and Titman, 2001, for an example of a model that incorporates such indirect effects.) Thus by distinguishing cash-flow and discount-rate movements we can shrink the set of possible explanations for asset price fluctuations.

Second, conservative long-term investors should view returns due to changes in discount rates differently from those due to changes in expected cash flows. A loss of current wealth caused by an increase in the discount rate is partially compensated by improved future investment opportunities, while a loss of wealth caused by a reduction in expected cash flows has no such compensation. The difference is easiest to see if one considers a portfolio of corporate bonds. The portfolio may lose value today because interest rates increase, or because some of the bonds default. A short-horizon investor who must sell the portfolio today cares only about current value, but a long-horizon investor loses more from default than from high interest rates. Campbell (1996) and Campbell and Vuolteenaho (2003) use this insight to develop an empirical implementation of Merton's (1973) ICAPM, in which investors with risk aversion greater than one demand a greater reward for bearing cash-flow risk than for bearing discount-rate risk.

Campbell and Shiller (1988a) provide a convenient framework for analyzing cash-flow and discount-rate shocks. They develop a loglinear approximate present-value relation that allows for time-varying discount rates. Linearity is achieved by approximating the definition of log return on a dividend-paying asset, $r_{t+1} \equiv \log(P_{t+1} + D_{t+1}) - \log(P_t)$, around the mean log dividend-price ratio, $(\overline{d_t - p_t})$, using a first-order Taylor expansion. Above, P denotes price, D dividend, and lower-case letters log transforms. The resulting approximation is $r_{t+1} \approx k + \rho p_{t+1} + (1-\rho) d_{t+1} - p_t$,where ρ and k are parameters of linearization defined by $\rho \equiv 1\big/\big(1 + \exp(\overline{d_t - p_t})\big)$ and $k \equiv -\log(\rho) - (1-\rho)\log(1/\rho - 1)$. When the dividend-price ratio is constant, then $\rho = P/(P+D)$, the ratio of the ex-dividend to the cum-dividend stock price. The approximation here replaces the log sum of price and dividend with a weighted average of log price and log dividend, where the weights are determined by the average relative magnitudes of these two variables.

Solving forward iteratively, imposing the "no-infinite-bubbles" terminal condition that $\lim_{j\to\infty} \rho^j (d_{t+j} - p_{t+j}) = 0$, taking expectations, and subtracting the current dividend, one gets

$$p_t - d_t = \frac{k}{1-\rho} + \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j [\Delta d_{t+1+j} - r_{t+1+j}] \ , \tag{1}$$

where Δd denotes log dividend growth. This equation says that the log price-dividend ratio is high when dividends are expected to grow rapidly, or when stock returns are expected to be low. The equation should be thought of as an accounting identity rather than a behavioral model; it has been obtained merely by approximating an identity, solving forward subject to a terminal condition, and taking expectations. Intuitively, if the stock price is high today, then from the definition of the return and the terminal condition that the dividend-price ratio is non-explosive, there must either be high dividends or low stock returns in the future. Investors must then expect some combination of high dividends and low stock returns if their expectations are to be consistent with the observed price.

Campbell (1991) extends the loglinear present-value approach to obtain a decomposition of returns. Substituting (1) into the approximate return equation gives

$$\begin{aligned} r_{t+1} - \mathrm{E}_t\, r_{t+1} &= (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \qquad (2) \\ &= N_{CF,t+1} - N_{DR,t+1}, \end{aligned}$$

where N_{CF} denotes news about future cash flows (i.e., dividends or consumption), and N_{DR} denotes news about future discount rates (i.e., expected returns). This equation says that unexpected stock returns must be associated with changes in expectations of future cash flows or discount rates. An increase in expected future cash flows is associated with a capital gain today, while an increase in discount rates is associated with a capital loss today. The reason is that with a given dividend stream, higher future returns can only be generated by future price appreciation from a lower current price.

If the decomposition is applied to the returns on the investor's portfolio, these return components can also be interpreted as permanent and transitory shocks to the investor's wealth. Returns generated by cash-flow news are never reversed subsequently, whereas returns generated by discount-rate news are offset by lower returns in the future. From this perspective it should not be surprising that conservative long-term investors are more averse to cash-flow risk than to discount-rate risk.

2.2 Measuring the components of returns

An important issue is how to measure the shocks to cash flows and to discount rates. One approach, introduced by Campbell (1991), is to estimate the cash-flow-news and discount-rate-news series using a vector autoregressive (VAR) model. This VAR methodology first estimates the terms $\mathrm{E}_t\, r_{t+1}$ and $(\mathrm{E}_{t+1} - \mathrm{E}_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}$ and then uses realization of r_{t+1} and equation (2) to back out the cash-flow news. This practice has an important advantage – one does not necessarily have to understand the short-run dynamics of dividends. Understanding the dynamics of expected returns is enough.

When extracting the news terms in our empirical tests, we assume that the data are generated by a first-order VAR model

$$z_{t+1} = a + \Gamma z_t + u_{t+1}, \tag{3}$$

where z_{t+1} is a m-by-1 state vector with r_{t+1} as its first element, a and Γ are m-by-1 vector and m-by-m matrix of constant parameters, and u_{t+1} an i.i.d. m-by-1 vector of shocks. Of course, this formulation also allows for higher-order VAR models via a simple redefinition of the state vector to include lagged values.

Provided that the process in equation (3) generates the data, $t+1$ cash-flow and discount-rate news are linear functions of the $t + 1$ shock vector:

$$N_{DR,t+1} = e1'\lambda u_{t+1}, \qquad (4)$$
$$N_{CF,t+1} = (e1' + e1'\lambda)\, u_{t+1}.$$

Above, $e1$ is a vector with first element equal to unity and the remaining elements equal to zeros. The VAR shocks are mapped to news by λ, defined as $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$. $e1'\lambda$ captures the long-run significance of each individual VAR shock to discount-rate expectations. The greater the absolute value of a variable's coefficient in the return prediction equation (the top row of Γ), the greater the weight the variable receives in the discount-rate-news formula. More persistent variables should also receive more weight, which is captured by the term $(I - \rho\Gamma)^{-1}$.

2.3 Decomposing betas

Previous empirical work uses Campbell's (1991) return decomposition to investigate betas in several different ways. Campbell and Mei (1993) break the return on portfolios of stocks, sorted by size or industry, into the cash-flow and discount-rate components. They ask whether the betas of these portfolios with the return on the market portfolio are determined primarily by their cash-flow news or their discount-rate news. That is, for portfolio i they measure the cash-flow news $N_{i,CF,t+1}$ and the (negtive of) discount-rate news $-N_{i,DR,t+1}$, and calculate $\mathrm{Cov}(N_{i,CF,t+1}, r_{M,t+1})$ and $\mathrm{Cov}(-N_{i,DR,t+1}, r_{M,t+1})$. Campbell and Mei define two beta components

$$\beta_{CFi,M} \equiv \frac{\mathrm{Cov}_t(N_{i,CF,t+1}, r_{M,t+1})}{\mathrm{Var}_t\left(r_{M,t+1}\right)} \qquad (5)$$

and

$$\beta_{DRi,M} \equiv \frac{\mathrm{Cov}_t(-N_{i,DR,t+1}, r_{M,t+1})}{\mathrm{Var}_t\left(r_{M,t+1}\right)}, \qquad (6)$$

which add up to the traditional market beta of the CAPM,

$$\beta_{i,M} = \beta_{CFi,M} + \beta_{DRi,M}. \qquad (7)$$

In their empirical implementation, Campbell and Mei assume that the conditional variances and covariances in (5) and (6) are constant. However, they do not look separately at the cash-flow and discount-rate shocks to the market portfolio.

Campbell and Vuolteenaho (2003), by contrast, break the *market* return into cash-flow and (negative of) discount-rate news $N_{M,CF,t+1}$ and $-N_{M,DR,t+1}$. They measure covariances $\mathrm{Cov}(r_{i,t+1}, N_{M,CF,t+1})$ and $\mathrm{Cov}(r_{i,t+1}, -N_{M,DR,t+1})$ and use these to define cash-flow and discount-rate betas,

$$\beta_{i,CFM} \equiv \frac{\mathrm{Cov}_t\left(r_{i,t+1}, N_{M,CF,t+1}\right)}{\mathrm{Var}_t\left(r_{M,t+1}\right)} \tag{8}$$

and

$$\beta_{i,DRM} \equiv \frac{\mathrm{Cov}_t\left(r_{i,t+1}, -N_{M,DR,t+1}\right)}{\mathrm{Var}_t\left(r_{M,t+1}\right)}, \tag{9}$$

which again add up to the traditional market beta of the CAPM,

$$\beta_{i,M} = \beta_{i,CFM} + \beta_{i,DRM}. \tag{10}$$

Campbell and Vuolteenaho (2003) show that the ICAPM implies a price of risk for $\beta_{i,DRM}$ equal to the variance of the return on the market portfolio, and a price of risk for $\beta_{i,CFM}$ that is γ times higher, where γ is the coefficient of relative risk aversion of a representative investor. This leads them to call $\beta_{i,DRM}$ the "good" beta and $\beta_{i,CFM}$ the "bad" beta, where the latter is of primary concern to conservative long-term investors. Empirically, Campbell and Vuolteenaho find that value stocks have always had a considerably higher bad beta than growth stocks. This finding is surprising, since in the post-1963 sample value stocks have had a lower CAPM beta than growth stocks. The higher CAPM beta of growth stocks in the post-1963 sample is due to their disproportionately high good beta. Campbell and Vuolteenaho also find that these properties of growth and value stock betas can explain the relative average returns on growth and value during this period.

