Growth or Glamour? Fundamentals and Systematic Risk in Stock Returns

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Abstract

The cash flows of growth stocks are particularly sensitive to temporary movements in aggregate stock prices (driven by movements in the equity risk premium), while the cash flows of value stocks 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. More generally, accounting measures of firm-level risk have predictive power for firms' betas with market-wide cash flows, and this predictive power arises from the behavior of firms' cash flows. The systematic risks of stocks with similar accounting characteristics are primarily driven by the systematic risks of their fundamentals.

JEL classification: G12, G14, N22

1 Introduction

Why do stock prices move together? If stocks are priced by discounting their cash flows at a rate which is constant over time, although possibly varying across stocks, then movements in stock prices are driven by news about cash flows. In this case common variation in prices must be attributable to common variation in cash flows. If discount rates vary over time, however, then groups of stocks can move together because of common shocks to discount rates rather than fundamentals. For example, a change in the market discount rate will have a particularly large effect on the prices of stocks whose cash flows occur in the distant future (Cornell 1999, Dechow, Sloan, and Soliman 2004). In the extreme, irrational investor sentiment can cause common variation in stock prices that is entirely unrelated to the characteristics of cash flows; Barberis, Shleifer, and Wurgler (2005) and Greenwood (2005) suggest that this explains the common movement of stocks that are included in the S&P 500 and Nikkei indexes.

Common variation in stock prices is particularly important when it affects the measures of systematic risk that rational investors use to evaluate stocks. In the Capital Asset Pricing Model (CAPM), the risk of each stock is measured by its beta with the market portfolio, and it is natural to ask whether betas are determined by shocks to cash flows or discount rates (Campbell and Mei 1993). Recently, Campbell (1993, 1996) and Campbell and Vuolteenaho (2004) have proposed 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 two-beta model, the required return on a stock is determined not by its overall beta with the market, but by its "bad beta" with market cash-flow shocks that earns a high premium and its "good beta" with market discount rates that earns a low premium. Campbell and Vuolteenaho (2004) find empirically that value stocks have relatively high bad betas while growth stocks have relatively high good betas. The high average return on value stocks, which is anomalous in the CAPM (Ball 1978, Basu 1977, 1983, Rosenberg, Reid, and Lanstein 1985, Fama and French 1992), is predicted by the two-beta model.

This paper asks whether stocks' bad betas and good betas are determined by the characteristics of their cash flows, or whether instead they arise from the discount rates, possibly driven by sentiment, that investors apply to those cash flows. We first study the common variation of growth and value stocks, and then we examine other common movements in stock returns that can be predicted using firm-level equity market and accounting data.

At least since the influential work of Fama and French (1993), it has been understood that value stocks and growth stocks tend to move together, so that an investor who holds them (and/or shorts growth stocks) takes on a common source of risk. An open question is what drives these common movements. One 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 (2004) suggest 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). 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.

The empirical literature contains some tantalizing evidence in support of the fundamentals view. Fama and French (1995) document common variation in the profitability of value and growth stocks, Cohen, Polk, and Vuolteenaho (2004) find that value stocks' profitability covaries more strongly with market-wide profitability than does growth stocks' profitability, and Liew and Vassalou (2000) show that value-minus-growth returns covary with future macroeconomic fundamentals. Bansal, Dittmar, and Lundblad (2003, 2005) and Hansen, Heaton, and Li (2004) use econometric methods similar to those in this paper to show that value stocks' cash flows have a higher long-run sensitivity to aggregate consumption growth than do growth stocks' cash flows.

An alternative view is that the stock market simply prices value and growth stocks differently at different times. Cornell (1999), for example, 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 (2005) 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 this view, changes in the market's mood or sentiment create correlated movements in the pricing of stocks that investors favor or disfavor.

This paper sets up direct tests of the fundamentals view against the sentiment view, using several alternative approaches. In a first test, we estimate a VAR in the manner of Campbell (1991), Campbell and Mei (1993), and Vuolteenaho (2002) to break firm-level stock returns into components driven by cash-flow shocks and discount-rate shocks. We aggregate the estimated firm-level shocks for those stocks that are included in value and growth portfolios, and regress portfolio-level cash-flow and discount-rate news on the market's cash-flow and discount-rate news to find out whether fundamentals or sentiment drive 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 test, we regress the accounting profitability of value and growth portfolios, measured by portfolio-level return on equity (ROE), on the two components of the market return estimated by Campbell and Vuolteenaho (2004), lengthening the horizon to emphasize longer-term trends rather than short-term fluctuations in profitability. We find that the ROE of value stocks is more sensitive to the market's cash-flow news than is the ROE of growth stocks, consistent with the findings of Cohen, Polk, and Vuolteenaho. More importantly, we are able to refute the pure-sentiment story by showing that the ROE of growth stocks is more sensitive to the market's discount-rate news than is the ROE of value stocks. We obtain similar results when we replace the VAR-based news terms with simple proxies at the market level also.

In a third test, we run cross-sectional regressions of realized firm-level betas onto firms' book-market ratios. We find that a firm's book-market ratio predicts its bad beta positively and its good beta negatively, consistent with the results of Campbell and Vuolteenaho (2004). When we decompose each firm's bad and good beta into components driven by the firm's cash-flow news and discount-rate news, we find that the book-market ratio primarily predicts the cash flow component of the bad beta, not the discount-rate component.

All three approaches tell us that the systematic risks of value and growth stocks are determined by the properties of their cash flows. These 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."

While Campbell and Vuolteenaho (2004) concentrate on value and growth portfolios, their two-beta model has broader application. In the second part of this paper we use cross-sectional stock-level regressions to identify characteristics of common stocks that predict their bad and good betas. We look at market-based historical risk measures, the lagged beta and volatility of stock returns; at accounting-based historical risk measures, the lagged beta and volatility of a firm's return on assets (ROA); and at accounting-based measures of a firm's financial status, including its ROA, debt-asset ratio, and capital investment-asset ratio.

