What Drives Anomaly Returns?

Lars A. Lochstoer
UCLA

Paul C. Tetlock*
Columbia Business School

December 2017

Abstract

We provide novel evidence on which theories best explain stock return anomalies by decomposing anomaly portfolio returns into shocks to the underlying firms' cash flows or their discount rates. We find common patterns across five well-known anomalies. The cash flow and discount rate components of each anomaly's returns are strongly negatively correlated, and this negative correlation is driven by shocks to long-run cash flows. Discount rate shocks to a mean-variance efficient (MVE) portfolio constructed from these anomalies are slightly *negatively* correlated with discount rate shocks to the market portfolio, while the cash flow shocks to this anomaly-based MVE portfolio are uncorrelated with market cash flow shocks. Our evidence is most consistent with theories in which investors overextrapolate news about firms' long-run cash flows and those in which firm risk increases following negative news about long-run cash flows.

*Comments welcome. We thank Francisco Gomes, Alan Moreira, and Shri Santosh, as well as seminar participants at the Chicago Asset Pricing Conference, Columbia University, Copenhagen Business School, Cornell University, Federal Reserve Board, London Business School, Q-group Spring Meeting 2017, SFS Finance Cavalcade 2017, Swedish House of Finance conference, UCLA, and UC Irvine for helpful comments. First draft: February 2016. Contact information: Lochstoer: UCLA Anderson School of Management, C-519, 110 Westwood Plaza, Los Angeles, CA 90095. E-mail: lars.lochstoer@anderson.ucla.edu. Tetlock: 811 Uris Hall, Columbia Business School, 3022 Broadway, New York, NY 10027. E-mail: paul.tetlock@columbia.edu.

1 Introduction

Researchers in the past 30 years have uncovered robust patterns in stock returns that contradict classic asset pricing theories. A prominent example is that value stocks outperform growth stocks, even though these stocks are similarly risky by conventional measures. In fact, most long-short anomaly portfolios (e.g., long value and short growth) have near-zero market betas. Furthermore, since anomaly portfolios comprise numerous stocks, they are also not exposed to idiosyncratic risks. The lack of market risk and idiosyncratic risk begs the question of what drives return volatility in these portfolios. To generate volatility, a source of risk (or shock) must have a common impact on stocks with similar characteristics, such as value stocks, and it must have a differential common impact on stocks with opposing characteristics, such as growth stocks. Historically, these systematic shocks to anomaly portfolios appear to be priced. Understanding sources of priced comovement is arguably the central question in asset pricing.

We provide novel evidence on the sources of long-short anomaly portfolio returns by decomposing realized anomaly returns into cash flow and discount rate components, building on Campbell (1991) and Vuolteenaho (2002). Unexpected returns must be due to shocks to expected cash flows—e.g., current and future dividends—or shocks to expected future returns—i.e., the price or quantity of risk. We introduce an efficient empirical technique to decompose long-short anomaly portfolio returns into cash flow and discount rate shocks.

Our evidence is useful for testing risk-based and behavioral asset pricing theories. All theories have implications for the magnitudes and correlations of anomaly and market cash flow and discount rate shocks. For example, some theories predict that discount rate fluctuations drive variation in the returns of anomaly portfolios, whereas other theories predict that cash flow variation is more important. At one extreme, consider the model of noise trader risk proposed by De Long et al. (1990). In this model, firm dividends (cash flows) are constant, implying that all return variation arises from changes in discount rates. At the other extreme, consider the simplest form of the CAPM in which firm betas and the market risk premium are constant. In this setting, expected returns (discount rates) are constant, implying that all return variation arises from changes in expected cash flows.

Our empirical work focuses on five well-known anomalies—value, size, profitability, investment, and momentum—and yields three sets of findings. First, for all five anomalies, cash flows explain more variation in anomaly returns than do discount rates. Second, for all five anomalies, shocks to cash flows and discount rates are strongly negatively correlated. This correlation is driven by shocks to long-run cash flows, as opposed to shocks to short-run (one-year) cash flows. That is, firms with negative news about long-run cash flows tend to experience persistent increases in discount rates. This association contributes significantly to return variance in anomaly portfolios. Third, for all five anomalies, anomaly cash flow and discount rate components exhibit weak correlations with market cash flow and discount rate components. In fact, when we combine all five anomalies into a mean-variance efficient (MVE) portfolio, this anomaly MVE portfolio exhibits discount rate shocks that are slightly negatively correlated with market discount rate shocks. This fact is surprising if one interprets discount rates as proxies for risk aversion as it suggests that increased aversion to market risk is, if anything, associated with decreased aversion to anomaly risks. Furthermore, cash flow shocks to the market are uncorrelated with cash flow shocks to the anomaly MVE portfolio, indicating that the two portfolios are exposed to distinct fundamental risks.

These findings cast doubt on three types of theories of anomalies. First, theories in which discount rate variation is the primary source of anomaly returns, such as De Long et al. (1990), are inconsistent with the evidence on the importance of cash flow variation. The main reason that anomaly portfolios are volatile is that cash flow shocks are highly correlated across firms with similar characteristics. For example, the long-short investment portfolio is volatile mainly because the cash flows of a typical high-investment firm are more strongly correlated with the cash flows of other high-investment firms than with those of low-investment firms. Second, theories that emphasize commonality in discount rates, such as theories of time-varying risk aversion and those of common investor sentiment, are inconsistent with the low correlations between discount rate shocks to anomaly returns and those to market returns. Third, theories in which anomaly cash flow shocks are strongly correlated with market cash flow shocks—i.e., cash flow beta stories—are inconsistent with the near-zero empirical correlations.

In contrast, theories of firm-specific biases in information processing and theories of firm-specific changes in risk are potentially consistent with our three main findings. Such theories include behavioral models in which investors overextrapolate news about firms' long-run cash flows and rational models in which firm risk increases after negative news about long-run cash flows. In these theories, discount rate shocks amplify the effect of cash flow shocks on returns, consistent with the robustly negative empirical correlation between these shocks. These theories are also consistent with low correlations between anomaly return components and market return components.

We further relate anomaly and market cash flow and discount rate shocks to proxies for macroeconomic fluctuations, including changes in aggregate risk aversion, investor sentiment, and intermediary leverage. Cash flow shocks to the anomaly MVE portfolio are significantly negatively correlated with changes in the labor share of income and broker-dealer leverage. Market cash flow shocks exhibit these same negative correlations. However, market cash flows are also significantly positively correlated with key macroeconomic aggregates, such as consumption and GDP growth, and negatively correlated with measures of aggregate risk aversion. Discount rate shocks to the anomaly MVE portfolio are positively correlated with the change in the labor share and negatively correlated with broker-dealer leverage. Thus, when labor's share of income increases, contemporaneous anomaly returns are low because of a negative cash flow shock and a positive discount rate shock. We find little evidence that anomaly cash flows or discount rates are related to consumption (or GDP) growth, measures of aggregate risk aversion, or sentiment.

Our approach builds on the present-value decomposition of Campbell and Shiller (1988) and Campbell (1991) that Vuolteenaho (2002) applies to individual firms. We directly estimate firms' discount rate shocks using an unbalanced panel vector autoregression (VAR) in which we impose the present-value relation to derive cash flow shocks. We differ from prior work in that we derive and analyze the implications of our firm-level estimates for priced (anomaly) factor portfolios to investigate the fundamental drivers of these factors' returns. The panel VAR, as opposed to a time-series VAR for each anomaly portfolio, fully exploits information about the cross-sectional relation between shocks to characteristics and returns. Our panel-based approach allows us to consider more return predictors, substantially increases the precision of the return decomposition, and mitigates small-sample issues.[1] Motivated by Chen and Zhao's (2009) finding that VAR results are often sensitive to variable selection, we show that our return decompositions are robust across many different specifications.

Vuolteenaho (2002) finds that at the firm-level, returns are mostly driven by cash flows, which we confirm in our sample. He further argues that at the market level, returns are driven mostly by discount rates. Cohen, Polk, and Vuolteenaho (2003) use a portfolio approach to analyze the dynamics of the value spread—i.e., the cross-sectional dispersion in book-to-market ratios. The study concludes that most of the spread comes from differences in expected cash flows. Our study differs in that we decompose portfolio returns (not valuation ratios), analyze multiple anomalies (not just value), and aggregate firm-level estimates based on a firm-level VAR with many predictors of returns and cash flows (not just book-to-market ratios).