In this paper we combine the asset-specific beta decomposition of Campbell and Mei (1993) with the market-level beta decomposition of Campbell and Vuolteenaho (2003). We measure four covariances and define

$$\beta_{CFi,CFM} \equiv \frac{\mathrm{Cov}_t(N_{i,CF,t+1}, N_{M,CF,t+1})}{\mathrm{Var}_t\left(r_{M,t+1}\right)}, \tag{11}$$

$$\beta_{DRi,CFM} \equiv \frac{\mathrm{Cov}_t(-N_{i,DR,t+1}, N_{M,CF,t+1})}{\mathrm{Var}_t\left(r_{M,t+1}\right)}, \tag{12}$$

$$\beta_{CFi,DRM} \equiv \frac{\text{Cov}_t(N_{i,CF,t+1}, -N_{M,DR,t+1})}{\text{Var}_t\left(r_{M,t+1}\right)}, \tag{13}$$

and

$$\beta_{DRi,DRM} \equiv \frac{\text{Cov}_t(-N_{i,DR,t+1}, -N_{M,DR,t+1})}{\text{Var}_t\left(r_{M,t+1}\right)}. \tag{14}$$

These four beta components add up to the overall market beta,

$$\beta_{i,M} = \beta_{CFi,CFM} + \beta_{DRi,CFM} + \beta_{CFi,DRM} + \beta_{DRi,DRM}. \tag{15}$$

The bad beta of Campbell and Vuolteenaho can be written as

$$\beta_{i,CFM} = \beta_{CFi,CFM} + \beta_{DRi,CFM}, \tag{16}$$

while the good beta can be written as

$$\beta_{i,DRM} = \beta_{CFi,DRM} + \beta_{DRi,DRM}. \tag{17}$$

This decomposition of beta allows us to ask whether the high bad beta of value stocks and the high good beta of growth stocks are attributable to their cash flows or to their discount rates.

An interesting early paper that explores a similar decomposition of beta is Pettit and Westerfield (1972). Pettit and Westerfield use earnings growth as a proxy for cash-flow news, and the change in the price-earnings ratio as a proxy for discount-rate news. They argue that stock-level cash-flow news should be correlated with market-wide cash-flow news, and that stock-level discount-rate news should be correlated with market-wide discount-rate news, but they assume zero cross-correlations between stock-level cash flows and market-wide discount rates, and between stock-level discount ratews and market-wide cash flows. That is, they assume $\beta_{DRi,CFM} = \beta_{CFi,DRM} = 0$ and work with an empirical two-way decomposition: $\beta_{i,M} = \beta_{CFi,CFM} + \beta_{DRi,DRM}$. Comparing value and growth stocks, our subsequent empirical analysis shows that there is interesting cross-sectional variation in $\beta_{CFi,DRM}$.

3 Data

3.1 Aggregate VAR data

In specifying the aggregate VAR, we follow Campbell and Vuolteenaho (2003) by choosing the same four state variables. However, unlike Campbell and Vuolteenaho, we implement the VAR using annual data in order to correspond to our estimation of the firm-level VAR, which is more naturally implemented using annual observations.

The aggregate-VAR state variables are defined as follows. First, the excess log return on the market (r^e_M) is the difference between the annual log return on the CRSP value-weighted stock index (r_M) and the annual log risk-free rate. Our basic risk-free-rate data are constructed by CRSP from Treasury bills with approximately three months to maturity. We assume rolling over a monthly position in these bills is the appropriate risk-free benchmark.

The term yield spread (TY) is provided by Global Financial Data and is computed as the yield difference between ten-year constant-maturity taxable bonds and short-term taxable notes, in percentage points. Keim and Stambaugh (1986) and Campbell (1987) point out that TY predicts excess returns on long-term bonds. These papers argue that since stocks are also long-term assets, TY should also forecast excess stock returns, if the expected returns of long-term assets move together.

We construct our third variable, Shiller's (2000) smoothed price-earnings ratio (PE), as the price of the S&P 500 index divided by a ten-year trailing moving average of aggregate earnings of companies in the S&P 500 index. Following Graham and Dodd (1934), Campbell and Shiller (1988b, 1998) advocate averaging earnings over several years to avoid temporary spikes in the price-earnings ratio caused by cyclical declines in earnings. As in Campbell and Vuolteenaho (2003), we construct the earnings series to avoid any forward-looking interpolation of earnings, ensuring all components of the time t earnings-price ratio are contemporaneously observable. Finally, we log transform the simple ratio.

Fourth, the small-stock value spread (VS) is computed using the data made available by Professor Kenneth French on his web site. The portfolios, which are constructed at the end of each June, are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in $t-1$ divided by ME for December of $t-1$. The BE/ME breakpoints are the 30th and 70th NYSE percentiles. At the end of June of year t, we construct the small-stock value spread as the difference between the $\log(BE/ME)$ of the small high-book-to-market portfolio and the $\log(BE/ME)$ of the small low-book-to-market portfolio, where BE and ME are measured at the end of December of year $t-1$. We include VS because of the evidence in Eleswarapu and Reinganum (2001), Brennan, Wang, and Xia (2001), and Campbell and Vuolteenaho (2003) that relatively high returns for small growth stocks predict low returns on the market as a whole.

To ensure consistency with Campbell and Vuolteenaho's (2003) study, we follow exactly their data construction steps. Consequently, our annual series of TY, PE, and VS are exactly equal to corresponding end-of-May values in Campbell and Vuolteenaho's data set.

3.2 Firm-level VAR data

The raw firm-level data comes from the merger of three databases. The first of these, the Center for Research in Securities Prices (CRSP) monthly stock file, provides monthly prices; shares outstanding; dividends; and returns for NYSE, AMEX, and NASDAQ stocks. The second database, the COMPUSTAT annual research file, contains the relevant accounting information for most publicly traded U.S. stocks. When using COMPUSTAT as our source of accounting information, we require that the firm must be on COMPUSTAT for two years. This requirement alleviates most of the potential survivor bias due to COMPUSTAT backfilling data. The COMPUSTAT accounting information is supplemented by the third database, Moody's book equity information for industrial firms as collected by Davis, Fama, and French (2000).

We implement the main specification of our firm-level VAR with the following three state variables. First, the log firm-level return (r_i) is the annual log value-weight return on a firm's common stock equity. Annual returns are compounded from monthly returns, recorded from the beginning of June to the end of May. We substitute zeros for missing monthly returns. Delisting returns are included when available. For missing delisting returns where the delisting is performance-related, we assume a -30 percent delisting return, following Shumway (1997). Otherwise, we assume a zero delisting return. The log transformations of a firm's stock return may turn extreme values into influential observations. We avoid this problem by unlevering the stock by 10 percent, that is, we define the stock return as a portfolio consisting of 90 percent of the firm's common stock and a 10 percent investment in Treasury Bills.[2]

Our second firm-level state variable is the log book-to-market equity ratio (we denote the transformed quantity by BM in contrast to simple book-to-market that is denoted by BE/ME) as of the end of May in year t. We include BM in the state vector to capture the well-known value effect in the cross section of average stock returns (Graham and Dodd, 1934). In particular, we choose book-to-market as our scaled price measure based on the evidence in Fama and French (1992) that this variable subsumes the information in many other scaled price measures concerning future relative returns.

We use BE for the fiscal year ending in calendar year $t-1$, and ME (market value of equity) at the end of May of year t. We require each firm-year observation to have a valid past BE/ME ratio that must be positive in value. Moreover, in order to eliminate likely data errors, we censor the BE/ME variables of these firms to the range (.01,100) by adjusting the book value. To avoid influential observations created by the log transform, we first shrink the BE/ME towards one by defining $BM \equiv \log[(.9BE + .1ME)/ME]$.

We define BE as stockholders' equity, plus balance sheet deferred taxes (COMPUSTAT data item 74) and investment tax credit (data item 208) (if available), plus post-retirement benefit liabilities (data item 330) (if available), minus the book value of preferred stock. Depending on availability, we use redemption (data item 56), liquidation (data item 10), or par value (data item 130) (in that order) for the book value of preferred stock. We calculate stockholders' equity used in the above formula as follows. We prefer the stockholders' equity number reported by Moody's, or COMPUSTAT (data item 216). If neither one is available, we measure stockholders' equity as the book value of common equity (data item 60), plus the book value of preferred stock. (Note that the preferred stock is added at this stage, because it is later subtracted in the book equity formula.) If common equity is not available, we compute stockholders' equity as the book value of assets (data item 6) minus total liabilities (data item 181), all from COMPUSTAT.