Accounting measures of stock-level risk are not emphasized in contemporary academic research, but were sometimes used to evaluate business risk and estimate the cost of capital for regulated industries in the period before the development of the CAPM (e.g. Bickley 1959). Recently, Morningstar Inc. has used accounting data to calculate costs of capital for individual stocks in the Morningstar stock rating system. Morningstar explicitly rejects the use of the CAPM and argues that accounting data may reveal information about long-run risk, very much in the spirit of Campbell and Vuolteenaho's "bad beta":

> In deciding the rate to discount future cash flows, we ignore stock-price volatility (which drives most estimates of beta) because we welcome volatility if it offers opportunities to buy a stock at a discount to its fair value. Instead, we focus on the fundamental risks facing a company's business. Ideally, we'd like our discount rates to reflect the risk of permanent capital loss to the investor. When assigning a cost of equity to a stock, our analysts score a company in the following areas: Financial leverage - the lower the debt the better. Cyclicality - the less cyclical the firm, the better. Size - we penalize very small firms. Free cash flows - the higher as a percentage of sales and the more sustainable, the better. (Morningstar 2004.)

Even in the CAPM, accounting data may be relevant if they help one predict the future market beta of a stock. This point has been emphasized by Myers and Turnbull (1977) among others, and has influenced the development of industry risk models. Our cross-sectional regressions show that accounting data do predict market betas.

Importantly, however, some accounting variables have disproportionate predictive power for bad betas, while lagged market betas and volatilities of stock returns have disproportionate predictive power for good betas. This result implies that accounting data are more important determinants of a firm's systematic risk and cost of capital in the two-beta model than in the CAPM.

Finally, we use the cross-sectional regression approach in combination with our firm-level VAR methodology to predict the components of a firm's bad and good beta that are determined by its cash flows and its discount rates. We find that stock-level characteristics generally predict the cash-flow components of a firm's bad and good beta, not the discount-rate components. The systematic risks of stocks with similar accounting characteristics are primarily driven by the systematic risks of their fundamentals, an important extension of our finding for growth and value stocks.

Both our portfolio analysis and our firm-level analysis are driven by a desire to understand the risk characteristics of publicly traded companies. It is important to note that those risks cannot be measured from the risk characteristics of dividend streams to dynamic trading strategies. The dividends paid by a dynamically rebalanced portfolio strategy may vary because the dividends of the firms in the portfolio change, but they may also vary if the stocks sold have systematically different dividend yields than stocks bought at the rebalance. For example, consider a dynamic strategy that buys non-dividend-paying stocks in recessions and dividend-paying stocks in booms. The dividends earned by this dynamic trading strategy will have a strong business-cycle component even if the dividends of all underlying companies do not.

Therefore, any sensible attempt to measure the risks of firms' cash flows at a portfolio level must use a "three-dimensional" data set, in which portfolios are formed each year and then those portfolios are followed into the future for a number of years without rebalancing. Such three-dimensional data sets have been used by Fama and French (1995) and Cohen, Polk, and Vuolteenaho (2003, 2004). We follow this methodology, and perform all our tests either at the firm level or using three-dimensional data sets that follow the cash flows of a particular portfolio through time without rebalancing.

The remainder of the paper is organized as follows. Section 2 motivates our empirical tests. Section 3 describes our aggregate and firm-level data, and section 4 presents aggregate and firm-level VAR estimates. Section 5 presents our empirical results on growth and value portfolios, section 6 discusses cross-sectional regressions using firm-level characteristics to predict good and bad betas, and section 7 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 (1993, 1996) and Campbell and Vuolteenaho (2004) 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:

$$\begin{aligned} N_{DR,t+1} &= e1'\lambda u_{t+1}, \\ N_{CF,t+1} &= (e1' + e1'\lambda)\, u_{t+1}. \end{aligned} \tag{4}$$

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 returns on stock portfolios, sorted by size or industry, into 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 $\text{Cov}(N_{i,CF,t+1}, r_{M,t+1})$ and $\text{Cov}(-N_{i,DR,t+1}, r_{M,t+1})$. Campbell and Mei define two beta components

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

and

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

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

$$\beta_{i,M} = \beta_{CFi,M} + \beta_{DRi,M}. \tag{7}$$

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 (2004), 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 $\text{Cov}(r_{i,t+1}, N_{M,CF,t+1})$ and $\text{Cov}(r_{i,t+1}, -N_{M,DR,t+1})$ and use these to define cash-flow and discount-rate betas,

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

and

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

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 (2004) 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 (2004). We measure four covariances and define

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

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

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

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 four-way 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 rates 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 $\beta_{CFi,DRM}$.

A very recent paper that explores the four-way decomposition of beta, written subsequent to the first draft of this paper, is Koubouros, Malliaropulos, and Panopoulou (KMP, 2004). KMP estimates separate risk prices for each of the four components of beta. Consistent with the asset pricing theory of Campbell and Vuolteenaho (2004), KMP finds that risk prices are sensitive to the use of cash-flow or discount-rate news at the market level, but not at the firm or portfolio level.

3 Data

3.1 Aggregate VAR data

In specifying the aggregate VAR, we follow Campbell and Vuolteenaho (2004) 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 riskfree rate, constructed by CRSP as the return from rolling over Treasury bills with approximately three months to maturity. We take the excess return series from Professor Kenneth French's website.

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. Fama and French (1989) show that TY tracks the business cycle, so this variable may also capture cyclical variation in the equity premium.

We construct our third variable, the 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 index. Following Graham and Dodd (1934), Campbell and Shiller (1988b, 1998) and Shiller (2000) advocate averaging earnings over several years to avoid temporary spikes in the price-earnings ratio caused by cyclical declines in earnings. This variable must predict low stock returns over the long run if smoothed earnings growth is close to unpredictable. As in Campbell and Vuolteenaho (2004), 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, we compute the small-stock value spread (VS) 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 Brennan, Wang, and Xia (2001), Campbell and Vuolteenaho (2004), and Eleswarapu and Reinganum (2004) that relatively high returns for small growth stocks predict low returns on the market as a whole. This variable can be motivated by the ICAPM itself. If small growth stocks have low and small value stocks have high expected returns, and this return differential is not explained by the static CAPM, the ICAPM requires that the excess return of small growth stocks over small value stocks be correlated with innovations in expected future market returns. There are other more direct stories that also suggest the small-stock value spread should be related to market-wide discount rates. One possibility is that small growth stocks generate cash flows in the more distant future and therefore their prices are more sensitive to changes in discount rates, just as coupon bonds with a high duration are more sensitive to interest-rate movements than are bonds with a low duration (Cornell 1999). Another possibility is that small growth companies are particularly dependent on external financing and thus are sensitive to equity market and broader financial conditions (Ng, Engle, and Rothschild 1992, Perez-Quiros and Timmermann 2000). Finally, it is possible that episodes of irrational investor optimism (Shiller 2000) have a particularly powerful effect on small growth stocks.