Fama and French (1995) document that changes in earnings-to-price ratios for their HML and SMB portfolios exhibit a factor structure, consistent with our findings. However, we examine cash flow shocks extracted using a present value equation in which myriad

[1] Further, more subtly, inferring cash flow and discount rate shocks directly from a VAR estimated using returns and cash flows of a rebalanced portfolios anomaly portfolio (a trading strategy) obfuscates the underlying sources of the anomaly returns. Firms' weights in anomaly portfolios can change dramatically with the realization of stock returns and firms' changing characteristics. In the Appendix, we provide extreme examples in which firms' expected cash flows and expected returns are constant and time-varying, respectively, but where the direct VAR estimation suggests that all return variation in a rebalanced portfolio comes from cash flow shocks.

characteristics predict earnings at various horizons. Unlike Fama and French (1995), we find a strong relation between the factor structure in cash flow shocks and the factor structure in returns. They acknowledge their failure to find this relation as the "weak link" in their story and "speculate that this negative result is caused by noise in [their] measure of shocks to expected earnings." Using the present value relation also allows us to analyze discount rates. Our analysis also includes investment, profitability, and momentum anomalies.

Lyle and Wang (2015) estimate the discount rate and cash flow components of firms' book-to-market ratios by forecasting one-year returns using return on equity and book-to-market ratios. They focus on stock return predictability at the firm level and do not analyze the sources of anomaly returns. Our work is related to studies that use the log-linear approximation of Campbell and Shiller (1988) for price-dividend ratios, typically applied to the market portfolio (see Campbell (1991), Larrain and Yogo (2008), van Binsbergen and Koijen (2010), and Kelly and Pruitt (2013)). We do not analyze the pricing of cash flow or discount rate shocks unlike the analyses of Campbell and Vuolteenaho (2004) and Kozak and Santosh (2017).

The paper proceeds as follows. Section 2 provides examples of theories' implications for anomaly cash flows and discount rates. Section 3 introduces the empirical model. Section 4 describes the data and specification choices. Section 5 discusses the VAR estimation, while Sections 6 presents firm- and portfolio-level results. Section 7 shows robustness tests, and Section 8 concludes.

2 Theory

Empirical research identifies several asset pricing anomalies in which firm characteristics, such as firm profitability and investment, predict firms' stock returns even after controlling for market beta. Theories of these anomalies propose that the properties of investor beliefs and firm cash flows vary with firm characteristics. Here we explain how decomposing anomaly returns into cash flow and discount rate shocks helps distinguish alternative explanations of anomalies. We first discuss this point in the context of specific theories. We then present our empirical model.

The well-known value premium provides a useful illustration. De Long et al. (1990) and Barberis, Shleifer and Vishny (1998) are examples of behavioral models that potentially explain this anomaly, while Zhang (2005) and Lettau and Wachter (2007) are examples of rational explanations.

To relate the these models' predictions to our study, recall from Campbell (1991) that we can approximately decompose shocks to log stock returns into shocks to expectations of future cash flows and returns:[2]

$$r_{i,t+1} - E_t\left[r_{i,t+1}\right] \approx CF^{shock}_{i,t+1} - DR^{shock}_{i,t+1}, \tag{1}$$

where

$$CF^{shock}_{i,t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \kappa^{j-1} \Delta d_{i,t+j}, \tag{2}$$

$$DR^{shock}_{i,t+1} = (E_{t+1} - E_t) \sum_{j=2}^{\infty} \kappa^{j-1} r_{i,t+j}, \tag{3}$$

and where $\Delta d_{i,t+j}$ $(r_{i,t+j})$ is the log of dividend growth (log of gross return) of firm i from time $t+j-1$ to time $t+j$, and κ is a log-linearization constant slightly less than 1.[3] In words, return innovations are due updates in beliefs about current and future dividend growth and/or future expected returns.

We define anomaly returns as the value-weighted returns of the stocks ranked in the highest quintile of a given priced characteristic minus the value-weighted returns of stocks ranked in the lowest quintile. We define anomaly cash flow shocks as the cash flow shocks to the top quintile portfolio minus the shocks to the bottom quintile portfolio. We similarly

[2] The operator $(E_{t+1} - E_t)\, x$ is short-hand for $E_{t+1}[x] - E_t[x]$; the update in the expected value of x from time t to time $t+1$. The equation relies on a log-linear approximation of the price-dividend ratio around its sample average.

[3] A similar decomposition holds for non-dividend paying firms, assuming clean-surplus earnings (see, Ohlson (1995), and Vuolteenaho (2002)). In this case, the relevant cash flows are the log of gross return on equity. The discount rate shock takes the same form as in Equation (3).

define anomaly discount rate shocks.

First, consider a multi-firm generalization of the De Long et al. (1990) model of noise trader risk. In this model, firm cash flows are constant but stock prices fluctuate because of random demand from noise traders correlated with the book-to-market characteristic. As the expectations in Equation (2) are rational, there are no cash flow shocks in this model. By Equation (1), all shocks to returns are due to discount rate shocks. Of course, the constant cash flow assumption is stylized and too extreme. But, if one in the spirit of this model assumes that value and growth firms have similar cash flow exposures, the variance of net cash flow shocks to the long-short portfolio would be small relative to the variance of discount rate shocks. Thus, a finding that discount rate shocks only explain a small fraction of the return variance to the long-short portfolio would be inconsistent with this model.

Barberis, Shleifer, and Vishny (BSV, 1998) propose a model in which investors overextrapolate from long sequences of past firm earnings when forecasting future firm earnings. Thus, a firm that repeatedly experiences low earnings will be underpriced (a value firm) as investors are too pessimistic about its future earnings. The firm will have high expected returns as future earnings on average are better than investors expect. Growth firms will have low expected returns for analogous reasons. In this model, cash flow and discount rate shocks are intimately linked. Negative shocks to cash flows lead to low expected future cash flows. However, these irrationally low expectations manifest as positive discount rate shocks in Equations (2) and (3), as the econometrician estimates expected values under the objective probability measure. Thus, this theory predicts a strong negative correlation between cash flow and discount rate shocks at the firm and anomaly levels.

Daniel, Hirshleifer, and Subrahmanyam (2001) argue that investor overconfidence about signals of firms' future earnings can explain several anomalies. In their model, overconfident investors overreact to informative signals about firm profitability. This leads to a negative correlation between cash flow and discount rate shocks in our decomposition. Unlike the extrapolation story of BSV, overconfidence can lead to a positive correlation between discount rate and short-run earnings shocks, while long-run earnings shocks are negatively correlated with discount rate shocks.

Zhang (2005) provides a rational explanation for the value premium by modeling firms' production decisions. Persistent idiosyncratic productivity (earnings) shocks render firms, by chance, as either value or growth firms. Value firms, which have low productivity, have more capital than optimal because of adjustment costs. These firms' values are very sensitive to negative aggregate productivity shocks as they have little ability to smooth such shocks through disinvesting. Growth firms, on the other hand, have high productivity and suboptimally low capital stocks and therefore are not as exposed to negative aggregate shocks. Value (growth) firms' high (low) betas with respect to aggregate shocks justify their high (low) expected returns. Similar to BSV, this model predicts a negative relation between firm cash flow and discount rate shocks. Different from BSV, the model predicts that the value anomaly portfolio has cash flow shocks that are positively related to market cash flow shocks on account of the high sensitivity to aggregate technology shocks of such a portfolio.

Lettau and Wachter (2007) propose a duration-based explanation of the value premium. In their model, growth firms are, relative to value firms, more exposed to shocks to market discount rates and long-run cash flows, which are not priced, and less exposed to market short-run cash flow shocks, which are priced. This model implies that short-run cash flows shock to the long-short value portfolio are strongly positively correlated with short-run market cash flows and that discount rate and long-run cash flow shocks to the long-short portfolio are negatively correlated with market discount rates and long-run cash flow shocks, respectively.