[2] See Vuolteenaho (2002) for additional details and justification.

Third, we calculate long-term profitability, $\overline{ROE}$, as the firm's average profitability over the last one to five years, depending on data availability. We generate our earnings series using the clean-surplus relation. In that relation, earnings, dividends, and book equity satisfy:

$$BE_t - BE_{t-1} = X_t - D_t^{net}$$

- book value today equals book value last year plus clean-surplus earnings (X_t) less (net) dividends. This approach is dictated by necessity (the early data consist of book-equity series but do not contain earnings). Note that in our data set, we construct clean-surplus earnings with an appropriate adjustment for equity offerings so that

$$X_t = \left[\frac{(1 + R_t)ME_{t-1} - D_t}{ME_t} \right] \times BE_t - BE_{t-1} + D_t,$$

where D_t is gross dividends, computed from CRSP. We define $\overline{ROE}$ as the trailing five-year average earnings divided by trailing five-year average of $(.9BE + .1ME)$. We choose $\overline{ROE}$ as the final element of our firm-level state vector to capture the evidence that firms with higher profitability (controlling for their book-to-market ratios) have earned higher average stock returns (Haugen and Baker, 1996). Vuolteenaho (2002) uses just the previous year's profitability in his firm-level VAR. We instead average over as many as five years of past profitability data due to the fact that unlike Vuolteenaho, we use much noisier clean-surplus earnings instead of GAAP earnings.

4 Empirical results

4.1 Aggregate VAR

Table 1 reports the VAR model parameters, estimated using OLS. Each row of the table corresponds to a different equation of the VAR. The first five columns report coefficients on the five explanatory variables: a constant, and lags of the excess market return, term yield spread, price-earnings ratio, and small-stock value spread. OLS standard errors are reported in parenthese below the coefficients.

The first row of Table 1 shows that three out of our four VAR state variables have some ability to predict annual excess returns on the aggregate stock market.

Unlike in the monthly data which exhibits some degree of momentum, annual market returns display a modest degree of reversal; the coefficient on the lagged excess market return is a statistically insignificant -.0534 with a t-statistic of -.5. The term yield spread positively predicts the market return with a t-statistic of 1.7, consistent with the findings of Keim and Stambaugh (1986), Campbell (1987), and Fama and French (1989). The smoothed price-earnings ratio negatively predicts the return with a t-statistic of 2.5, consistent with the finding that various scaled-price variables forecast aggregate returns (Campbell and Shiller, 1988ab, 1998; Rozeff 1984; Fama and French 1988, 1989). Finally, the small-stock value spread negatively predicts the return with a t-statistic of 2.2, consistent with Eleswarapu and Reinganum (2002) and Brennan, Wang, and Xia (2001). In summary, the estimated coefficients, both in terms of signs and t-statistics, are consitent with our prior beliefs and findings in previous research.

The remaining rows of Table 1 summarize the dynamics of the explanatory variables. The term spread can be predicted with its own lagged value and the lagged small-stock value spread. The price-earnings ratio is highly persistent, and approximately an AR(1) process. Finally, the small-stock value spread is also a highly persistent AR(1) process.

The sixth column of Table 1 computes the coefficients of the linear function that maps the VAR shocks to discount-rate news, $e1'\lambda$. We define $\lambda \equiv \rho\Gamma(I-\rho\Gamma)^{-1}$, where Γ is the estimated VAR transition matrix from Table 1. Following Campbell and Vuolteenaho (2003), we set ρ equal to .95 throughout the paper. Interestingly, the coefficients of $e1'\lambda$ are very similar to those estimated by Campbell and Vuolteenaho from monthly data, with the exception of the coefficient on stock-return shock, which is larger in absolute value in the function computed from annual VAR parameter estimates. As a further robustness check, we compared our annual news terms to corresponding twelve-month sums of Campbell and Vuolteenaho's news terms and observed a high degree of consistency (a correlation of .98 for N_{DR} and .88 for N_{CF}).

The persistence of the VAR explanatory variables raises some difficult statistical issues. It is well known that estimates of persistent AR(1) coefficients are biased downwards in finite samples, and that this causes bias in the estimates of predictive regressions for returns if return innovations are highly correlated with innovations in predictor variables (Stambaugh 1999). There is an active debate about the effect of this on the strength of the evidence for return predictability (Ang and Bekaert 2001, Campbell and Yogo 2002, Lewellen 2002, Torous, Valkanov, and Yan 2001, Polk, Thompson, and Vuolteenaho, 2003). Our interpretation of the findings in this literature is that there is some statistical evidence of return predictability based on variables similar to ours. However, an additional complication is that the statistical significance of the one-period return-prediction equation does not guarantee that our news terms are not materially affected by the above-mentioned small-sample bias and sampling uncertainty. This is because the news terms are computed using a complicated nonlinear transformation of the VAR parameter estimates. With these caveats, we proceed with news terms extracted using the point estimates reported in Table 1.

Figure 1 plots centered three-year moving avegares of $-N_{M,DR}$ (line with squares) and $N_{M,CF}$ (thick solid line). Both moving-average series are normalized to have a unit standard deviation. The figure shows stock prices declining because of discount-rate news in the early 1930's, late 40's, late 60's, mid 70's, and early 80's. Aggregate stock prices increased because of discount-rate news in the late 1930's, early and mid 60's, and for a long period from the mid 1980's to late 90's. Good cash-flow news were experienced in the period from the mid 1940's to late 50's, late 60's, late 70's, and 90's, while bad cash-flow news dominate the 1930's, early 70's, and 80's. Since we are interested in separating the effects of discount-rate and cash-flow news, the 1950's, late 70's, and the period from the late 1980's to early 90's are all influental observations during which the two news terms pushed stock prices in opposite directions.

Table 2 puts these extracted news terms to work. In this table, we estimate the good discount-rate betas ($\beta_{i,DR}$) and bad cash-flow betas ($\beta_{i,CF}$) for portfolios of value and growth stocks. Each year, we form quintile value-weight portfolios based on firms' book-to-market ratios, and denote the extreme growth portfolio with 1 and the extreme value portfolio with 5. Since growth firms are typically much larger than value firms, when forming the portfolios we allocate an equal amount of market capitalization to each portfolio. This is in contrast to the typical approach, which allocates an equal number of firms to each portfolio. We then regress the simple portfolio returns on the scaled news series $N_{M,DR} \times \mathrm{Var}\left(r_M^e\right)/\mathrm{Var}(N_{M,DR})$ and $N_{M,CF} \times \mathrm{Var}\left(r_M^e\right)/\mathrm{Var}(N_{M,CF})$. The scaling normalizes the regression coefficients to correspond to our definitions of $\beta_{i,DR}$ and $\beta_{i,CF}$, which add up to the CAPM beta.

The point estimates in the second panel of Table 2 show that value stocks have higher cash-flow betas than growth stocks in the full sample as well as in both subperiods. The estimated difference between extreme growth and value portfolio's cash-flow beta is -.14, and this difference is stable accross subperiods. In contrast, the pattern in discount-rate betas changes from one subperiod to another. While growth stocks' discount rate betas are always slightly below one, value stocks' discount rate betas decline from 1.5 in the first subsample to .5 in the second subsample. Overall, the return betas estimated from the annual data are consistent with those estimated from monthly data by Campbell and Vuolteenaho (2003).

The full-period estimates of bad and good beta for the market portfolio (as well as for many growth portfolios) sum up to approximately one. Curiously, however, the sum of estimated bad and good betas for these portfolios is above one for the first subperiod and below one for the second subperiod. The fact that these subperiod betas deviate from one is caused by our practice of removing the conditional expectation from the market's return ($N_{M,CF} - N_{M,DR}$ equals the unexpected return) but not from the test asset's return. Because the aggregate VAR is estimated from the full sample, in the subsamples there is no guarantee that the estimated conditional expectated return is exactly uncorrelated with unexpected returns. Thus, in the subsamples, the expected test-asset return may contribute to the beta, moving it away from unity.

The standard errors in Table 2, as well as the standard errors in all subsequent tables that use estimated news terms, require a caveat. We present the simple OLS standard errors from the regressions, which do not take into account the estimation uncertainty in the news terms. Thus, while the t-statistics in Table 2 are generally high in absolute value, the true statistical precision of these estimates is likely to be lower.

4.2 Firm-level VAR

The firm-level VAR generates market-adjusted cash-flow and discount-rate news for each firm each year. Since relatively few firms survive the full time period; since conditioning on survival may bias our coefficient estimates; and since the average number of firms we consider is greater than the number of annual observations, we assume that the VAR transition matrix is equal for all firms and estimate the VAR parameters with pooled regressions.