To ensure consistency with Campbell and Vuolteenaho's (2004) 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. We estimate the VAR over the period 1928-2001, with 74 annual observations.

3.2 Firm-level VAR data

The raw firm-level data come 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). This database enables us to estimate the firm-level VAR over the period 1929-2001.

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 measure BE for the fiscal year ending in calendar year $t-1$, and ME (market

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

value of equity) at the end of May of year t.[3] 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 $BM \equiv \log[(.9BE + .1ME)/ME]$.

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 the 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, Kovtunenko and Sosner 2003). Vuolteenaho (2002) uses just the previous year's profitability in his

[3]Following Fama and French, 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.

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 VAR Estimation

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 -.0354 with a t-statistic of -.3. The regression coefficient on past values of the term yield spread is positive, consistent with the findings of Keim and Stambaugh (1986), Campbell (1987), and Fama and French (1989), though the associated t-statistic of 1.4 is somewhat modest. The smoothed price-earnings ratio negatively predicts the return with a t-statistic of 2.6, 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 2.1, consistent with Brennan, Wang, and Xia (2001) and Eleswarapu and Reinganum (2004). In summary, the estimated coefficients, both in terms of signs and t-statistics, are generally consistent 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 (2004), 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 2003, Campbell and Yogo 2005, Lewellen 2004, Polk, Thompson, and Vuolteenaho 2005, Torous, Valkanov, and Yan 2005). 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.[4] With these caveats, we proceed with news terms extracted using the point estimates reported in Table 1.

Figure 1 plots centered three-year moving averages 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

[4] The appendix to Campbell and Vuolteenaho (2004), available online at http://kuznets.fas.harvard.edu/~campbell/papers/BBGBAppendix20040624.pdf, presents evidence that there is little finite-sample bias in the estimated news terms used in that paper.

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-weighted portfolios based on firms' book-to-market ratios, and denote the extreme growth portfolio with 1 and the extreme value portfolio with 5. When forming the portfolios we allocate an equal amount of market capitalization to each portfolio, in order to ensure that all the portfolios are economically meaningful.[5] We regress these portfolios' simple returns on the scaled news 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 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 the extreme growth and value portfolios' cash-flow betas is -.13, and this difference is stable across subperiods. In contrast, the pattern in discount-rate betas changes from one subperiod to another. Growth stocks' discount-rate betas are significantly below one in the early subperiod and very close to one in the later subperiod. More striking is that value stocks' discount-rate betas decline from 1.18 in the first subsample to .48 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 (2004).

The full-period estimates of bad and good beta for the market portfolio sum up to approximately one. Curiously, however, the sum of estimated bad and good betas 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 expected return is exactly uncorrelated with unexpected

[5] The typical approach allocates an equal number of firms to each portfolio. Since growth firms are typically much larger than value firms, this approach generates value portfolios that contain only a small fraction of the capitalization of the market.

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 parameter estimates translate into a function $e1'\lambda$ that has positive weights on all state-variable shocks. The t-statistics on the coefficients in $e1'\lambda$ are 2.1 for past return, 2.6 for book-to-market, and 1.8 for profitability. Contrasting the firm-level $e1'\lambda$ estimates to those obtained from the aggregate VAR of Table 1, it is 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. The positive firm-level effect is consistent with the literature on momentum in the cross-section of stock returns.

Table 3 also reports a variance decomposition for firm-level market-adjusted stock returns. The total variance of the return is the sum of the variance of expected-return news (0.0048, corresponding to a standard deviation of 7%), the variance of cash-flow news (0.1411, corresponding to a standard deviation of 38%), and twice the covariance between them (0.0046, corresponding to a correlation of 0.18). The total return variance is 0.1551, corresponding to a return standard deviation of almost 40%. Thus the firm-level VAR attributes 97% of the variance of firm-level market-adjusted returns to cash-flow news, and only 3% to discount-rate news. If one adds back the aggregate market return to construct a variance decomposition for total firm-level returns, cash-flow news accounts for 80% of the variance and discount-rate news for 20%. This result, due originally to Vuolteenaho (2002), is consistent with a much lower share of cash-flow news in the aggregate VAR because most firm-level cash-flow news is idiosyncratic, so it averages out at the market level.

The high share of cash-flow news implied by the firm-level VAR results in part from the 1929-2001 sample period over which the VAR is estimated. In the online Appendix to this paper, Campbell, Polk, and Vuolteenaho (2005), we report firm-level VAR estimates for the period 1963-2001. Over this period the VAR explanatory variables are stronger predictors of market-adjusted firm-level stock returns. The implied variance of expected-return news is 0.025, corresponding to a standard deviation of almost 16%, and the variance of cash-flow news is 0.166, corresponding to a standard deviation of 41%. Although expected-return news is more volatile in the 1963-2001 period, the beta patterns we discuss later in the paper are very similar.

We construct cash-flow and discount-rate news for our 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-weighted average of the firms' news. The portfolios 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.

5 Beta Decomposition for Growth and Value Portfolios

5.1 VAR-based beta decomposition

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 $N_{M,DR} \times \mathrm{Var}\left(r_M^e\right)/\mathrm{Var}(N_{M,DR})$ and $N_{M,CF} \times \mathrm{Var}\left(r_M^e\right)/\mathrm{Var}(N_{M,CF})$. The 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 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, the left-hand panel of Table 5 regresses the portfolio-level cash-flow news on the estimated $-N_{M,DR,t+1}$ and $N_{M,CF,t+1}$ in a multiple regression. We show results for three portfolios (1, 3, and 5) to save space. 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 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 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 over time, 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 (negative) discount-rate news appear 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' 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).

All these results are based on a firm-level VAR that is estimated over the whole sample period 1929-2001. The Appendix, Campbell, Polk, and Vuolteenaho (2005), reports similar beta patterns in the modern subsample 1963-2001 when the VAR is estimated just over that subsample.

5.2 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.

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 arise from 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 the 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 (2003, 2004) have argued for the use of the discounted sum of ROE 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 examining 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.[6]

The right-hand panels of Table 5 show the multiple regression coefficients for three portfolios (1, 3, and 5). Despite the fact that the dependent variables are now constructed using simple accounting measures, the patterns in these panels are virtually identical to those in the left panel that uses cash-flow news extracted from a firm-level VAR. In summary, this evidence refutes 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.

Regressions of direct cash-flow measures on alternative proxies for 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:

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

[6] 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.

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 $\ln(P/E)_M$ 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.