In sum, models of anomaly returns have direct implications for the magnitudes and correlations of anomaly and market cash flow and discount rate shocks. We are unaware of any prior study that estimates these empirical moments. Fundamental theories of anomalies apply to individual firms. Thus, one must analyze firm-level cash flow and discount rate shocks and then aggregate these into anomaly portfolio shocks.[4]

2.1 The Empirical Model

We assume the following model for firm-level expected log returns:

$$E_t\left[r_{i,t+1}\right] = \delta_0 + \delta_1' X_{it} + \delta_2' X_{At}. \tag{4}$$

Here, X_{it} is a vector of observable firm-specific characteristics, such as the log book-to-market ratio or profitability, and X_{At} is a vector of aggregate observable variables, such as the log risk-free rate and aggregate book-to-market ratio. Define the $K \times 1$ composite vector:

$$Z_{it} = \begin{bmatrix} r_{it} - \bar{r}_{it} \\ X_{it} - \bar{X}_{it} \\ X_{At} - \bar{X}_{At} \end{bmatrix}, \tag{5}$$

where the bar over the variable means the average value across firms and time. Assume a VAR(1) model for the evolution:

$$Z_{i,t+1} = AZ_{i,t} + \varepsilon_{i,t+1}, \tag{6}$$

where $\varepsilon_{i,t+1}$ is a vector of conditionally mean-zero, but potentially heteroskedastic, shocks. The companion matrix A is a $K \times K$ matrix. Discount rate shocks can then be written:

$$\begin{aligned} DR_{i,t+1}^{shock} &= E_{t+1}\sum_{j=2}^{\infty}\kappa^{j-1}r_{i,t+j} - E_t\sum_{j=2}^{\infty}\kappa^{j-1}r_{i,t+j} \\ &= e_1'\sum_{j=1}^{\infty}\kappa^j A^j Z_{i,t+1} - e_1' A\sum_{j=1}^{\infty}\kappa^j A^j Z_{i,t} \\ &= e_1'\sum_{j=1}^{\infty}\kappa^j A^j \varepsilon_{i,t+1} = e_1'\kappa A\left(I_K - \kappa A\right)^{-1}\varepsilon_{i,t+1}. \end{aligned} \tag{7}$$

[4] Extracting cash flow and discount rate shocks indirectly from dynamic trading strategies, such as the Fama-French value and growth portfolios, can lead to mistaken inferences as the trading itself confounds the underlying firms' cash flow and discount rate shocks. In the Appendix, we provide an example of a value-based trading strategy. The underlying firms only experience discount rate shocks, but the traded portfolio is driven solely by cash flow shocks as a result of rebalancing.

Here, e_1 is a column vector with same dimension as $Z_{i,t}$, with a 1 in the first element and zero otherwise. I_K is the $K \times K$ identity matrix.

We can also extract the cash flow shock using the VAR by combining Equation (1) and the above expression for discount rate shocks:

$$\begin{aligned} CF_{i,t+1}^{shock} &= r_{i,t+1} - E_t\left[r_{i,t+1}\right] + DR_{i,t+1}^{shock} \\ &= e_1'\left(I_K + \kappa A\left(I_K - \kappa A\right)^{-1}\right)\varepsilon_{i,t+1}. \end{aligned} \quad (8)$$

Thus, we impose the present-value relation when estimating the joint dynamics of firm cash flows and discount rates.

While the general math here is from Campbell (1991), note that the companion matrix does not have an i subscript – it is constant across firms. Thus, the firm-level model is a panel VAR(1), as in Vuolteenaho (2002). Also note that the assumption of the same A matrix across firms means that identification of the coefficients in A will come from both the time-series and the cross-section. Predictive regressions are noisy and often plagued by small-sample problems, for instance the Stambaugh (1999) bias, but the panel approach alleviates these issues, at the cost of potentially not capturing all heterogeneity in the data. We will choose the elements in the vectors X_{it} and X_{At}, along with extensive robustness checks, to ensure we capture a broad array of the determinants of expected returns. Finally, we do not impose any particular structure on the error terms across firms or over time, noting that OLS still yields consistent estimates. We will adjust standard errors for dependence across firms and time.

We obtain portfolio-level variance decompositions by aggregating the portfolio constituents' $CF_{i,t}^{shock}$ and $DR_{i,t}^{shock}$. Because the firm-level variance decomposition applies to log returns, the portfolio cash flow and discount rate shocks are not simple weighted averages of the individual firms' cash flow and discount rate shocks. Therefore we approximate each firm's gross return using a second-order Taylor expansion around its current expected log return and then aggregate shocks to firms' gross returns using portfolio weights.

The first step in this process is to express gross returns in terms of the components of log returns using:

$$\begin{aligned} R_{i,t+1} &\equiv \exp\left(r_{i,t+1}\right) \\ &= \exp\left(E_t r_{i,t+1}\right)\exp\left(CF^{shock}_{i,t+1} - DR^{shock}_{i,t+1}\right), \end{aligned} \tag{9}$$

where $E_t r_{i,t+1}$ is the predicted value and $CF^{shock}_{i,t}$ and $DR^{shock}_{i,t}$ are estimated shocks from firm-level VAR regressions in which we impose the present-value relation. A second-order expansion at time t around a value of zero for both of the shocks yields:

$$R_{i,t+1} \approx \exp\left(E_t r_{i,t+1}\right)\left\{1 + CF^{shock}_{i,t+1} + \frac{1}{2}\left(CF^{shock}_{i,t+1}\right)^2 - DR^{shock}_{i,t+1} + \frac{1}{2}\left(DR^{shock}_{i,t+1}\right)^2 + CF^{shock}_{i,t+1}DR^{shock}_{i,t+1}\right\}. \tag{10}$$

We find that this approximation works very well in practice. Next we define the cash flow and discount rate shocks to firm returns measured in levels as:

$$CF^{level\_shock}_{i,t+1} \equiv \exp\left(E_t r_{i,t+1}\right)\left\{CF^{shock}_{i,t+1} + \frac{1}{2}\left(CF^{shock}_{i,t+1}\right)^2\right\}, \tag{11}$$

$$DR^{level\_shock}_{i,t+1} \equiv \exp\left(E_t r_{i,t+1}\right)\left\{DR^{shock}_{i,t+1} - \frac{1}{2}\left(DR^{shock}_{i,t+1}\right)^2\right\}, \tag{12}$$

$$CFDR^{cross}_{i,t+1} \equiv \exp\left(E_t r_{i,t+1}\right)CF^{shock}_{i,t+1}DR^{shock}_{i,t+1}. \tag{13}$$

For a portfolio with weights $\omega^p_{i,t}$ on firms, we can approximate the portfolio return measured in levels using:

$$R_{p,t+1} - \sum_{i=1}^{n}\omega^p_{i,t}\exp\left(E_t r_{i,t+1}\right) \approx CF^{level\_shock}_{p,t+1} - DR^{level\_shock}_{p,t+1} + CFDR^{cross}_{p,t+1}, \tag{14}$$

where

$$CF^{level\_shock}_{p,t+1} = \sum_{i=1}^{n} \omega^{p}_{i,t} CF^{level\_shock}_{i,t+1}, \tag{15}$$

$$DR^{level\_shock}_{p,t+1} = \sum_{i=1}^{n} \omega^{p}_{i,t} DR^{level\_shock}_{i,t+1}, \tag{16}$$

$$CFDR^{cross}_{p,t+1} = \sum_{i=1}^{n} \omega^{p}_{i,t} CFDR^{cross}_{i,t+1}. \tag{17}$$

Note that summing over the individual firms' level cash flow and discount rate shocks implies that the conditional covariance structure of the shocks is taken into account when looking at portfolio-level cash flow and discount rate shocks. We decompose the variance of portfolio returns using

$$\begin{aligned} var\left(\tilde{R}_{p,t+1}\right) \approx\ & var\left(CF^{level\_shock}_{p,t+1}\right) + var\left(DR^{level\_shock}_{p,t+1}\right) \\ & -2cov\left(CF^{level\_shock}_{p,t+1}, DR^{level\_shock}_{p,t+1}\right) \\ & +var\left(CFDR^{cross}_{p,t+1}\right), \end{aligned} \tag{18}$$

where $\tilde{R}_{p,t+1} \equiv R_{p,t+1} - \sum_{i=1}^{n} \omega^{p}_{i,t} \exp\left(E_t r_{i,t+1}\right)$. We ignore covariance terms involving $CFDR^{cross}_{p,t+1}$ as these are very small in practice.