We remove year-specific means from the state variables by subtracting $r_{M,t}$ from $r_{i,t}$ and cross-sectional means from $BM_{i,t}$ and $\overline{ROE}_{i,t}$. Instead of subtracting the equal-weight cross-sectional mean from $r_{i,t}$, we subtract the log value-weight CRSP index return instead, because this will allow us to undo the market adjustment simply by adding back the cash-flow and discount-rate news extracted from the aggregate VAR.

After cross-sectionally demeaning the data, we estimate the coefficients of the firm-level VAR using WLS. Specifically, we multiply each observation by the inverse of the number of cross-sectional observation that year, thus weighing each cross-section equally. This ensures that our estimates are not dominated by the large cross sections near the end of the sample period. We impose zero intercepts on all state variables, even though the market-adjusted returns do not necessarily have a zero mean in each sample. Allowing for a free intercept does not alter any of our results in a measurable way.

Parameter estimates (presented in Table 3) imply that expected returns are high when past one-year return, the book-to-market ratio, and profitability are high. Book-to-market is the statistically most significant predictor, while the firm's own stock return is the statistically least significant predictor. Expected profitability is high when past stock return and past profitability are high and the book-to-market ratio is low. The expected future book-to-market ratio is mostly affected by the past book-to-market ratio.

These VAR parameters estimates translate into $e1'\lambda$ function that has positive weights on all state-variable shocks. The t-statistic on the coefficient of past return is 2.1, book-to-market 2.6, and profitability 1.8. Contrasting the firm-level lambda estimates to those obtained from the aggregate VAR of Table 1, it interesting to note that the partial relation between expected-return news and stock return is positive at the firm level and negative at the market level.

We construct the cash-flow and discount-rate news for the BE/ME-sorted portfolios as follows. We first take the market-adjusted news terms extracted using the firm-level VAR in Table 3 and add back the market's news terms for the corresponding period. This add-back procedure scales our subsequent beta estimates, but does not affect the differences in betas between stocks. Then, each year we form portfolio-level news as the value-weight average of the firms' news. The portfolio are constructed by sorting firms into five portfolios on their BE/ME's each year. As before, we set BE/ME breakpoints so that an equal amount of market capitalization is in each quintile each year. As a result, we have series that closely approximate the cash-flow and discount-rate news on these quintile portfolios.

4.3 Beta decomposition results

Table 4 uses the portfolio-level and market-level news terms to decompose the CAPM beta into four components: $\beta_{CFi,CFM}$, $\beta_{DRi,CFM}$, $\beta_{CFi,DRM}$, and $\beta_{DRi,DRM}$. For each portfolio, we run four simple regressions, the portfolio-level news on scaled series $N_{M,DR} \times \text{Var}\left(r_M^e\right)/\text{Var}(N_{M,DR})$ and $N_{M,CF} \times \text{Var}\left(r_M^e\right)/\text{Var}(N_{M,CF})$. The portfolio $i = 1$ is the extreme growth portfolio (low BE/ME) and $i = 5$ the extreme value portfolio (high BE/ME). In the table, "1-5" denotes the difference between extreme growth (1) and value (5) portfolios.

Table 4 shows that the cross-sectional beta patterns visible in Table 2 are entirely due to cross-sectional variation in firms' $\beta_{CFi,CFM}$ and $\beta_{CFi,DRM}$. In other words, although the components $\beta_{DRi,CFM}$ and $\beta_{DRi,DRM}$ are important determinants of the overall level of betas, they are approximately constant across value and growth portfolios.

A caveat about the standard errors is in order. All standard errors in tables that use estimated news terms ignore the estimation uncertainty in extraction of the news terms. Thus, the generally high t-statistics in Table 4 and the subsequent tables may be overstated.

While the simple regressions of Table 4 neatly correspond to the beta decomposition of economically interesting betas from the asset-pricing perspective, multiple regressions may be more appropriate in understanding the sources of these sensitivities. Suppose that the technology employed by value and growth firms is such that firms' cash flows are determined by a constant linear function of the market-wide discount-rate and cash-flow news, plus an error term. Then, the simple regression coefficients (and thus our beta decomposition) may be subject to change as the correlation between the market's news terms changes. In particular, the in-sample correlation of $N_{M,CF,t+1}$ and $-N_{M,DR,t+1}$ is slightly positive in the early subsample but slightly negative in the modern subsample.

To examine the partial sensitivity of firms' cash flows to the market's discount-rate and cash-flow news, in Table 5 we regress the portfolio-level cash-flow news on the estimated $-N_{M,DR,t+1}$ and $N_{M,CF,t+1}$ in a multiple regression. The multiple regressions tell an interesting story. In the full-period regressions, growth stocks' cash-flow news is more sensitive to $-N_{M,DR,t+1}$ and less sensitive to $N_{M,CF,t+1}$ than that of value stocks.

In the subperiod analysis, the sensitivities of growth and value stocks cash-flow news to the market's cash-flow news appears to be roughly constant. (This is in contrast with the simple regression results, which are influenced by the sample-specific correlation of the market's news terms.) The extreme growth stocks' cash-flow news has a .07 loading on the market's cash-flow news during in the early subsample and .03 in the second subsample, while the extreme value stocks' cash-flow news has a .13 loading on the market's cash-flow news during in the early subsample and .15 in the second subsample. Thus, the partial sensitivities to the market's cash-flow news seem to be relatively stable with value stocks' sensitivity at a higher level than that of growth stocks.

The sensitivities of growth and value stocks cash-flow news to the market's (minus) discount-rate news appears to have changed across samples. In the early sample, value stocks cash flows seem to be slightly more sensitive to the market's valuation levels than growth stocks's cash flows (1-5 difference -.11, t-stat -2.0). In the modern subsample, this pattern is reversed: Growth stocks now have a higher multiple-regression coefficient on $-N_{M,DR,t+1}$ than value stocks (1-5 difference .44, t-stat 4.1).

4.4 An alternative to the VAR approach

The VAR methodology used in the above tests relies on specific assumptions about the data-generating process. In this section, we show that our main result – that growth stocks' cash flows are more sensitive to the market's discount rates than value stocks' cash flows – can also be verified with much simpler although less elegant methods.

4.4.1 Regressions of direct cash-flow measures on discount-rate and cash-flow news

Our VAR-based results show that the good discount-rate beta of growth stocks and the bad cash-flow beta of value stocks is due to covariances of aggregate factors with value and growth stocks' cash-flow news. To demonstrate the robustness of this finding, we regress direct cash-flow measures on the market's cash-flow and discount-rate news. Consistent with VAR results, we find that value stocks cash flows covary with the market's cash-flow news and growth stocks' cash flows with the market's discount rates.

We use portfolio-level accounting return on equity (ROE) as our direct cash-flow measure. Vuolteenaho (2002) and Cohen, Polk, and Vuolteenaho (2002, 2003) have argued for the use of discounted ROE sum as a good measure of firm-level cash-flow fundamentals. Thus, our ROE-based proxy for portfolio-level cash-flow news is the following:

$$N_{i,CF,t+1} \approx \sum_{k=1}^{K} \rho^{k-1} roe_{i,t,t+k}, \tag{18}$$

where $roe = \ln(1+ROE) - \log(1+y_{t+k})$, where $ROE_{i,t,t+k}$ is the year $t+k$ clean-surplus return on book equity (for portfolio i sorted at t) and y the Treasury-bill return.. The subscripts denote the portfolio number (one for growth and five for value), the year of sort and portfolio formation, and the year of measurement. This direct proxy of cash flows is regressed on contemporanous multi-year discounted sums of the market's news terms extracted from the VAR. We emphasize longer-term trends rather than short-term fluctuations in profitability by examine horizons (K) from two years up to five years out.

As in the previous VAR approach, each year we form quintile portfolios based on firm's BE/ME. In contrast to the VAR implementation, however, after portfolio formation we follow the portfolios for five years while holding the portfolio definitions constant. The long horizon is necessary since over the course of the first post-formation year the market learns about not only the unexpected component of that year's cash-flow realizations but also updates expectations concerning future cash flows. Because we perform a new sort every year, our final annual data set is three dimensional: the number of portfolios formed in each sort times the number of years we follow the portfolios times the time dimension of our panel.[3]

Table 6 shows the multiple regression coefficients for three portfolios (1, 3, and 5) to save space. Despite the fact that the dependent variables in Table 6 are constructed using simple accounting measures, the patterns in the table are virtually indentical to those in Table 5 that uses cash-flow news extracted from a VAR as

[3]In the portfolio approach, missing data are treated as follows. If a stock was included in a portfolio but its book equity is temporarily unavailable at the end of some future year t, we assume that the firm's book-to-market ratio has not changed from $t-1$ and compute the book-equity proxy from the last period's book-to-market and this period's market equity. We treat firm-level observations with negative or zero book-equity values as missing. We then use the portfolio-level dividend and book-equity figures in computing clean-surplus earnings at the portfolio level.

the dependent variable. In summary, with the evidence in Table 6 we are able to refute the pure-sentiment story by showing that growth stocks' ROE is more sensitive to the market's discount-rate news than that of value stocks. The point estimates also indicate that value stocks ROE is more sensitive to the market's cash-flow news than that of growth stocks. Thus, our ROE regressions are consistent with the VAR results.