In the online Appendix to this paper, Campbell, Polk and Vuolteenaho (2005), we report 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, with a t statistic of 3.9.

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 the Appendix again confirms that the reason growth stocks 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, the Appendix also 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 may be driven by predictable components in our discounted ROE sums. One reason there may be predictable components is purely mechanical. 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, 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. We can 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.

We have implemented these two robustness checks both for regressions of discounted ROE sums on the market's cash-flow and discount-rate news as defined by the aggregate VAR, and on regressions of discounted ROE sums on proxies for these news terms. The results are consistent with those throughout the paper, again rejecting the pure-sentiment story.

6 Bad Beta, Good Beta, and Stock-Level Characteristics

In this section we run regressions predicting both the bad and good beta components of a firm's market beta using annual observations of firm characteristics as of the end of May each year. Our first approach takes advantage of the fact that estimating covariances is generally easier with higher frequency data. Specifically, we average the cross products of each firm's monthly simple returns with contemporaneous and one-month lagged monthly market news terms over all months within the year in question. The use of lagged monthly news terms, following Scholes and Williams (1977), captures sluggish responses of some stocks to market movements. Campbell and Vuolteenaho (2004) find that this is important in estimating bad and good betas, particularly for smaller stocks. Our regressions can be written as a system:

$$\sum_{j=1}^{12}\begin{bmatrix} (N_{M,CF,t,j}-N_{M,DR,t,j}+N_{M,CF,t,j-1}-N_{M,DR,t,j-1})*R_{i,t,j} \\ (N_{M,CF,t,j}+N_{CF,t,j-1})*R_{i,t,j} \\ (-N_{DR,t,j}-N_{DR,t,j-1})*R_{i,t,j} \end{bmatrix} = X_{i,t-1}\mathbf{B}+\boldsymbol{\varepsilon}_{i,t}, \tag{20}$$

where t indexes years, j indexes months, i indexes firms, and the dependent variables in the three rows are firm- and year-specific ex post market beta, bad beta, and good beta respectively.

In order to further split betas into components that are attributable to firm-specific cash-flow and discount-rate news, we are forced to turn to annual returns, as the firm-specific return decomposition relies on the annual firm-level VAR. In this case we estimate

$$\begin{bmatrix} (N_{M,CF,t} - N_{M,DR,t}) * (N_{i,CF,t} - N_{i,DR,t}) \\ (N_{M,CF,t}) * (N_{i,CF,t} - N_{i,DR,t}) \\ (-N_{M,DR,t}) * (N_{i,CF,t} - N_{iDR,t}) \\ (N_{M,CF,t}) * (N_{i,CF,t}) \\ (-N_{M,DR,t}) * (N_{i,CF,t}) \\ (N_{M,CF,t}) * (-N_{iDR,t}) \\ (-N_{M,DR,t}) * (-N_{i,DR,t}) \end{bmatrix} = X_{i,t-1}\mathbf{B} + \boldsymbol{\varepsilon}_{i,t} \tag{21}$$

In either approach, we estimate simple regressions linking the components of firms' risks to each characteristic as well as multiple regression specifications using all variables. We remove year-specific means from both the dependent and independent variables. After cross-sectionally demeaning the data, we then normalize each independent variable to have unit variance. We then estimate regression coefficients in equations (20) and (21) using WLS. Specifically, we multiply each observation by the inverse of the number of cross-sectional observations that year, 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. Finally, we report every regression coefficient after dividing by the estimated market return variance. As a result, each coefficient represents the change, in units of beta, of a one standard deviation change in an independent variable. The sample period for all regressions is the Compustat data period, 1963–2000.

6.1 The value effect in stock-level regressions

As a first empirical exercise, we use stock-level regressions to reconfirm the results on value and growth stocks reported in the previous section. Table 6 shows the coefficients of simple regressions of annual cross-products onto market capitalization, book-market ratios, and lagged market betas. The first column shows the effect of explanatory variables on market beta, the second and third columns break this down into the effect on bad and good beta, and the remaining four columns show the four-way decomposition into cash-flow- and discount-rate-driven bad and good beta.

Table 7 summarizes these results in a different way. For the same regressions, the first column reports the share of each variable's effect on market beta that is attributed to its effect on bad beta with the market's cash flows; the second column shows the share of each variable's effect on bad beta that is estimated to work through firm-specific cash flows; and the third column shows the share of each variable's effect on good beta that is estimated to work through firm-specific cash flows.

The first three columns of Table 6 reconfirm the findings of Campbell and Vuolteenaho (2004). Large stocks typically have lower betas, and about 30% of the beta difference is attributed to bad beta. Value stocks have lower betas than growth stocks in this sample period, but this is entirely due to their lower discount-rate betas; value stocks actually have slightly higher bad betas with market cash flows. Stocks with high past betas have higher future betas, but this beta difference is entirely due to a difference in good beta, not bad beta. These patterns were used by Campbell and Vuolteenaho to account for the size and value effects, and the excessively flat security market line, in recent decades.

The last four columns of Table 6 show that these beta patterns are driven by the cash-flow behavior of stocks sorted by size, value, and past beta. These characteristics have very little ability to forecast the discount-rate behavior of stocks. Accordingly, Table 7 reports cash-flow shares close to one when decomposing good and bad beta into components driven by the cash-flow and discount-rate behavior of individual stocks. Thus the cross-sectional regression approach confirms the portfolio results that we reported in the previous section.

The Appendix, Campbell, Polk, and Vuolteenaho (2005), reports similar results for multiple regressions that include size, book-market, and lagged betas simultaneously. The results are generally comparable to those in simple regressions.

6.2 Firm-level determinants of systematic risk

Within the cross-sectional regression approach, there is no reason to confine our attention to firm characteristics such as value, size, and beta that have been found to predict average stock returns. Instead, we can consider variables that have been proposed as indicators of risk at the firm level. We first run monthly regressions in Table 8. These regressions give us relatively precise estimates but only allow us to decompose market betas into their bad and good components. We then go on to run annual regressions which allow us to calculate four-way beta decompositions. Table 9 reports regression results and Table 10 shows the implied beta shares. All these tables use multiple regressions; the Appendix reports the corresponding simple regression results.