In the Appendix, we show how the VAR specification is related to standard asset pricing models. In particular, the VAR specification concisely summarizes the dynamics of expected cash flows and returns, even when both consist of multiple components fluctuating at different frequencies. Fundamentally, shocks to a firm's discount rates arise from shocks to the product of the firm-specific quantity of risk and the aggregate price of risk, as well as shocks to the risk-free rate. When analyzing cash flow and discount rate shocks to long-short portfolios, we obtain the anomaly cash flow (discount rate) shock as the difference in the cash flow (discount rate) shocks between the long and short portfolios.

3 Data

We use Compustat and CRSP data from 1962 through 2015 to estimate the components in the present-value equation. Our analysis requires panel data on firms' returns, book values, market values, earnings, and other accounting information, as well as time series data on factor returns, risk-free rates, and price indexes. Because computations of certain variables in the VAR require three years of historical accounting information, our estimation focuses on the period from 1964 through 2015.

We obtain all accounting data from Compustat, though we augment our book data with that from Davis, Fama, and French (2000). We obtain data on stock prices, returns, and shares outstanding from the Center for Research on Securities Prices (CRSP). We obtain one-month and one-year risk-free rate data from one-month and one-year yields of US Treasury Bills, which are available on Kenneth French's website and the Fama Files in the Monthly CRSP US Treasury Database, respectively. We obtain inflation data from the Consumer Price Index (CPI) series in CRSP.

We impose sample restrictions to ensure the availability of high-quality accounting and stock price information. We exclude firms with negative book values as we cannot compute the logarithms of their book-to-market ratios, which are key elements in the present-value equation. We include only firms with nonmissing market equity data at the end of the most recent calendar year. Firms also must have nonmissing stock return data for at least 225 days in the past year, which is necessary to accurately estimate stock return variance as discussed below. We exclude firms in the bottom quintile of the size distribution for the New York Stock Exchange to minimize concerns about illiquidity and survivorship bias. Lastly, we exclude firms in the finance and utility industries because accounting and regulatory practices distort these firms' valuation ratios and cash flows. We impose these restrictions ex ante and compute subsequent book-to-market ratios, earnings, and returns as permitted by data availability. We use CRSP delisting returns and assume a delisting return is -90% in the rare cases in which the delisting return is missing.

When computing a firm's book-to-market ratio, we adopt the convention of dividing its book equity by its market equity at the end of the June immediately after the calendar year of the book equity. With this convention, the timing of market equity coincides with the beginning of the stock return measurement period, allowing us to use the clean-surplus equation below. We compute book equity using Compustat data when available, supplementing it with hand-collected data from the Davis, Fama, and French (2000) study. We adopt the Fama and French (1992) procedure for computing book equity. Market equity is equal to shares outstanding times stock price per share. We sum market equity across firms that have more than one share class of stock. We define lnBM as the natural log of book-to-market ratio.

We compute log stock returns in real terms by subtracting the log of inflation, as measured by the log change in the CPI, from the log nominal return. Following the convention in asset pricing, we compute annual returns from the end of June to the following end of June. The benefit of this timing convention is that investors have access to December accounting data prior to the ensuing June-to-June period over which we measure returns.

We construct a measure of log clean-surplus return on equity, $lnROE^{CS}$, as the residual from the equation:

$$lnROE^{CS}_{i,t+1} \equiv r_{i,t+1} + \kappa bm_{i,t+1} - bm_{i,t}. \tag{19}$$

This measure corresponds to actual return on equity if clean-surplus accounting and the log-linearization both hold, as Ohlson (1995) and Vuolteenaho (2002) assume.[5] The benefit of constructing this metric is two-fold. First, it is a timely, June-to-June, earnings measure that exactly satisfies the equation:

$$CF^{shock}_{i,t+1} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \kappa^{j-1} lnROE^{CS}_{i,t+j}. \tag{20}$$

Thus, one can reasonably use $lnROE^{CS}$ in the VAR to obtain expected cash flows and cash

[5] Violations in clean-surplus accounting occasionally arise from share issuance or merger events.

flow shocks at different horizons. Second, as Equation (19) shows, adding $lnROE^{CS}$ in the VAR is equivalent to adding another lag of the book-to-market ratio.

The log of return on equity derived from firms' annual reports is defined as log of one plus net income divided by last year's inferred book equity, where we substitute income before extraordinary items if net income is unavailable. We infer last year's book equity using current accounting information and the clean surplus relation—i.e., last year's book equity is this year's book equity plus dividends minus net income. We subtract the log inflation rate, based on the average CPI during the year, from log return on equity to obtain $lnROE$. We winsorize both earnings measures at ln(0.01) when earnings is less than -99%. We follow the same procedure for log returns and for log firm characteristics that represent percentages with minimum bounds of -100%. Alternative winsorizing or truncation procedures have little impact on our results.

We compute several firm characteristics that predict short-term stock returns in historical samples. We compute each firm's market equity (ME) or size as shares outstanding times share price. Following Fama and French (2015), we compute profitability (Prof) as annual revenues minus costs of goods sold, interest expense, and selling, general, and administrative expenses, all divided by book equity from the same fiscal year.[6] Following Cooper, Gulen, and Schill (2008) and Fama and French (2015), we compute investment (Inv) as the annual percentage growth in total assets. Our data is annual, which is an issue for the medium-frequency momentum anomaly. In Jegadeesh and Titman (1993), the maximum momentum profits accrue when the formation and holding periods sum to 15 to 18 months. Therefore, we construct a six-month momentum variable based on the percentage rank of each firm's January to June return. The subsequent holding period implicit in the VAR is one year, from July through June. We transform each measure by adding one and taking its log, resulting in the following variables: lnME, lnProf, lnInv, and lnMom6_pct. We also subtract the log of gross domestic product from lnME to ensure stationarity. We use an alternative stationary

[6]Novy-Marx (2013) uses a similar definition for profitability, except that the denominator is total assets instead of book equity.

measure of firm size (SizeWt), equal to firm market capitalization divided by the total market capitalization of all firms in the sample, when applying value weights to firms' returns in portfolio formation.

We compute stocks' annual return variances based on daily excess log returns, which are daily log stock returns minus the daily log return from the one-month risk-free rate as of the beginning of the month. A stock's realized variance is the annualized average value of its squared daily excess log returns during the past year. In this calculation, we do not subtract each stock's mean squared excess return to minimize estimation error. We transform realized variance by adding one and taking its log, resulting in the variable lnRV.

Table 1 presents summary statistics for the variables in our analysis. For ease of interpretation, we show statistics for nominal annual stock returns (AnnRet), nominal risk-free rates (Rf), and inflation (Inflat) before we apply the log transformation. Similarly, we summarize stock return volatility (Volat) instead of log variance. We multiply all statistics by 100 to convert them to percentages, except lnBM and lnME, which retain their original scale.

Panel A displays the number of observations, means, standard deviations, and percentiles for each variable. The median firm has a log book-to-market ratio of -0.66, which translates into a market-to-book ratio of $e^{0.66} = 1.94$. Valuation ratios range widely, as shown by the 10th and 90th percentiles of market-to-book ratios of 0.75 and 5.93. The variation in stock returns is substantial, ranging from -40% to 66% for the 10th and 90th percentiles. Panel B shows correlations among the accounting characteristics in the VAR, which are all modest.

4 VAR Estimation

We estimate the firm-specific and common predictors of firms' (log) returns and cash flows using a panel VAR system. Natural predictors of returns include characteristics that serve as proxies for firms' risk exposures or stock mispricing. As predictors of earnings, we use characteristics based on accounting metrics and market prices that forecast firm cash flows in theory and practice.