4.4.2 Regressions of direct cash-flow measures on alternative proxies of discount-rate and cash-flow news

To further examine the robustness of our results, we replace the market's news terms with simple and transparent proxies:

$$N_{M,CF,t+1} \approx \sum_{k=1}^{K} \rho^{k-1} roe_{M,t+k} \text{ and } N_{M,DR,t+1} \approx -\sum_{k=1}^{K} [\rho^{k-1} \mathbf{\Delta}_{t+k} \ln(\mathbf{P}/\mathbf{E})]. \qquad (19)$$

Since Campbell and Shiller (1988a, 1988b) and others document that discount-rate news dominates cash-flow news in aggregate returns and price volatility, we use annual increments in $\ln(P/E)$ as a natural proxy for $-N_{M,DR,t+1}$. The market's log profitability provides a natural direct proxy for the market's cash-flow news.

Table 7 reports the multiple regression coefficients from regressions of the discounted ROE sum on our two proxies for aggregate discount news and cash-flow news defined in equation (19). Again we restrict our focus to three of the BE/ME-sorted portfolios (1, 3, and 5). Now both our dependent and independent variables use only simple accounting measures to test the pure-sentiment story. We find that in the modern period, the three-year, discounted ROE sum of growth stocks has a statistically significant regression coefficient on the three-year discounted sum of annual increments in $\ln(P/E)$ of .24 (t-statistic of 2.6). This is in contrast to the corresponding coefficient for value stocks; that estimate is -.09 with an associated t-statistic of -4.5. As one would expect, the difference between these two coefficients (.33) is quite statistically significant.

We estimate similar coefficients for four-year and five-year discounted ROE sums. Though we find similar patterns for our two-year discounted ROE sum regressions, the difference is only half as large and is not statistically significant at usual levels of significance. However, one would expect that sums of only two years of accounting ROE would be a poorer proxy for cash-flow news. Thus the evidence in Table 7 again confirms that the reason growth stocks returns are more sensitive to changes in aggregate discount rates is because their cash-flow fundamentals are more sensitive to these movements.

As a final robustness check, Table 8 reports the results from additional specifications where the independent variable continues to be the direct cash flows of value-growth portfolios. These specifications adddress the concern that our results maybe driven by predictable components in our discounted ROE sums. One reason there may be predictable components is purely mechanical. Note we compute clean-surplus ROE in the first year after the sort by using the change in BE from t-1 to t. But that initial book equity is known many months before the actual sort occurs in May of year t. Thus a portion of the cashflows we are using to proxy for cash flow news are known as of the time of the sort and cannot be news. In response to this problem, throughout Table 8 our discounted ROE sums start with ROE in year t+2 instead of year t+1.

More generally it is possible that the level of our left-hand side variable is naturally forecastable. In panels II and IV, we include an additional independent variable to make sure that this forecastability does not drive our results. As a firm's level of profitability is quite persistent, a natural control is the difference in past year t ROE for the firms currently in the extreme growth and extreme value portfolios.

Panels I and II of Table 8 implement these two robustness checks for Table 6's multiple regression of discounted ROE sums on the market's cash-flow and discount-rate news as defined by the aggregate VAR. At all horizons, growth stocks' relatively higher ROE sensitivity to aggregate discount rate news in the modern period is statistically and economically significant. At the K=5 horizon in Panel I, the t-statistic is a strong 9.2. Though the coefficient (not reported) on the difference in year t ROE is statistically significant, the inclusion of that control has little effect on our results. Panels III and IV of Table 8 implement these two robustness checks for Table 7's multiple regression of discounted ROE sums on proxies for these news terms. These results are consistent with those throughout the paper, rejecting the pure-sentiment story.

5 Conclusions

This paper explores the economic origins of systematic risks for value and growth stocks. The question about the sources of systematic risks is part of a broader debate, going back at least to LeRoy and Porter (1981) and Shiller (1981), about the economic forces that determine the volatility of stock prices.

Our empirical results show that growth stocks' cash flows are particularly sensitive to temporary movements in aggregate stock prices (driven by movements in the equity risk premium), while value stocks' cash flows are particularly sensitive to permanent movements (driven by market-wide shocks to cash flows.)

In the first set of tests, we break firm-level stock returns of value and growth stocks into components driven by cash-flow shocks and discount-rate shocks. We then regress these firm-level cash-flow and discount-rate news on the market's cash-flow and discount-rate news to find out whether sentiment or cash-flow fundamentals drive the systematic risks of value and growth stocks. In a second set of tests, we regress the accounting profitability of value and growth stocks on market's cash-flow and discount-rate news estimated by Campbell and Vuolteenaho (2003), lengthening the horizon to emphasize longer-term trends rather than short-term fluctuations in profitability.

Both procedures give a similar answer: The high betas of growth stocks with the market's discount-rate shocks, and of value stocks with the market's cash-flow shocks, are determined by the cash-flow fundamentals of growth and value companies. Thus, growth stocks are not merely "glamour stocks" whose systematic risks are purely driven by investor sentiment.

References

Baker, Malcolm, Jeremy C. Stein, and Jeffrey Wurgler, 2003, When does the stock market matter? Stock prices and the investment of equity-dependent firms, forthcoming *Quarterly Journal of Economics*.

Ball, R., 1978, Anomalies in relationships between securities' yields and yield-surrogates, *Journal of Financial Economics* 6, 103–126.

Barberis, Nicholas and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics*.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2002, Comovement, NBER Working Paper No. 8895.

Basu, Sanjoy, 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, Sanjoy, 1983, The relationship between earnings yield, market value, and return for NYSE common stocks: Further evidence, *Journal of Financial Economics* 12, 129–156.

Brennan, Michael J., Ashley Wang, and Yihong Xia, 2001, A simple model of intertemporal capital asset pricing and its implications for the Fama-French three factor model, unpublished paper, Anderson Graduate School of Management, UCLA.

Campbell, John Y., Stock returns and the term structure, *Journal of Financial Economics* 18, 373-399.

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

Campbell, John Y., 1996, Understanding risk and return, *Journal of Political Economy* 104, 298–345.

Campbell, John Y. and Jianping Mei, 1993, Where do betas come from? Asset price dynamics and the sources of systematic risk, *Review of Financial Studies* 6, 567–592.

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, 195–228.

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

Campbell, John Y. and Robert J. Shiller, 2003, The long-run outlook for the US stock market: An update, forthcoming in Nicholas Barberis and Richard Thaler eds., *Advances in Behavioral Finance Vol. II*, Russell Sage Foundation, New York, NY.

Campbell, John Y. and Tuomo Vuolteenaho, 2003, Bad beta, good beta, NBER Working Paper No. 9509.

Campbell, John Y. and Motohiro Yogo, 2002, Efficient tests of stock return predictability, unpublished paper, Harvard University.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2002, Does risk or mispricing explain the cross-section of stock prices?, unpublished paper, Harvard University.

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

Cornell, Bradford, 1999, Risk, duration, and capital budgeting: New evidence on some old questions, *Journal of Business* 72, 183–200.

Eleswarapu, Venkat R. and Marc R. Reinganum, 2002, The predictability of aggregate stock market returns: Evidence based on glamour stocks, forthcoming *Journal of Business*.

Fama, Eugene F. and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F. and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Graham, Benjamin and David L. Dodd, 1934, *Security Analysis*, first edition, McGraw Hill, New York.

Haugen, Robert A. and Nardin L. Baker, 1996, Commonality in the determinants of expected stock returns, *Journal of Financial Economics* 41, 401-439.

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

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–1578.

La Porta, Rafael, 1996, Expectations and the cross-section of returns, *Journal of Finance* 51, 1715–1742.

La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert W. Vishny, 1997, Good news for value stocks: Further evidence on market efficiency, *Journal of Finance* 52, 859–874.

LeRoy, Stephen and Richard Porter, 1981, The present value relation: Tests based on variance bounds, *Econometrica* 49, 555–577.

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

Liew, Jimmy and Maria Vassalou, 2000, Can book-to-market, size, and momentum be risk factors that predict economic growth?, *Journal of Financial Economics* 57, 221–245.

Ng, Victor, Robert F. Engle, and Michael Rothschild, 1992, A multi-dynamic-factor model for stock returns, *Journal of Econometrics* 52, 245266.

Perez-Quiros, Gabriel and Allan Timmermann, 2000, Firm Size and Cyclical Variations in Stock Returns, *Journal of Finance* 55, 1229-1262

Pettit, R. Richardson and Randolph Westerfield, 1972, A model of capital asset risk, *Journal of Financial and Quantitative Analysis* 7, 1649–1668.

Polk, Christopher, Samuel Thompson, and Tuomo Vuolteenaho, 2003, New forecasts of the equity premium, unpublished paper, Northwestern University and Harvard University.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9–17.