In each of these tables we consider variables that intuitively might be linked to cross-sectional variation in systematic risk exposures. Rolling firm-level monthly market-model regressions are one obvious source of such characteristics, providing two measures. The first measure of risk from this regression is estimated market beta, $\widehat{\beta}_{i,t}$. We estimate betas using at least one and up to three years of monthly returns in an OLS regression on a constant and the contemporaneous return on the value-weight NYSE-AMEX-NASDAQ portfolio. We skip those months in which a firm is missing returns. However, we require all observations to occur within a four-year window. As we sometimes estimate beta using only twelve returns, we censor each firm's individual monthly return to the range (-50%,100%) to limit the influence of extreme firm-specific outliers. The residual standard deviation from these market-model regressions, $\widehat{\sigma}_{i,t}$, provides our second measure of risk.

We also generate intuitive measures of risk from a firm's cash flows, in particular from the history of a firm's return on assets, ROA_i. We construct this measure as earnings before extraordinary items (COMPUSTAT data item 18) over the book value of assets (COMPUSTAT data item 6). First and most simply, we use a firm's most current ROA_i as our measure of firm profitability. We then measure the degree of systematic risk in a firm's cash flows by averaging the product of a firm's cross-sectionally demeaned ROA with the marketwide (asset-weighted) ROA over the last five years. We call this average cross product β^{ROA}. Our final profitability measure captures not only systematic but also idiosyncratic risk and is the time-series volatility of each firm's ROA over the past five years, $\sigma_i(ROA_i)$.

Capital expenditure and book leverage round out the characteristics we use to predict firm risks. We measure investment as net capital expenditure—capital expenditure (COMPUSTAT data item 128) minus depreciation (COMPUSTAT data item 14)—scaled by book assets, $CAPX_i/A_i$. Book leverage is the sum of short- and long-term debt over total assets, $Debt_i/A_i$. Short-term debt is COMPUSTAT data item 34 while long-term debt is COMPUSTAT data item 9.

Table 8 shows that lagged market beta and idiosyncratic risk have strong predictive power for a firm's future market beta. Only 10% of this predictive power, however, is attributable to bad beta. Thus sorting stocks on past equity market risk measures does not generate a wide spread in bad beta. If the two-beta model of Campbell and Vuolteenaho (2004) is correct, this popular approach will not generate accurate measures of the cost of capital at the firm level.

Accounting variables can also be used to predict market betas at the firm level. Some of these variables, such as the volatility of ROA, behave like market-based risk measures in that they primarily predict good beta. Others, however, do have strong explanatory power for bad beta. Around 40% of the predictive power of leverage and investment for market beta is attributed to the ability of these variables to predict bad beta. Profitable companies with high ROA tend to have low market betas, and over two-thirds of this effect is attributed to the fact that these companies have low bad betas.

Table 9 and Table 10 repeat these results using annual regressions that allow a four-way decomposition of beta. The main results are consistent with Table 8, although with higher standard errors. Equity market risk measures primarily predict good beta, while profitability and leverage have substantial predictive power for bad beta. The new finding in these tables is that all these effects are attributed to the systematic risks in company cash flows, rather than the systematic risk in company discount rates. The cash-flow shares in the right two columns of Table 10 are consistently close to one. Systematic risks, as measured by firm-level accounting data, seem to be driven primarily by fundamentals.

7 Conclusion

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.

The first systematic risk pattern we analyze is the finding of Campbell and Vuolteenaho (2004) 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 a first test, we break firm-level returns of value and growth stocks into components driven by cash-flow shocks and discount-rate shocks. We then aggregate these components for value and growth portfolios. We regress portfolio-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 test, we regress the accounting profitability of value and growth portfolios on the market's cash-flow and discount-rate news, estimated from a VAR or using simpler earnings-based proxies, lengthening the horizon to emphasize longer-term trends rather than short-term fluctuations in profitability. In a third test, we run cross-sectional firm-level regressions of ex post beta components onto the book-market ratio.

All of these approaches 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.

This paper also begins a broader exploration of firm-level characteristics that predict firms' sensitivities to market cash-flow and discount-rate shocks. We find that historical return betas and return volatilities strongly predict firms' sensitivities to market discount rates, but are much less useful for predicting sensitivities to market cash flows. Accounting data, however, particularly the return on assets and the debt-asset ratio, are important predictors of firms' sensitivities to market cash flows. This finding implies that accounting data should play a more important role in determining a firm's cost of capital in a two-beta model like that of Campbell and Vuolteenaho (2004), which stresses the importance of cash-flow sensitivity, than in the traditional CAPM.

Finally, we show that these effects of firm characteristics on firm sensitivities to market cash flows and discount rates operate primarily through firm-level cash flows rather than through firm-level discount rates. This result generalizes our finding for growth and value stocks, and suggests that fundamentals have a dominant influence on cross-sectional patterns of systematic risk in the stock market.

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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^e_M), 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 $(e1'+e1'\lambda)u$ where u is the matrix of residuals from the VAR. 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	$e1'\lambda$
$r^e_{M,t+1}$	.8967	-.0354	.0643	-.2133	-.1642	-.1010
	(.2982)	(.1142)	(.0456)	(.0811)	(.0778)	(.0322)
TY_{t+1}	-.0479	.0250	.3437	-.1303	.5173	.0372
	(.7059)	(.2778)	(.1095)	(.1945)	(.1874)	(.0259)
PE_{t+1}	.6345	.0810	.0478	.8354	-.1149	-.8530
	(.2715)	(.1066)	(.0419)	(.0750)	(.0750)	(.1264)
VS_{t+1}	.3166	.0291	-.0429	-.0515	.9133	-.2178
	(.2164)	(.0856)	(.0335)	(.0599)	(.0574)	(.1481)

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.

Growth and value returns on the market's $-N_{dr}$

	1	2	3	4	5	1-5
1929-2000	**0.86**	**0.88**	**0.84**	**0.82**	**0.97**	**-0.11**
	(13.6)	(11.2)	(10.8)	(9.6)	(8.3)	(-1.1)
1929-1962	**0.78**	**0.90**	**0.91**	**0.92**	**1.18**	**-0.40**
	(10.0)	(8.3)	(8.9)	(8.2)	(7.4)	(-3.1)
1963-2000	**1.06**	**0.83**	**0.68**	**0.58**	**0.48**	**0.58**
	(8.6)	(7.6)	(6.1)	(4.8)	(3.8)	(4.0)

Growth and value returns on the market's N_{cf}

	1	2	3	4	5	1-5
1929-2000	**0.07**	**0.11**	**0.13**	**0.16**	**0.20**	**-0.13**
	(1.6)	(2.4)	(3.0)	(3.8)	(3.5)	(-3.5)
1929-1962	**0.16**	**0.18**	**0.20**	**0.22**	**0.27**	**-0.11**
	(3.2)	(2.8)	(3.2)	(3.6)	(3.2)	(-2.1)
1963-2000	**-0.15**	**-0.08**	**-0.05**	**-0.00**	**-0.01**	**-0.14**
	(-2.2)	(-1.3)	(-0.9)	(-0.0)	(-0.1)	(-2.6)