4.1 Specification

Our primary VAR specification includes eight firm-specific characteristics: firm returns and clean-surplus earnings (lnRet and lnROE^{CS}), as well as lnBM, lnProf, lnInv, lnME, and lnMom6_pct. The eighth firm characteristic is log realized variance (lnRV), intended to capture omitted factor exposures as well as potential differences between expected log returns and the log of expected returns. We standardize each independent variable by its full-sample standard deviation to facilitate interpretation of the regression coefficients. The only exceptions are lnBM, lnRet, and lnROE^{CS}, which are not standardized to enable imposing the present-value relation in the VAR estimation. All log return and log earnings forecasting regressions include the log real risk-free rate (lnRf) to capture common time-series variation in firm valuations resulting from changes in market-wide discount rates. Finally, we add interactions of the forecasting characteristics (lnBM, lnProf, lnME, lnInv, and lnMom6_pct) with lnBM. In particular, we for each of these characteristics create a variable that equals 1 if the stock is in the top quintile of the characteristic, -1 if the stock is in the bottom quintile of the characteristic, and 0 otherwise. This way, we allow the loading on lagged lnBM to be different for stocks associated with the long-short portfolios we seek to analyze than for stocks in the 'middle' of the characteristics distribution.

We estimate a first-order autoregressive system, allowing for one lag of each characteristic. A first-order VAR allows us to estimate the long-run dynamics of log returns and log earnings based on the short-run properties of a broad cross section of firms. We do not need to impose restrictions on which firms survive for multiple years, thereby mitigating statistical noise and survivorship concerns. As a robustness check, we investigate the second-order VAR specification and find very similar results as the second lags of characteristics add little explanatory power.

The VAR system also includes forecasting regressions for firm and aggregate variables. We regress lnRet, lnROE^{CS}, and lnBM on all available characteristics. For each of the other characteristics, the only predictors are the firm's lagged characteristic and the firm's lagged log book-to-market ratio. For example, the only predictors of log investment are lagged log investment and lagged log book-to-market ratio. This restriction improves estimation efficiency without significantly reducing the explanatory power of the regressions. We model the real risk-free rate as a simple first-order autoregressive process.

The main concern with our panel VAR specification is that it omits an important common component in firms' expected cash flows and discount rates. We address this issue in Section 7 by considering alternative VAR specifications that include the market-wide valuation ratio and its interactions with firm-level characteristics. Here we also discuss the implications of data mining of the characteristics and industry fixed effects in accounting variables. Our primary specification omits aggregate variables other than the risk-free rate because, as we show, they do not materially increase the explanatory power of the return and cash flow forecasting regressions and result in extremely high standard errors in return variance decompositions. Of course, it is possible that another not-yet-identified aggregate variable would materially improve on our forecasting regressions. We conduct all tests using standard equal-weighted regressions, but our findings are robust to applying value weights to each observation. Overall, our findings are robust to alternative specifications.

4.2 Baseline Panel VAR Estimation

The first two columns of Table 2 report the coefficients in the forecasting regressions for firms' log returns and earnings. The third column in Table 2 shows the implied coefficients on firms' log book-to-market ratios based on the clean-surplus relation between log returns, log earnings, and log valuations (see Equation (19)). We use OLS to estimate each row in the A matrix of the VAR. Standard errors are clustered by year and firm, following Petersen (2009), and appear in parentheses below the coefficients.

The findings in the log return regressions are consistent with those of the large literature on short-horizon forecasts of returns. Firms' log book-to-market ratios and profitability are positive predictors of their log returns at the annual frequency, whereas log investment is a negative predictor of log returns. Log firm size and realized variance weakly predict returns with the expected negative signs, while momentum has a positive sign, though these coefficients are not statistically significant in this multivariate panel regression. The largest standardized coefficients are those for firm-specific log book-to-market ($0.042 = 0.83 \times 0.051$), profitability (0.043), and investment (-0.051). These coefficients represent the change in expected annual return from a one standard deviation change in each characteristic holding other predictors constant.

The second column of Table 2 shows the regressions predicting annual log earnings. The main result is that log book-to-market ratio is by far the strongest predictor of log earnings. The coefficient on lagged lnBM is -0.109. The two other strong predictors of log earnings are the logs of firm-level returns and profitability, which both predict with a positive sign. Other significant predictors of log earnings include past earnings and several of the interaction terms.

The third column in Table 2 shows the coefficients of each lagged characteristic in a regression predicting log book-to-market ratios. Log book-to-market ratios are quite persistent as shown by the 0.875 coefficient on lagged log book-to-market. More interestingly, log investment is a significant positive predictor of log book-to-market, meaning that market-to-book ratios tend to decrease following high investment. These relations play a role in the long-run dynamics of expected log earnings and log returns of firms with high investment. Analogous reasoning applies to the positive coefficient on lagged log returns, which is statistically significant at the 10% level.

Table 3 shows regressions of firm characteristics on lagged characteristics and lagged book-to-market ratio. The most persistent characteristic is log firm size, which has a persistence coefficient of 0.978. We can, however, reject the hypothesis that this coefficient is 1.000, based on standard errors with firm and year clustering. The persistence coefficients on the logs of profitability and realized variance are 0.734 and 0.688. The persistence coefficients on the log of investment and momentum are just 0.157 and 0.048. All else equal, characteristics with high (low) persistence coefficients will be more important determinants of long-run cash flows and discount rates. Lagged log book-to-market is a significant predictor of the logs of profitability, investment, issuance, and realized variance, but the incremental explanatory power from lagged valuations is modest in all regressions except the investment regression. Table 3 also shows that the aggregate variable, the lagged real risk-free rate (lnRf), is reasonably persistent with a coefficient of 0.603. This estimate has little impact on expected long-run returns and cash flows simply because the risk-free rate is not a significant predictor of returns or cash flows, as shown in Table 2.

We now translate the VAR coefficients into estimates of cumulative expected returns and cash flows at horizons (N) ranging from 1 to 20 years. We compute the cumulative coefficients for predicting log returns by summing expected log returns across horizons, discounting by κ, enabling us to express the N-year discount rate component ($\widetilde{DR}_{i,t}^{(N)}$) as:

$$\widetilde{DR}_{i,t}^{(N)} = E_t \sum_{j=1}^{N} \kappa^{j-1} \tilde{r}_{i,t+j}, \tag{21}$$

where a tilde above a variable refers to its demeaned value. We plot these for a one-standard deviation increase in each characteristics in Figure 1. Similarly, Figure 2 plots the cumulative coefficients for predicting log earnings at horizons from 1 to 20 years. We obtain the N-year cash flow component of valuations ($\widetilde{CF}_{i,t}^{(N)}$) from the equation:

$$\widetilde{CF}_{i,t}^{(N)} = \sum_{j=1}^{N} \kappa^{j-1} E_t \left[ln\widetilde{ROE}^{CS}{}_{i,t+j} \right]. \tag{22}$$

These cumulative coefficients allow us to represent the discount rate and cash flow level components in log book-to-market ratios from years 1 through 20 as affine functions of the characteristics in year 0.

Figure 1 shows that book-to-market and size are the most important predictors of long-run discount rates. The 20-year coefficient on log book-to-market is 26%, while the coefficient on log size is -18%. The high persistence of both variables implies that their long-run impacts on valuation are much larger than their short-run impacts. In contrast, some effective predictors of short-run returns, such as log investment, have little long-run impact mainly because they are not highly persistent. In addition, investment positively predicts book-to-market ratios, which limits the extent to which its long-run impact can be negative. The long-run value and size coefficients imply that investors heavily discount the cash flows of value firms, whereas they pay more for the cash flows of large firms. Other notable predictors of 20-year cumulative log returns include log firm profitability and realized variance, which have coefficients of 17% and −7%, respectively. The negative effect of realized variance could arise because of the difference between expected log returns and log expected returns, or because realized variance negatively forecasts returns as found in Ang et al. (2006).

Figure 2 shows that book-to-market and size are also the most important predictors of long-run cash flows. The coefficients on log book-to-market and log size are about −58% and −14%, respectively, for predicting cumulative log earnings at the 20-year horizon. In addition, profitability has a 20-year cumulative effect of 17%. These findings indicate that CF and DR shocks are largely driven by shocks to the three most persistent predictive characteristics: lnBM, lnME, and lnProf.