Shiller, Robert J., 1981, Do stock prices move too much to be justified by subsequent changes in dividends?, *American Economic Review* 71, 421–436.

Shiller, Robert J., 2000, Irrational Exuberance, Princeton University Press, Princeton, NJ.

Subrahmanyam, Avanidhar, and Sheridan Titman, 2001, Feedback from Stock Prices to Cash Flows, *Journal of Finance* 56, 2389–2413.

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

Zhang, Lu and Ralitsa Petkova, 2002, Is value riskier than growth?, unpublished paper, University of Rochester.

Table 1: Aggregate VAR parameter estimates

The table shows the OLS parameter estimates for a first-order aggregate VAR model including a constant, the log excess market return (r_M^e), term yield spread (TY), price-earnings ratio (PE), and small-stock value spread (VS). Each set of two rows corresponds to a different dependent variable. The first five columns report coefficients on the five explanatory variables, and the last column shows λ-estimates, computed from the point estimates using the formula $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$. The market's N_{DR} is computed as $e1'\lambda u$ and N_{CF} as $(e1' + e1'\lambda)u$. Standard errors are in parentheses. Sample period for the dependent variables is 1928-2001, 74 annual data points.

	constant	$r^e_{M,t}$	TY_t	PE_t	VS_t	$e1'\lambda$
$r^e_{M,t+1}$	.8699	-.0534	.0794	-.2056	-.1700	-.0921
	(.2982)	(.1157)	(.0470)	(.0819)	(.0789)	(TBA)
TY_{t+1}	.0152	.1006	.2772	-.1524	.5559	.0226
	(.6944)	(.2694)	(.1094)	(.1908)	(.1837)	(TBA)
PE_{t+1}	.5881	.0546	.0697	.8480	-.1214	-.8899
	(.2705)	(.1050)	(.0426)	(.0743)	(.0743)	(TBA)
VS_{t+1}	.2263	.0081	-.0284	-.0308	.9234	-.2609
	(.2113)	(.0820)	(.0333)	(.0581)	(.0559)	(TBA)

Table 2: "Bad" cash-flow and "good" discount-rate betas of value and growth stocks
The table reports the "good" discount-rate betas (top panel) and "bad" cash-flow betas (bottom panel) of quintile portfolios formed each year by sorting firms on year-t BE/ME. We allocate 20% of the market value to each portfolio. The portfolio $i = 1$ is the extreme growth portfolio (low BE/ME) and $i = 5$ the extreme value portfolio (high BE/ME). "1-5" denotes the difference between extreme growth and value portfolios. Portfolios are value-weighted. BE/ME used in sorts is computed as year $t-1$ BE divided by May-year-t ME. The market's N_{DR} and N_{CF} are factors extracted using the VAR of Table 1. The t-statistics (in parentheses) do not account for the estimation uncertainty in extraction of the market's news terms.

$\beta_{i,DRM}$: Growth and value returns on the market's $-N_{DR}$

	1	2	3	4	5	1-5
1929-2000	.90	.81	.89	1.04	1.17	-.27
	(13.2)	(10.4)	(8.9)	(7.0)	(6.4)	(-1.9)
1929-1962	.87	.87	1.04	1.28	1.48	-.61
	(9.3)	(8.7)	(7.9)	(6.0)	(5.7)	(-3.2)
1963-2000	.98	.66	.54	.48	.41	.57
	(8.9)	(5.5)	(4.1)	(3.8)	(2.7)	(3.9)

$\beta_{i,CFM}$: Growth and value returns on the market's N_{CF}

	1	2	3	4	5	1-5
1929-2000	0.09	.14	.19	.21	.23	-.14
	(2.1)	(3.4)	(3.9)	(3.2)	(2.9)	(-2.7)
1929-1962	.18	.21	.26	.28	.30	-.13
	(3.0)	(3.6)	(3.6)	(2.7)	(2.4)	(-1.6)
1963-2000	-.11	-.02	.00	.01	.01	-.12
	(-1.8)	(-.4)	(.1)	(.1)	(.2)	(-2.3)

Table 3: Firm-level VAR parameter estimates

The table shows the pooled-WLS parameter estimates for a first-order firm-level VAR model. The model state vector includes the log stock return (r), log book-to-market (BM), and five-year average profitability ($\overline{ROE}$). All three variables are market adjusted, r by subtracting r_M and BM and $\overline{ROE}$ by removing the respective year-specific cross-section means. Rows corresponds to dependent variables and columns to independent (lagged dependent) variables. The first three columns report coefficients on the three explanatory variables, and the last column shows λ-estimates, computed from the point estimates using the formula $\lambda \equiv \rho\Gamma(I - \rho\Gamma)^{-1}$. $N_{i,DR}$ is computed as $e1'\lambda u_i$ and $N_{i,CF}$ as $(e1' + e1'\lambda)u_i$. Standard errors are in parentheses. Sample period for the dependent variables is 1929-2001, 72 annual cross-sections and 158,878 firm-years.

	$r_{i,t}$	$BM_{i,t}$	$\overline{ROE}_{i,t}$	$e1'\lambda$
$r_{i,t+1}$	.0655	.0410	.0817	.0803
	(.0375)	(.0156)	(.0443)	(.0381)
$BM_{i,t+1}$	.0454	.8631	-.0499	.2075
	(.0278)	(.0238)	(.0517)	(.0807)
$\overline{ROE}_{i,t+1}$	.0217	-.0249	.6639	.2004
	(.0045)	(.0033)	(.0306)	(.1112)

Table 4: Firm-level and the market's cash-flow and discount-rate news

The table reports the "good" discount-rate betas and "bad" cash-flow betas of quintile portfolios formed each year by sorting firms on year-t BE/ME. The portfolio $i = 1$ is the extreme growth portfolio (low BE/ME) and $i = 5$ the extreme value portfolio (high BE/ME). "1-5" denotes the difference between extreme growth (1) and value (5) portfolios. BE/ME used in sorts is computed as year $t-1$ BE divided by May-year-t ME. The market's N_{DR} and N_{CF} are extracted using the VAR of Table 1. To construct the portfolio news terms, the firm-level $N_{i,DR}$ and $N_{i,CF}$ are first extracted from a market-adjusted firm-level panel VAR of Table 3 and the corresponding market-wide news term is added back to these market-adjusted news terms. Portfolio news terms are then computed as a value-weight average of firms' news terms. The t-statistics do not account for the estimation uncertainty in extraction of the news terms.

	1		2		3		4		5		1-5	
period	**coef**	t	**coef**	t	**coef**	t	**coef**	t	**coef**	t	**coef**	t
$\beta_{DRi,DRM}$: Growth and value $-N_{DR}$ on the market's $-N_{DR}$												
1929-2000	**.76**	74	**.79**	76	**.79**	86	**.80**	88	**.80**	106	**-.04**	-3.9
1929-1962	**.68**	61	**.72**	54	**.72**	66	**.74**	72	**.73**	102	**-.05**	-4.0
1963-2000	**.95**	44	**.96**	51	**.96**	52	**.95**	50	**.96**	54	**-.01**	-.6
$\beta_{CFi,DRM}$: Growth and value N_{CF} on the market's $-N_{DR}$												
1929-2000	**.03**	.9	**-.08**	-1.8	**-.01**	-.1	**.01**	.2	**.05**	.7	**-.02**	-.3
1929-1962	**.02**	.4	**-.04**	-.8	**.11**	1.7	**.15**	1.9	**.23**	2.6	**-.22**	-3.0
1963-2000	**.08**	1.4	**-.16**	-1.9	**-.27**	-3.0	**-.33**	-3.1	**-.39**	-3.6	**.48**	4.3
$\beta_{DRi,CFM}$: Growth and value $-N_{DR}$ on the market's N_{CF}												
1929-2000	**.04**	1.2	**.05**	1.3	**.05**	1.4	**.05**	1.5	**.05**	1.4	**-.01**	-2.5
1929-1962	**.08**	1.8	**.08**	1.9	**.09**	2.0	**0.10**	2.1	**.09**	1.9	**-.01**	-2.4
1963-2000	**-.04**	-.8	**-.04**	-.7	**-.04**	-.7	**-.04**	-.7	**-.04**	-.7	**-.00**	-.7
$\beta_{CFi,CFM}$: Growth and value N_{CF} on the market's N_{CF}												
1929-2000	**.07**	8.8	**.11**	10	**.14**	14	**.15**	8.8	**.15**	7.3	**-.08**	-3.4
1929-1962	**.07**	8.6	**.08**	6.1	**.13**	13.1	**.13**	6.1	**.14**	4.9	**-.07**	-2.4
1963-2000	**.06**	3.5	**.15**	9.1	**.16**	7.1	**.17**	5.8	**.16**	4.9	**-.10**	-2.4

Table 5: Firm-level cash-flow news on the market's news terms

The table reports the multiple-regression betas of the portfolios' cash-flow news on the market's discount-rate and cash-flow news:

$$N_{i,CF,t} = \alpha_i + \beta_{DR,i}(-N_{M,DR,t}) + \beta_{CF,i}N_{M,CF,t} + \varepsilon_{i,t}$$

We form quintile portfolios formed each year by sorting firms on year-t BE/ME. The portfolio $i = 1$ is the extreme growth portfolio (low BE/ME) and $i = 5$ the extreme value portfolio (high BE/ME). "1-5" denotes the difference between extreme growth and value portfolios. BE/ME used in sorts is computed as year $t-1$ BE divided by May-year-t ME. The market's $N_{M,DR}$ and $N_{M,CF}$ are extracted using the VAR of Table 1. To construct the portfolio news terms, $N_{i,CF}$ are first extracted from a market-adjusted firm-level panel VAR of Table 3 and the corresponding market-wide news term ($N_{M,CF}$) is added back to these market-adjusted news terms. Portfolio news terms are then computed as a value-weight average of firms' news terms.