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 $(e1' + e1'\lambda)u_i$ where u_i is the firm-specific matrix of residuals from the VAR. These news terms imply a variance decomposition of firm-level returns. Standard errors (in parentheses) take into accounting clustering in each cross section. 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)
Variance Decomposition	Nr	Ncf		
Expected-return news (Nr)	0.0048	0.0044		
	(0.0037)	(0.0080)		
Cash-flow news (Ncf)	0.0022	0.1411		
	(0.0080)	(.0191)		

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 the BE/ME-sorted portfolios described in Table 2. Portfolio $i = 1$ is the extreme growth portfolio (low BE/ME) and $i = 5$ is the extreme value portfolio (high BE/ME). "1-5" denotes the difference between extreme growth (1) and value (5) portfolios. 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 (in parentheses) do not account for the estimation uncertainty in extraction of the news terms.

	1	2	3	4	5	1-5
$\beta_{DRi,DRM}$: Growth and value $-N_{DR}$ on the market's $-N_{DR}$						
1929-2000	**.74**	**.77**	**.77**	**.80**	**.80**	**-.06**
	(60)	(78)	(85)	(74)	(98)	(-5.7)
1929-1962	**.66**	**.69**	**.69**	**.72**	**.73**	**-.07**
	(45)	(69)	(78)	(53)	(88)	(-5.3)
1963-2000	**.94**	**.95**	**.95**	**.97**	**.97**	**-.03**
	(68)	(103)	(114)	(93)	(91)	(-1.8)
$\beta_{CFi,DRM}$: Growth and value N_{CF} on the market's $-N_{DR}$						
1929-2000	**.03**	**-.00**	**-.04**	**-.09**	**.01**	**.02**
	(.86)	(-.06)	(-.99)	(-1.8)	(.18)	(.34)
1929-1962	**.00**	**.03**	**.01**	**-.03**	**.16**	**-.16**
	(-.02)	(.63)	(.29)	(-.42)	(2.3)	(-2.7)
1963-2000	**.13**	**-.05**	**-.15**	**-.24**	**-.35**	**.48**
	(1.92)	(-.89)	(-2.4)	(-2.6)	(-3.6)	(4.0)
$\beta_{DRi,CFM}$: Growth and value $-N_{DR}$ on the market's N_{CF}						
1929-2000	**.04**	**.04**	**.04**	**.05**	**.05**	**-.01**
	(1.2)	(91.2)	(1.3)	(1.4)	(1.5)	(-3.1)
1929-1962	**.08**	**.08**	**.08**	**.08**	**.09**	**-.02**
	(1.8)	(1.7)	(1.9)	(1.8)	(2.0)	(-2.7)
1963-2000	**-.04**	**-.04**	**-.04**	**-.04**	**-.04**	**-.00**
	(-.80)	(-.78)	(-.72)	(-.71)	(-.69)	(-.87)
$\beta_{CFi,CFM}$: Growth and value N_{CF} on the market's N_{CF}						
1929-2000	**.06**	**.08**	**.10**	**.12**	**.14**	**-.09**
	(4.8)	(11)	(11)	(10)	(11)	(-4.1)
1929-1962	**.06**	**.07**	**.08**	**.09**	**.13**	**-.07**
	(4.9)	(7.0)	(6.8)	(6.3)	(8.7)	(-3.3)
1963-2000	**.03**	**.09**	**.12**	**.17**	**.16**	**-.13**
	(1.2)	(8.8)	(10)	(9.3)	(5.8)	(-3.0)

Table 5: Value and growth stocks' fundamentals on the market's news terms
The table reports the betas from multiple regressions of cash-flow-news proxies for the BE/ME-sorted portfolios described in Table 2 on the market's discount-rate and cash-flow news . In the "News" panel, a portfolio's cash-flow news is proxied by the value-weight average of firms' news terms from the firm-level panel VAR of Table 3. In that panel, the market's $N_{M,DR}$ and $N_{M,CF}$ are extracted using the VAR of Table 1. In the other panels ("K=3", etc.), portfolio cash-flow news is proxied by $\sum_{k=1}^{K}[\rho^{k-1} roe_{i,t,t+k}]$ with $roe_{i,t,t+k}$ 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. In those panels, market news, $\sum_{k=1}^{K}[\rho^{k-1}(-N_{M,DR,t+k})]$ and $\sum_{k=1}^{K}[\rho^{k-1} N_{M,CF,t+k}]$, is discounted and summed in a corresponding fashion.

	News			K=3			K=4			K=5		
1929-2000:												
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	.01	.06	23%	.14	.29	11%	.17	.35	16%	.15	.52	27%
	(.21)	(4.7)		(3.0)	(1.7)		(3.0)	(1.6)		(2.6)	(3.2)	
3	-.09	.10	70%	.01	.59	43%	.02	.65	50%	-.01	.71	58%
	(-3.9)	(12.7)		(.4)	(5.8)		(.4)	(5.6)		(-.2)	(6.5)	
5	-.05	.15	62%	-.02	.76	59%	-.01	.79	64%	-.02	.83	72%
	(-1.5)	(10.7)		(.5)	(6.2)		(-.2)	(5.9)		(-.64)	(6.6)	
1-5	.06	-.09	19%	.16	-.48	17%	.17	-.44	21%	.18	-.31	18%
	(1.1)	(-4.3)		(2.9)	(-3.4)		(2.8)	(-2.4)		(2.6)	(-2.2)	
1929-1962:												
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	.07	45%	.04	.22	0%	.03	.24	0%	-.02	.39	10%
	(-1.7)	(5.4)		(.5)	(.9)		(.2)	(.7)		(-.1)	(1.4)	
3	-.06	.09	61%	.04	.57	49%	.09	.62	54%	.07	.64	58%
	(-1.9)	(7.3)		(.8)	(3.8)		(1.2)	(3.6)		(.9)	(3.9)	
5	.05	.13	70%	.00	.83	62%	.05	.89	68%	.05	.94	74%
	(1.2)	(8.0)		(.0)	(4.7)		(.6)	(4.7)		(.7)	(5.5)	
1-5	-.11	-.06	29%	.04	-.61	17%	-.02	-.66	29%	-.07	-.55	23%
	(-2.0)	(-2.6)		(.5)	(-3.2)		(-.2)	(-2.6)		(-.5)	(-3.2)	
1963-2000:												
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	.14	.03	10%	.26	.46	41%	.26	.41	44%	.24	.54	49%
	(2.1)	(1.5)		(5.7)	(2.0)		(6.9)	(1.7)		(5.7)	(1.8)	
3	-.11	.11	82%	.01	.28	2%	-.01	.38	7%	-.05	.68	27%
	(-3.9)	(11.8)		(.3)	(1.5)		(-.2)	(2.1)		(-.8)	(3.3)	
5	-.30	.15	66%	-.04	.53	32%	-.03	.53	32%	-.05	.67	52%
	(-4.6)	(6.7)		(-1.6)	(4.3)		(-1.0)	(6.1)		(-1.9)	(6.3)	
1-5	.44	-.11	43%	.29	-.07	39%	.29	-.11	44%	.30	-.14	54%
	(4.1)	(-3.1)		(6.7)	(-.3)		(10.8)	(-.5)		(11.3)	(-.6)	