5 Firm-level Analysis

We now examine the decomposition of firms' log book-to-market ratios and returns implied by the regression results. We first analyze the correlations and covariances between total log book-to-market (lnBM) and its two components (CF and DR). Table 4 shows that DR and CF variation respectively account for 22.5% and 53.3% of return variation. Interestingly, covariation between DR and CF tends to amplify return variance, contributing a highly significant amount (24.3%) of variance. The last column shows that the correlation between the CF and DR components is significantly negative (−0.351). In economic terms, this correlation means that low expected cash flows are associated with high discount rates. The negative correlation in cash flow and discount rate shocks could arise for behavioral or rational reasons. Investor overreaction to positive firm-specific cash flow shocks could lower effective firm discount rates (negative discount rate shocks). Alternatively firms with negative cash flow shocks could become more exposed to systematic risks, increasing their discount rates (positive discount rate shocks).

6 Portfolio-level Analysis

Now we analyze the implied discount rate (DR) and cash flow (CF) variation in returns to important portfolios, including the market portfolio and anomaly portfolios formed by cross-sectional sorts on value, size, profitability, investment, and momentum. We compute weighted averages of firm-level DR and CF estimates to obtain portfolio-level DR and CF estimates. We apply the approximation and aggregation procedure described in Section 2.

6.1 The Market Portfolio

We define the market portfolio as the value-weighted average of individual firms. We obtain firm-level expected log returns and log earnings from the VAR and apply the procedure in Section 2 to obtain the corresponding market-level discount rates and expected cash flows.

We compare the estimates from our aggregation approach to those from a standard aggregate-level VAR in the spirit of Campbell (1991). In the aggregate VAR, we use only the logs of (market-level) book-to-market ratio (lnBM_mkt) and the real risk-free (lnRf) as predictors of the logs of market-level earnings and returns. Accordingly, this specification entails just three regressions in which market-level earnings, returns, and risk-free rates are the dependent variables and lagged book-to-market and risk-free rates are the independent variables.

We validate our panel VAR approach and compare it to the market-level VAR in Figure 3, which shows market cash flow and discount rate components from both VARs alongside realized market earnings and returns over the next 10 years. We construct the series of 10-year realized earnings (returns) based on firms' current market weights and their future 10-year earnings (returns). Thus, we forecast 10-year buy-and-hold returns to the market portfolio, not the returns to an annually-rebalanced trading strategy. We do not rebalance the portfolio because the underlying discount rate estimates from the panel VAR are specific to firms. This distinction is important insofar as firm entry, exit, issuance, and repurchases occur.

The dashed red and dotted black lines in the top plot in Figure 3 are the predicted 10-year market earnings from our panel VAR and from the market-level VAR, respectively. Both predictions track realized 10-year market earnings well, with a somewhat higher R^2 of 73% for the panel VAR than 55% for the market VAR. The bottom plot in Figure 3 shows that the predictions of 10-year returns from the two VARs are also similar, except that the panel VAR predicts lower returns around the 2000 period. Both sets of predictions exhibit positive relationships with realized 10-year returns. The R^2 of the panel VAR is 41%, whereas the R^2 of the market-level VAR is 19%. The plots in Figure 3 suggest that both VAR methods yield meaningful decompositions of valuations into CF and DR components. Even though the panel VAR does not directly analyze the market portfolio, aggregating the panel VAR's firm-level predictions results in forecasts of market cash flows and returns that slightly outperform forecasts based on the traditional approach.

Next we compare the implications of the two VARs for the sources of market returns. We compute the shocks to market cash flows and discount rates from both VARs, as in Equations (8) and (7) in Section 2, and analyze the covariance matrix of these shocks. When calculating the aggregated panel VAR shock from time t to time $t+1$, the updated expectation is based on the firms in the market portfolio at time t. Similarly, the shock from time $t+1$ to $t+2$ is based on the firms in the market portfolio at time $t+1$.

Table 4 presents variance decompositions of market returns based on the panel VAR and the time-series VAR. The first four columns decompose the variance of predicted market returns from our approximation into four nearly exhaustive components: the variance of DR, variance of CF, variance of the cross term (CF*DR), and the covariance between CF and DR. All quantities are normalized by the variance of return innovations, so the components add to one. We do not report the covariances between the cross term and the CF and DR terms because these covariances are negligible. The fifth column reports the correlation between the DR and CF components of market returns. The last column reports the correlation between our approximation of market returns and actual market returns. This column shows that correlation is 0.985, indicating that our approximation is accurate. Standard errors based on the delta method appear in parentheses.

Table 4 shows that the panel and market-level VARs predict similar amounts of discount rate variation (17.8% and 28.1%, respectively), but the estimate from the panel VAR is more precise as measured by its standard error. Both estimates of DR variation are lower than those reported in prior studies. By restricting the sample of the time-series VAR to 1964 to 1990, we can reproduce the traditional finding that DR variation explains most of the variation in market returns.

The estimates from the panel VAR imply that shocks to market cash flows account for 55.2% of market return variance, whereas the market-level VAR implies that CF shocks explain just 24.8% of return variance. The two VARs also differ in the implied correlations between the CF and DR components. The panel VAR indicates that the correlation is just -0.492, whereas the market-level VAR implies a correlation of -0.892.

One possible explanation for the difference in the two VARs is that the panel VAR relies on two log-linear approximations of market returns, which could introduce errors in the variance decomposition. However, we find that the predicted (log) market return based on the panel aggregation and approximations exhibits a correlation of 0.985 with the actual (log) market return. In addition, the cross term (CF*DR), which is unique to the approximate panel aggregation, accounts for less than 1% of market return variance.

A more likely reason for the discrepancy is that the panel VAR employs far more predictive variables than the market-level VAR, leading to a more accurate description of expected cash flows and discount rates. Another possible reason is that the time-series VAR suffers from two related biases induced by the reliance on aggregate book-to-market ratios (lnBM_mkt). The time-series properties of lnBM_mkt cause two problems: 1) this highly persistent regressor causes a substantial Stambaugh (1999) bias given the relatively short sample; and 2) an apparent structural break in lnBM_mkt occurs around 1990, as noted by Lettau and van Nieuwerburgh (2008) in the context of the market price-dividend ratio, implying that this regressor is actually non-stationary. Based on these considerations, we exclude lnBM_mkt from our primary panel VAR specification, though we consider its impact on our conclusions in robustness specifications (Spec2 and Spec3).

6.2 Anomaly Portfolios

We now analyze the returns of long-short anomaly portfolios. Our goal is to bring new facts to the ongoing debate on the sources of anomalies. We estimate the cash flow and discount rate components of historical anomaly returns and analyze the covariance matrix of these shocks. We then evaluate whether theories of anomalies make reasonable predictions about the cash flow and discount rate components of anomaly returns.

The anomaly portfolios represent trading strategies, where the underlying firms in the portfolio change every year based on firms' characteristic rankings in June. However, for any given year, the portfolio return is driven by the cash flow and discount rate shocks of the individual firms in the portfolio in that year. The firm-level VAR allows us to relate anomaly returns to underlying firm fundamentals. We aggregate the firm-level estimates using value weights within each quintile and then analyze portfolios with long positions in quintile 5 and short positions in quintile 1 according to firms' characteristic rankings. The aggregation procedure is otherwise analogous to that used for the market portfolio.

The plots in Figure 4 show that the estimated expected cash flow and discount rate components of the value portfolio indeed forecast the respective 10-year earnings and returns for this portfolio. The predictor in the top plot in Figure 4 is the difference between the CF component of value and growth firms. Similarly, realized cash flows in this plot represent the difference in 10-year earnings of value and growth firms. The plot shows that predicted earnings are correlated with future 10-year earnings, primarily in the second half of the sample. The overall R^2 is modest at 24%. The bottom plot in Figure 4 depicts the relationship between the DR component of the value spread and future 10-year returns. This relationship is strong in both halves of the sample, and the overall R^2 is high at 48%.

Figure 5 presents the analogous R^2 statistics for the cash flow and discount rate components of the five long-short anomaly portfolios and the market portfolio. The DR component of the size anomaly portfolio forecasts its 10-year returns quite well ($R^2 = 61\%$), whereas the DR component of the momentum portfolio has modest forecasting power for 10-year momentum anomaly returns ($R^2 = 16\%$). The R^2 values in Figure 5 range from 16% to 73%, implying correlations between the CF and DR components and their realized counterparts that range between 0.40 and 0.85. We conclude from this analysis that the aggregated cash flow and discount rate components plausibly reflect the long-short portfolios' cash flow and discount rate components.