1929-2000:

1 (Growth)		2		3		4		5 (Value)		1-5	
β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}
.01	.06	-.04	.09	-.09	.10	-.15	.13	-.05	.15	.06	-.09
(.2)	(4.7)	(-1.9)	(11.3)	(-3.9)	(12.7)	(-5.5	(13.1)	(-1.5)	(10.7)	(1.1)	(-4.3)

1929-1962:

1 (Growth)		2		3		4		5 (Value)		1-5	
β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}
-.06	.07	-.04	.07	-.06	.09	-.12	.11	.05	.13	-.11	-.06
(-1.7)	(5.4)	(-1.3)	(7.2)	(-1.9)	(7.3)	(-3.1	(7.7)	(1.2)	(8.0)	(-2.0)	(-2.6)

1963-2000:

1 (Growth)		2		3		4		5 (Value)		1-5	
β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}	β_{DR}	β_{CF}
.14	.03	-.02	.09	-.11	.11	-.18	.16	-.30	.15	.44	-.11
(2.1)	(1.5)	(-.6)	(8.6)	(-3.9)	(11.8)	(-4.2	(10.7)	(-4.6)	(6.7)	(4.1)	(-3.1)

Table 6: Value and growth stocks' ROE on the market's news terms

The table reports the OLS multiple-regression coefficients, Newey-West t-statistics, and adjusted R^2 for regressions $\sum_{k=1}^{K}[\rho^{k-1}roe_{i,t,t+k}] = \alpha + \beta_{DR,i}\sum_{k=1}^{K}[\rho^{k-1}(-N_{M,DR,t+k})] + \beta_{CF,i}\sum_{k=1}^{K}[\rho^{k-1}N_{M,CF,t+k}] + \varepsilon_{i,t,t+k}$. The portfolio $i = 1$ is the extreme growth and $i = 5$ the extreme value portfolio. The market's $N_{M,DR}$ and $N_{M,CF}$ are extracted using the VAR of Table 1. $roe_{i,t,t+k}$ is defined as $\log(1 + ROE_{i,t,t+k}) - \log(1 + y_{t+k})$, where $ROE_{i,t,t+k}$ is the year $t + k$ clean-surplus return on book equity (for portfolio i sorted at t) and y the Treasury-bill return.

1929-2000:

	K=2			K=3			K=4			K=5		
i	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2
1	.08	.22	2%	.14	.29	11%	.17	.35	16%	.15	.52	27%
	(1.4)	(1.6)		(3.0)	(1.7)		(3.0)	(1.6)		(2.6)	(3.2)	
3	.02	.45	27%	.01	.59	43%	.02	.65	50%	-.01	.71	58%
	(.7)	(5.8)		(.4)	(5.8)		(.4)	(5.6)		(-.2)	(6.5)	
5	.01	.64	45%	-.02	.76	59%	-.01	.79	64%	-.02	.83	72%
	(.2)	(7.2)		(.5)	(6.2)		(-.2)	(5.9)		(-.64)	(6.6)	
1-5	.08	-.42	5%	.16	-.48	17%	.17	-.44	21%	.18	-.31	16%
	(1.2)	(-3.0)		(2.9)	(-3.4)		(2.8)	(-2.4)		(2.6)	(-2.2)	

1929-1962:

	K=2			K=3			K=4			K=5		
i	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%
1	-.02	.11	0%	.04	.22	0%	.03	.24	0%	-.02	.39	10%
	(-.2)	(.5)		(.5)	(.9)		(.2)	(.7)		(-.1)	(1.4)	
3	.01	.44	31%	.04	.57	49%	.09	.62	54%	.07	.64	58%
	(.2)	(4.4)		(.8)	(3.8)		(1.2)	(3.6)		(.9)	(3.9)	
5	.03	.73	53%	.00	.83	62%	.05	.89	68%	.05	.94	74%
	(.4)	(5.9)		(.0)	(4.7)		(.6)	(4.7)		(.7)	(5.5)	
1-5	-.04	-.62	12%	.04	-.61	17%	-.02	-.66	29%	-.07	-.55	23%
	(-.6)	(-3.2)		(.5)	(-3.2)		(-.2)	(-2.6)		(-.5)	(-3.2)	

1963-2000:

	K=2			K=3			K=4			K=5		
i	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%
1	.23	.64	32%	.26	.46	41%	.26	.41	44%	.24	.54	49%
	(4.2)	(1.9)		(5.7)	(2.0)		(6.9)	(1.7)		(5.7)	(1.8)	
3	.06	.31	7%	.01	.28	2%	-.01	.38	7%	-.05	.68	27%
	(1.3)	(1.1)		(.3)	(1.5)		(-.2)	(2.1)		(-.8)	(3.3)	
5	-.02	.30	9%	-.04	.53	32%	-.03	.53	32%	-.05	.67	52%
	(-.8)	(2.6)		(-1.6)	(4.3)		(-1.0)	(6.1)		(-1.9)	(6.3)	
1-5	.26	.34	21%	.29	-.07	39%	.29	-.11	44%	.30	-.14	54%
	(4.2)	(.9)		(6.7)	(-.3)		(10.8)	(-.5)		(11.3)	(-.6)	

Table 7: Value and growth stocks' ROE on the market's simple news proxies

The table reports the OLS regression coefficients, Newey-West t-statistics, and adjusted R^2 for regressions $\sum_{k=1}^{K}[\rho^{k-1}roe_{i,t,t+k}] = \alpha + \beta_{DR,i}\sum_{k=1}^{K}[\rho^{k-1}\mathbf{\Delta}_{t+k}\ln(\mathbf{P}/\mathbf{E})] + \beta_{CF,i}\sum_{k=1}^{K}[\rho^{k-1}roe_{M,t+k}]+\varepsilon_{i,t,t+k}$. The portfolio $i = 1$ is the extreme growth and $i = 5$ the extreme value portfolio. $\mathbf{\Delta}_{t+k}\ln(\mathbf{P}/\mathbf{E})$ is the change in log smoothed price-earnings ratio from $t + k - 1$ to $t + k$. $roe_{i,t,t+k}$ is $\log(1 + ROE_{i,t,t+k}) - \log(1 + y_{t+k})$, where $ROE_{i,t,t+k}$ is the year $t + k$ clean-surplus return on book equity (for portfolio i sorted at t) and y the Treasury-bill return.

1929-2000:

	K=2			K=3			K=4			K=5		
i	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2
1	-.03	.69	12%	.04	.61	20%	.07	.65	29%	.07	.71	38%
	(-0.4)	(3.2)		(.9)	(5.8)		(1.2)	(6.0)		(1.0)	(5.8)	
3	-.01	.87	72%	.01	.87	82%	.01	.86	82%	-.02	.88	82%
	(-.4)	(18)		(.3)	(14)		(.3)	(12)		(-.4)	(11)	
5	.03	1.03	90%	-.01	1.02	93%	.00	1.00	94%	-.01	1.00	95%
	(1.7)	(25)		(-.4)	(27)		(.0)	(27)		(-.4)	(24)	
1-5	-.06	-.34	2%	.05	-.41	5%	.07	-.35	6%	.08	-.29	5%
	(-.7)	(-1.5)		(.9)	(-3.4)		(1.0)	(-2.7)		(.9)	(-1.9)	

1929-1962:

	K=2			K=3			K=4			K=5		
i	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%
1	-.06	.70	10%	-.01	.58	17%	.01	.58	24%	-.01	.60	31%
	(-.7)	(2.9)		(-.1)	(6.2)		(.1)	(6.5)		(-.1)	(7.0)	
3	.01	.78	88%	.04	.76	89%	.06	.73	89%	.05	.74	88%
	(.6)	(15)		(1.7)	(15)		(1.9)	(15)		(1.3)	(13)	
5	.04	1.04	97%	.01	.97	97%	.03	1.03	97%	.03	1.04	98%
	(4.5)	(49)		(1.2)	(48)		(1.9)	(47)		(1.4)	(41)	
1-5	-.22	-.35	4%	-.02	-.45	8%	-.02	-.45	11%	-.04	-.44	14%
	(-1.1)	(-1.4)		(-.3)	(-4.4)		(-.2)	(-4.3)		(-.3)	(-4.0)	