Table 6: "Bad" cash-flow and "good" discount-rate betas' components: firm-level regressions, annual returns

The table shows pooled-WLS parameter estimates of firm-level simple regressions forecasting the annual cross products $(N_{DR}+N_{CF})*(N_{CF,i}+N_{DR,i})$, $(N_{CF})*(N_{CF,i}+N_{DR,i})$, $(N_{DR})*(N_{CF,i}+N_{DR,i})$, $(N_{CF})*(N_{CF,i})$, $(N_{DR})*(N_{CF,i})$, $(N_{CF})*(N_{DR,i})$, $(N_{DR})*(N_{DR,i})$. The market's N_{DR} and N_{CF} are extracted using the VAR of Table 1. All variables are market adjusted by removing the corresponding year-specific cross-section mean. Independent variables, described in the text, are normalized to have unit variance. Regression coefficients are divided by the estimated market annual return variance. All t-statistics (in parentheses) take into accounting clustering in each cross section but do not account for the estimation uncertainty in extraction of the market's news terms.

	β	β_{CFM}	β_{DRM}	$\beta_{CFi,CFM}$	$\beta_{CFi,DRM}$	$\beta_{DRi,CFM}$	$\beta_{DRi,DRM}$
ME_i	-0.130	-0.040	-0.090	-0.039	-0.077	0.000	-0.013
	(-1.54)	(-1.91)	(-1.23)	(-2.05)	(-1.18)	(-0.10)	(-1.23)
	0.39%	0.30%	0.20%	0.34%	0.17%	0.00%	0.14%
BE_i/ME_i	-0.075	0.008	-0.083	0.009	-0.085	-0.001	0.002
	(-1.86)	(0.81)	(-2.27)	(0.99)	(-2.31)	(-0.89)	(0.42)
	0.14%	0.01%	0.18%	0.02%	0.22%	0.01%	0.00%
$Beta_i$	0.174	0.000	0.174	-0.001	0.151	0.000	0.024
	(2.21)	(-0.02)	(2.45)	(-0.05)	(2.40)	(0.19)	(2.55)
	0.71%	0.00%	0.76%	0.00%	0.66%	0.00%	0.44%

Table 7: "Bad" cash-flow and "good" discount-rate betas': implied shares
This table reports the bad beta share, the CF bad beta share, and the CF good beta share implied by the previous table. Standard errors (in braces) are calculated using the delta method and take into accounting clustering in each cross section but do not account for the estimation uncertainty in extraction of the market's news terms.

	$\frac{\beta_{CFM}}{\beta}$	$\frac{\beta_{CFi,CFM}}{\beta_{CFM}}$	$\frac{\beta_{CFi,DRM}}{\beta_{DRM}}$
ME_i	0.306	0.993	0.851
	[0.16]	[0.07]	[0.08]
BE_i/ME_i	-0.107	1.178	1.028
	[0.17]	[0.33]	[0.07]
$Beta_i$	-0.003	1.775	0.865
	[0.11]	[36.01]	[0.02]

Table 8: "Bad" cash-flow and "good" discount-rate betas: firm-level regressions, monthly covariances

The table shows pooled-WLS parameter estimates of firm-level multiple regressions annually forecasting the subsequent average monthly cross products $(N_{DR,t}+N_{CF,t}+N_{DR,t-1}+N_{CF,t-1})*(R_{i,t})$, $(N_{CF,t}+N_{CF,t-1})*(R_{i,t})$, and $(N_{DR,t}+N_{DR,t-1})*(R_{i,t})$. The market's N_{DR} and N_{CF} are the monthly news terms from Campbell and Vuolteenaho (2004). All variables are market adjusted by removing the corresponding year-specific cross-section mean. Independent variables, described in the text, are scaled to have unit variance. Regression coefficients are divided by the estimated market monthly return variance. All t-statistics (in parentheses) and standard errors (in braces) take into accounting clustering in each cross section but do not account for the estimation uncertainty in extraction of the market's news terms.

	β		β_{CFM}		β_{DRM}		$\frac{\beta_{CFM}}{\beta}$	
$Beta_i$	0.1212	(4.37)	0.0117	(1.85)	0.1095	(4.26)	0.10	[0.05]
$\sigma_i(r_i)$	0.1207	(3.70)	0.0040	(0.46)	0.1167	(4.24)	0.03	[0.07]
β_i^{ROA}	-0.0060	(-0.32)	0.0036	(1.16)	-0.0096	(-0.47)	-0.60	[1.67]
$\sigma_i(ROA_i)$	0.0579	(5.44)	0.0099	(2.82)	0.0479	(4.48)	0.17	[0.06]
ROA_i	-0.0316	(-1.90)	-0.0216	(-3.95)	-0.0100	(-0.51)	0.68	[0.46]
$Debt_i/A_i$	0.0197	(1.63)	0.0073	(2.03)	0.0125	(1.17)	0.37	[0.20]
$CAPX_i/A_i$	-0.0154	(-1.89)	-0.0060	(-2.00)	-0.0095	(-1.36)	0.39	[0.19]
	3.89%		0.60%		3.33%			

Table 9: "Bad" cash-flow and "good" discount-rate betas: firm-level tests, annual returns

The table shows pooled-WLS parameter estimates of firm-level multiple regressions forecasting the annual cross products $(N_{DR}+N_{CF})*(N_{CF,i}+N_{DR,i})$, $(N_{CF})*(N_{CF,i}+N_{DR,i})$, $(N_{DR})*(N_{CF,i}+N_{DR,i})$, $(N_{CF})*(N_{CF,i})$, $(N_{DR})*(N_{CF,i})$, $(N_{CF})*(N_{DR,i})$, $(N_{DR})*(N_{DR,i})$. The market's N_{DR} and N_{CF} are extracted using the VAR of Table 1. All variables are market adjusted by removing the corresponding year-specific cross-section mean. Independent variables, described in the text, are normalized to have unit variance. Regression coefficients are scaled by an estimate of the market's variance. All t-statistics (in parentheses) take into accounting clustering in each cross section but do not account for the estimation uncertainty in extraction of the market's news terms.