Panel A of Table 5 presents variance decompositions of anomaly returns for the five anomalies and is analogous to Table 4 for the market. Table 5 reveals remarkably consistent patterns across the five anomaly portfolios. Cash flow variation accounts for 40% to 56% of variation in anomaly returns, whereas discount rate variation by itself accounts for just 16% to 23% of anomaly return variance. The covariance between CF and DR is consistently negative, and this covariance term accounts for 32% to 37% of anomaly return variance. The cross term (CF*DR) accounts for only 2% to 4% of anomaly return variance. The standard errors on the main variance components range from 10% to 20%, indicating the high precision of these findings. The last column shows that the correlation between the approximation of anomaly returns and actual anomaly returns ranges from 0.88 to 0.96, indicating our approximation is quite accurate.

The relative importance of cash flows and the negative correlation between CF and DR are the most prominent effects. Theories of anomalies that rely heavily on independent variation in DR shocks, such as De Long et al. (1990), are inconsistent with the evidence in

Table 5. In contrast, theories in which CF shocks are tightly linked with DR shocks have the potential to explain the patterns in Table 5. Rational theories in which firm risk increases after negative cash flow realizations predict negative correlations between CF and DR shocks. Behavioral theories in which investors overreact to cash flow news are also consistent with this evidence.

While the decompositions are quite similar across anomalies, this finding is not mechanical even though the decompositions are derived from the same VAR. First, the interaction terms in the VAR allows the loading on lagged book-to-market to vary with the anomaly. Second, the aggregation into (long-short) portfolios diversifies away idiosyncratic cash flow and discount rate shocks, focusing the analysis on common cash flow and discount rate variation within the long-short portfolios. Ex ante, one anomaly could have a substantially larger, say, cash flow component or correlation between cash flow and discount rate shocks relative to another, depending on the cross-correlation of shocks and characteristics across the assets. Ex post, we find that the decompositions are in fact quite similar across anomalies.

Panel B of Table 5 decomposes return variance of in-sample mean-variance efficient portfolios. The first line shows the decomposition for the ex post mean-variance efficient (MVE) portfolio composed of only the five long-short anomaly portfolios. An arbitrageur would hold this portfolio if one thinks of anomalies as arising from mispricing. This MVE portfolio has a discount rate component of 14%, a cash flow component of 44%, with a correlation of cash flow and discount rates of -0.75. Thus, aggregating across anomalies does not materially affect the variance decomposition. Cash flow shocks are still the most important contributor to variance, and the correlation between cash flow and discount rate shocks becomes even more negative. The next line shows the in-sample MVE portfolio that includes the market portfolio. This portfolio represents an estimate of the portfolio with a return that covaries most negatively with the marginal agent's marginal utility. The cash flow component of this MVE portfolio is even stronger at 58%. Discount rate variation accounts for 13% of return variance, and the correlation between CF and DR shocks is still significantly negative at

-0.58.

Panel A of Table 6 displays correlations between the components of market returns and those of anomaly returns. The four columns indicate the correlations between market cash flow and discount rate shocks and anomaly cash flow and discount rate shocks. Standard errors based on the delta method appear in parentheses.

The striking result in the first column of Panel A of Table 6 is that none of the five anomaly cash flow shocks exhibits a significant correlation with market cash flows. The correlations between market cash flows and the cash flows from the five anomalies range between -0.12 and 0.08 and are statistically indistinguishable from zero. These findings cast doubt on theories of anomalies that rely on cross-sectional differences in firms' earnings sensitivities to aggregate cash flows. The evidence is ostensibly inconsistent with a broad category of risk-based explanations of anomalies.

The fourth column in Table 6 reveals that discount rate shocks to four of the five anomalies have insignificant correlations with discount rate shocks to the market. However, DR shocks to the profitability anomaly are significantly negatively correlated (-0.45) with DR shocks to the market. One interpretation is that increases in the market-wide cost of capital are associated with a flight to quality in which investors become relatively eager to finance projects of firms with high profits.

The second and third columns in Table 6 reveal three notable cross-correlations between market and anomaly CF and DR shocks. The three correlations that exceed 0.3 in absolute value are economically material and statistically significant at the 5% level. The positive correlation of 0.36 between the CF shock to the market and the (negative) DR shock to the size portfolio suggests that small firms have lower costs of capital during good economic times. The correlations between CF shocks to value and investment portfolios and DR shocks to the market are consistent with the idea that firms with high investment and high valuations have higher expected cash flows when market-wide discount rates fall. Because we are simultaneously testing many hypotheses, we are reluctant to overinterpret these cross-correlations.

The low correlation between market and anomaly return components is consistent with theories in which idiosyncratic cash flow shocks affect firms' expected returns—e.g., Babenko, Boguth, and Tserlukevich (2016).

Panel B of Table 6 shows the correlation between the CF and DR shocks to the MVE portfolio based only on anomaly long-short portfolios with the market CF and DR shocks. The correlation of CF shocks to this anomaly MVE portfolio with market CF shocks is close to zero (-0.01), offering no evidence that cash flow betas with respect to the market are the source of anomaly risk premiums. The correlations between DR shocks to the market and anomaly MVE portfolio are actually negative at -0.27, casting doubt on the idea that arbitrageurs exploiting anomalies are exposed to the same shocks to risk preferences as investors holding the market. Instead, the evidence suggests distinct forces drive market and anomaly return components.

Generalizing from the last column in Table 6, the weak correlation between most anomalies' DR shocks and market DR shocks is inconsistent with theories of common DR shocks. In theories such as Campbell and Cochrane (1999), commonality in DR shocks occurs because risk aversion varies over time. Similarly, theories in which anomalies are driven by common shocks to investor sentiment, such as Baker and Wurgler (2006), that affect groups of stocks and the market are at odds with the evidence on the lack of correlation in anomaly and market DR shocks.

To explore these relations further, Figure 6 plots anomaly MVE and market CF shocks in Panel A and the corresponding DR shocks in Panel B. In the financial crisis of 2008-2009, both the market and anomaly MVE exhibited negative CF shocks. Both portfolios also experienced positive DR shocks, though this effect is more pronounced for the anomaly portfolio. In contrast, during the dot-com boom of the late 1990s and the ensuing crash, the market and anomaly MVE DR shocks diverge from each other. In the boom, market DR shocks were negative, while anomaly MVE DR shocks were positive, with the opposite pattern holding for the crash. This pattern reflects the success of low investment, low profitability, and low book-to-market firms during the dot-com boom, and their poor performance during the crash.

6.3 Short-run vs. Long-run Cash Flow Shocks

We now decompose cash flow shocks into short-run (one-year) and long-run cash flow shocks. In particular, for each firm i, define:

$$CF_{i,t+1}^{short-run} = lnROE_{i,t+1}^{CS} - E_t\left[lnROE_{i,t+1}^{CS}\right],$$

where the expected cash flow comes from the VAR. We define long-run cash flow shocks as:

$$CF_{i,t+1}^{long-run} = CF_{i,t+1} - CF_{i,t+1}^{short-run}.$$

We aggregate firm-level CF shocks into portfolio CF shocks for long-short anomalies and the market using the same procedure applied to the total cash flow shock, $CF_{i,t+1}$.

Table 7 shows that the negative correlation between cash flow and discount rate shocks is due to the long-run cash flow shock, $CF_{i,t+1}^{long-run}$. The correlations between the long-run cash flow shocks and discount rate shocks of each anomaly are strongly negative. With the exception of the profitability anomaly, all of these correlations are less than -0.5 and are statistically significant at the 1% level. In contrast, the correlations between the short-run cash flow shocks and discount rate shocks are statistically insignificant and economically small for all anomalies. These facts support models in which correlated shocks to long-run firm earnings drive discount rate shocks, such as the model of investor overconfidence of Daniel, Hirshleifer, and Subrahmanyam (2001). For the market portfolio, none of correlations is statistically significant. Although we cannot draw robust inferences regarding this portfolio's short- and long-run cash flow correlation structure, we note that the signs and magnitudes of the correlations are the same as those of the anomaly portfolios—discount rates exhibit no correlation with short-run cash flow shocks and a large negative correlation with long-run cash flow shocks.