1963-2000:

	K=2			K=3			K=4			K=5		
i	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%	β_{DR}	β_{CF}	R^2%
1	.11	1.04	11%	.24	1.20	31%	.27	1.41	47%	.26	1.70	61%
	(1.0)	(2.2)		(2.6)	(2.7)		(3.2)	(3.6)		(3.4)	(5.0)	
3	-.04	1.19	47%	-.02	1.10	67%	-.05	1.08	70%	-.08	1.18	73%
	(-1.3)	(5.4)		(-.5)	(8.5)		(-1.0)	(8.7)		(-1.8)	(8.1)	
5	-.05	.95	62%	-.09	.93	79%	-.08	.93	84%	-.07	.92	84%
	(-1.7)	(6.6)		(-4.5)	(11)		(-4.12)	(14)		(-4.3)	(16)	
1-5	.16	.09	0%	.33	.27	21%	.35	.48	30%	.34	.78	42%
	(1.3)	(.2)		(3.9)	(.6)		(4.3)	(1.1)		(4.6)	(2.1)	

Table 8: Alternative specifications for ROE regressions

The table reports the OLS regression coefficients, Newey-West t-statistics, and adjusted R^2 for the regression shown in each panel. The dependent variable is $\sum_{k=2}^{K}[\rho^{k-1}(roe_{1,t,t+k} - roe_{5,t,t+k})]$, where $i = 1$ denotes the extreme growth and $i = 5$ the extreme value portfolio. The market's N_{DR} and N_{CF} are extracted using the VAR of Table 1. $\mathbf{\Delta}_{t+k}\ln(\mathbf{P}/\mathbf{E})$ is the change in log smoothed price-earnings ratio from $t+k-1$ to $t+k$. $roe_{i,t,t+k}$ is $\log(1+ROE_{i,t,t+k}) - \log(1+y_{t+k})$, where $ROE_{i,t,t+k}$ is the year $t+k$ clean-surplus return on book equity (for portfolio i sorted at t) and y the Treasury-bill return.

	K=2			K=3			K=4			K=5		
$I:\ \alpha + \beta_{DR}\sum_{k=2}^{K}[\rho^{k-1}(-N_{DR,t+k})] + \beta_{CF}\sum_{k=2}^{K}[\rho^{k-1}N_{CF,t+k}]+\varepsilon$												
	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2
1929-	.05	-.11	7%	.11	-.14	20%	.12	-.11	20%	.12	-.10	20%
2000	(2.2)	(-2.4)		(3.5)	(-2.5)		(3.3)	(-1.5)		(3.1)	(-1.2)	
1929-	.01	-.13	13%	.05	-.15	14%	.04	-.15	10%	.01	-.18	11%
1962	(.7)	(-2.9)		(1.2)	(-2.0)		(.06)	(-1.8)		(.2)	(-2.2)	
1963-	.10	.07	9%	.16	-.00	26%	.16	-.06	34%	.17	-.07	45%
2000	(2.5)	(.5)		(3.7)	(-.0)		(5.6)	(-.4)		(9.2)	(-.6)	
$II:\ \alpha + \gamma(roe_{1,t,t} - roe_{5,t,t}) + \beta_{DR}\sum_{k=2}^{K}[\rho^{k-1}(-N_{DR,t+k})] + \beta_{CF}\sum_{k=2}^{K}[\rho^{k-1}N_{CF,t+k}]+\varepsilon$												
	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2
1929-	.05	-.11	6%	.11	-.15	19%	.12	-.13	21%	.12	-.11	20%
2000	(2.2)	(-2.3)		(3.6)	(-2.6)		(3.4)	(-1.7)		(3.1)	(-1.3)	
1929-	.01	-.13	11%	.05	-.16	14%	.04	-.18	14%	.01	-.20	14%
1962	(.7)	(-2.9)		(1.2)	(-2.1)		(.6)	(-2.2)		(.1)	(-2.5)	
1963-	.09	.14	11%	.15	-.02	24%	.16	-.05	32%	.17	-.05	44%
2000	(2.5)	(.8)		(3.8)	(.1)		(5.1)	(-.3)		(8.9)	(-.4)	
$III:\ \alpha + \beta_{DR}\sum_{k=2}^{K}[\rho^{k-1}\mathbf{\Delta}_{t+k}\ln(\mathbf{P}/\mathbf{E})] + \beta_{CF}\sum_{k=2}^{K}[\rho^{k-1}roe_{M,t+k}]+\varepsilon$												
	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2
1929-	.02	-.36	6%	.08	-.30	12%	.09	-.21	11%	.09	-.14	7%
2000	(1.3)	(-3.5)		(3.4)	(-3.0)		(2.4)	(-1.7)		(1.9)	(-1.0)	
1929-	.02	-.36	22%	.06	-.33	25%	.07	-.27	18%	.07	-.25	13%
1962	(1.2)	(-3.4)		(1.8)	(-2.6)		(1.3)	(-2.1)		(.9)	(-1.7)	
1963-	.02	-.14	0%	.13	.19	6%	.17	.33	17%	.17	.50	27%
2000	(.4)	(-.3)		(2.6)	(.5)		(3.3)	(.9)		(3.2)	(1.4)	
$IV:\ \alpha + \gamma(roe_{1,t,t} - roe_{5,t,t}) + \beta_{DR}\sum_{k=2}^{K}[\rho^{k-1}\mathbf{\Delta}_{t+k}\ln(\mathbf{P}/\mathbf{E})] + \beta_{CF}\sum_{k=2}^{K}[\rho^{k-1}roe_{M,t+k}]+\varepsilon$												
	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2	β_{DR}	β_{CF}	R^2
1929-	.02	-.36	6%	.08	-.30	10%	.09	-.21	10%	.09	-.15	6%
2000	(1.2)	(-3.5)		(3.4)	(-3.0)		(2.4)	(-1.7)		(1.8)	(-1.0)	
1929-	.02	-.36	20%	.06	-.33	24%	.07	-.28	17%	.06	-.25	13%
1962	(1.2)	(-3.4)		(1.9)	(-2.8)		(1.2)	(-2.2)		(.8)	(-1.8)	
1963-	.02	-.16	0%	.13	.16	4%	.17	.32	15%	.17	.50	27%
2000	(.4)	(-.4)		(2.6)	(.5)		(3.2)	(.9)		(3.2)	(1.5)	

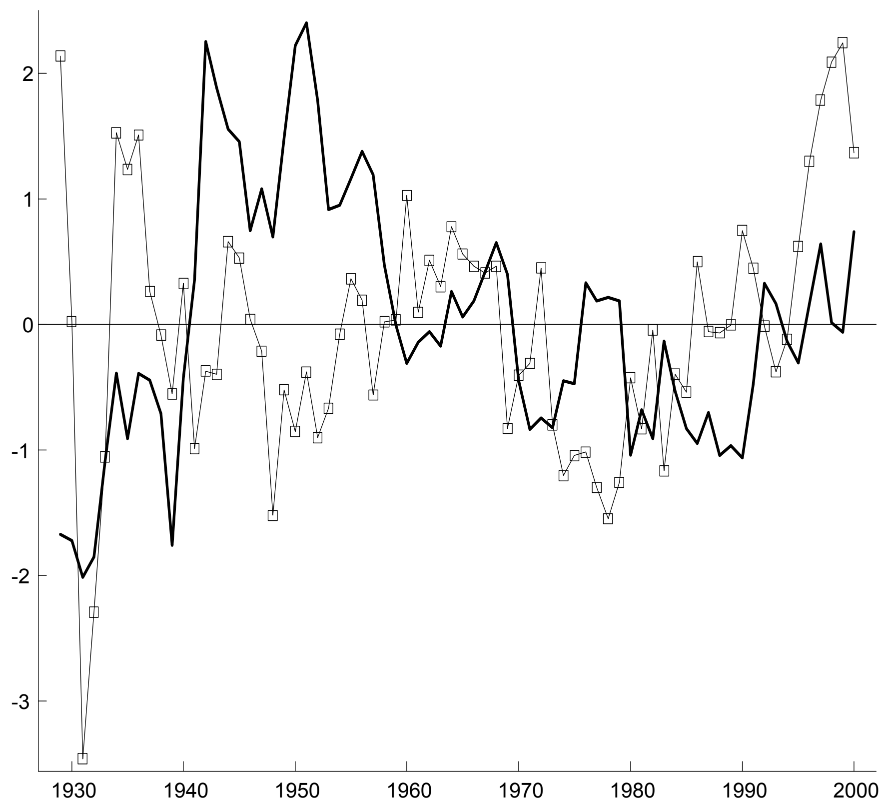

Figure 1: The figure plots three-year centered moving averages of $-N_{M,DR}$ (line with squares) and $N_{M,CF}$ (thick solid line). The news terms are extracted from the VAR model of Table 1. Both moving-average series are normalized to have a unit standard deviation.