	β	β_{CFM}	β_{DRM}	$\beta_{CFi,CFM}$	$\beta_{CFi,DRM}$	$\beta_{DRi,CFM}$	$\beta_{DRi,DRM}$
$Beta_i$	0.092	-0.002	0.093	-0.002	0.078	0.001	0.015
	(3.05)	(-0.21)	(3.23)	(-0.30)	(3.17)	(0.42)	(2.67)
$\sigma_i(r_i)$	0.090	0.012	0.077	0.011	0.075	0.001	0.003
	(1.45)	(1.27)	(1.39)	(1.25)	(1.41)	(0.79)	(0.67)
$Beta_i^{ROA}$	0.003	-0.002	0.005	0.000	0.014	-0.002	-0.009
	(0.10)	(-0.57)	(0.20)	(-0.08)	(0.64)	(-1.72)	(-1.35)
$\sigma_i(ROA_i)$	0.045	0.003	0.042	0.004	0.041	-0.002	0.002
	(2.20)	(0.35)	(2.22)	(0.58)	(2.21)	(-1.99)	(0.69)
ROA_i	0.021	0.011	0.009	0.016	0.011	-0.004	-0.002
	(1.02)	(1.69)	(0.55)	(2.18)	(0.61)	(-1.52)	(-0.19)
$Debt_i/A_i$	0.015	0.007	0.008	0.005	0.007	0.002	0.001
	(0.70)	(1.18)	(0.43)	(0.82)	(0.39)	(1.79)	(0.25)
$CAPX_i/A_i$	-0.009	-0.001	-0.009	-0.001	-0.008	0.000	0.000
	(-0.48)	(-0.16)	(-0.47)	(-0.28)	(-0.49)	(0.92)	(-0.21)
	1.36%	0.21%	1.22%	0.27%	1.18%	0.21%	0.60%

Table 10: "Bad" cash-flow and "good" discount-rate betas: firm-level tests
This table reports the bad beta share, the CF bad beta share, and the CF good beta share implied by the multiple regressions in the previous table. Standard errors (in braces) are calculated using the delta method and take into accounting clustering in each cross section but do not account for the estimation uncertainty in extraction of the market's news terms.

	$\frac{\beta_{CFM}}{\beta}$	$\frac{\beta_{CFi,CFM}}{\beta_{CFM}}$	$\frac{\beta_{CFi,DRM}}{\beta_{DRM}}$
$Beta_i$	-0.020	1.277	0.840
	[0.10]	[1.88]	[0.04]
$\sigma_i(r_i)$	0.135	0.927	0.964
	[0.08]	[0.08]	[0.04]
$Beta_i^{ROA}$	-0.859	0.148	2.584
	[9.31]	[1.49]	[8.78]
$\sigma_i(ROA_i)$	0.060	1.574	0.961
	[0.16]	[1.80]	[0.05]
ROA_i	0.549	1.372	1.161
	[0.42]	[0.34]	[0.91]
$Debt_i/A_i$	0.488	0.663	0.889
	[0.54]	[0.29]	[0.46]
$CAPX_i/A_i$	0.080	1.643	0.950
	[0.47]	[4.59]	[0.17]

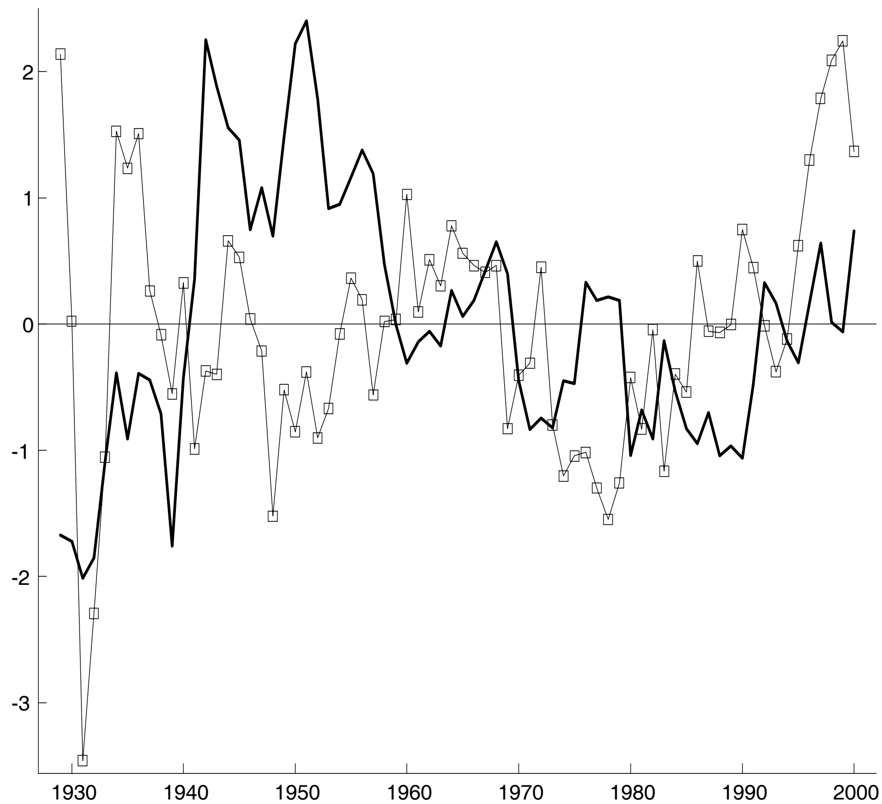

Figure 1: The figure plots three-year centered moving averages of $-N_{M,DR}$ (line with squares) and $N_{M,CF}$ (thick solid line). The news terms are extracted from the VAR model of Table 1. Both moving-average series are normalized to have a unit standard deviation.