6.4 Correlations with Aggregate Shocks

In Table 8, we report contemporaneous (June to June) correlations of CF and DR shocks to the market and anomaly portfolios with various aggregate shocks of interest. One group of aggregate shocks reflects macroeconomic cash flow shocks: one- and three-year real per-capita consumption and GDP growth and one-year log difference in the labor share. The other group represents plausible measures of shocks to aggregate risk aversion or 'bad times': one-year change in the default spread (Baa - Aaa corporate bonds); one-year change in the term spread (10-year constant maturity Treasury minus federal funds rate); change in one-year sentiment (orthogonalized from macroeconomic data, obtained from Jeff Wurgler's website, 1965 to 2010), one-year change in three-month T-bill rate; and the broker-dealer leverage factor of Adrien, Etula, and Muir (2014).

Consistent with intuition, market CF shocks are positively correlated with macroeconomic cash flow indicators. Positive shocks to the labor share and thus negative shocks to the capital share are negatively correlated with market CF shocks. Market CF shocks are negatively correlated with indicators of 'bad times,' such as changes in the default and term spreads. Market CF shocks are also significantly positively related to broker-dealer leverage shocks, consistent with broker-dealers increasing leverage in good times. However, market DR shocks are not significantly correlated with any of the aggregate shocks. Based on point estimates, market discount rates decrease when three-year consumption and GDP growth rates are high and when default spreads are low, which makes economic sense.

We observe two main patterns in anomaly CF and DR shocks. First, the broker-dealer leverage shock exhibits a consistent relation with all anomalies. When broker-dealers increase leverage, presumably in good times, anomaly cash flows are higher and discount rates are lower. Second, the anomaly portfolio CF and DR shocks are generally uncorrelated with macroeconomic shocks. The exception is momentum, which has discount rate shocks that are significantly negatively correlated with consumption and GDP growth, and CF (DR) shocks that are negatively (positively) correlated with the change in labor share.

Overall, the anomaly CF and DR shocks exhibit inconsistent correlations with aggregate shocks, with the notable exception of the broker-dealer shock. However, under the interpretation that the broker-dealer leverage shock measures shocks to arbitrageurs' wealth, these correlations do not by themselves suggest a fundamental explanation for anomaly CF and DR comovement.

In our view, the evidence points towards a theory in which investors overextrapolate long-run cash flow news. Our evidence suggests that firms' exposures to this cash flow news are correlated with anomaly characteristics. For example, a technology shock could increase growth firms' cash flows and decrease value firms' cash flows. Investor overreaction to this technology shock would reduce growth firms' discount rates and increase value firms' discount rates. Alternatively, a rational theory in which a technology shock decreases growth firms' risks and increases value firms' risks could be consistent with the evidence. We note that such cash flow shocks are not market-level shocks or industry shocks, as they exhibit low correlations with market CF and DR shocks and industry exposures do not appear to be priced.

6.5 Effects of Data Mining

Some characteristics could appear to predict returns only because researchers constantly searching for return predictability eventually will find characteristics that appear to predict returns in historical samples. Importantly, using data mined characteristics in our VAR framework would bias estimates of return predictability upward. As a result, data mining increases the volatility of discount rate shocks. In addition, data mining increases the correlation between implied cash flow shocks and discount rate shocks because CF shocks must offset the impact of DR shocks in total returns, which we can observe directly. Our main findings indicate that cash flow shocks are the dominant component of anomaly returns and that the correlation between discount rate and cash flow shocks is negative. Without data mining of VAR characteristics, these two main conclusions would be even more pronounced.

7 Alternative Specifications

Here we consider five alternative specifications of the firm-level VAR in which we include different predictors of cash flows and returns. The first alternative specification ($Spec1$) uses the same predictors as our main specification ($Spec0$), except that it excludes the interaction terms between valuation ratios and anomaly characteristics. Because this specification is the most parsimonious, we use $Spec1$ as a baseline for all other alternative specifications.

The second alternative specification ($Spec2$) adds only the market-wide book-to-market ratio, as measured by the value-weighted average of sample firms' log book-to-market ratios, to our main specification ($Spec1$). The third alternative specification ($Spec3$) augments $Spec1$ by including interaction terms between market-wide valuations and the five firm-level log characteristics as well as firm-level log realized variance. Market valuations could capture common variation in firms' cash flows and discount rates and interactions with firm characteristics could capture firms' differential exposures to market-wide variation.

The estimation of the key return and cash flow forecasting regressions in the VAR indicates that these additional regressors only modestly contribute to explanatory power. The adjusted R^2 in the return regression increases from 4.6% in $Spec1$ to 5.5% in $Spec2$, and the coefficient on the added market-wide valuation variable is only marginally statistically significant ($p\text{-}value = 0.053$). In the earnings regression, the coefficient on market-wide valuation is robust statistically significant at the 1% level, but the adjusted R^2 barely increases from 24.3% in $Spec1$ to 24.9% in $Spec2$. The findings for the third alternative specification, $Spec3$, suggest that the six interaction terms do not contribute incremental explanatory power beyond $Spec2$. Specifically, the adjusted R^2 for the return and earnings regressions are equal to or less than those for $Spec2$ and the vast majority of the interaction coefficients are statistically insignificant. Overall, these two sets of regressions do not provide strong evidence that the most parsimonious specification, $Spec1$, is misspecified.

We now evaluate the implications of the alternative specifications for return variance decompositions. Table 9 shows the components of market return variance implied by $Spec2$

and *Spec*3. The difference between Table 9 and Table 4, which shows the results for *Spec*0, is striking. Whereas discount rate variation accounts for just 21% of return variance in *Spec*1, it accounts for 107% and 150% of variation in *Spec*2 and *Spec*3, respectively. The main reason is that high market-wide book-to-market ratios apparently forecast higher returns and such valuations ratios are highly persistent, implying that their long-run impact is potentially large. However, this predictive relationship is very weak statistically, so the standard errors on the variance decompositions are enormous in *Spec*2 and *Spec*3. In fact, in both cases, the hypothesis that DR variation accounts for 0% of variation in returns is within one standard error. Thus, the striking differences in point estimates across the specifications do not necessarily imply strikingly different conclusions.

Table 10 shows the components of anomaly return variance implied by *Spec*2 and *Spec*3. Comparing Tables 10 and 5, we see that cash flow variation accounts for the bulk of anomaly return variance in all three VAR specifications. The finding that discount rates are negatively correlated with expected cash flows also generalizes from *Spec*1 to *Spec*2. In *Spec*3, which allows for interaction terms between market-wide valuations and firm-level characteristics,.the standard errors in *Spec*3 are too large to draw reliable inferences about the CF-DR correlation.

To assess which VAR specification provides the most meaningful decomposition of market and anomaly returns, we analyze the long-term forecasting power implied by each specification. Figure 7 shows the 10-year forecasts of market earnings and returns from *Spec*2, just as Figure 4 shows these forecasts for our main panel specification (*Spec*0). Although adding market-wide valuations slightly improves the forecasting power in the one-year earnings regression, 10-year predictions based on the *Spec*2 model are vastly inferior to those based on the more parsimonious *Spec*1 model. The adjusted R^2 values of 73% for *Spec*0 compared to just 0.3% for *Spec*2 confirm the visual impression from the figures. The two specifications exhibit little difference in their ability to predict 10-year market returns ($R^2 = 41\%$ for *Spec*0 vs. $R^2 = 33\%$ for *Spec*2).

Figure 8 shows the 10-year forecasting power (R^2) of five specifications for market earnings and returns as well as the earnings and returns of the five anomalies. The most notable difference arises in the forecasting power for market earnings. Both specifications that include market-wide valuations give rise to especially poor forecasts of 10-year market earnings. Apparent structural breaks in market-wide valuations, such as those proposed by Lettau and van Nieuwerburgh (2008), could help explain the poor long-term forecasting power of these two VAR specifications. There are few notable differences in the three specifications' abilities to predict long-term anomaly returns and earnings. This similarity is not surprising in light of the similar anomaly return decompositions predicted by the three specifications. We conclude that our baseline panel VAR ($Spec0$) not only gives rise to the most precise estimates of market and anomaly return components, but it also exhibits the most desirable long-term forecasting properties.

We also consider two specifications designed to capture industry and firm fixed effects.[7] However, as noted by Nickell (1981), adding actual fixed effects into a dynamic panel regression such as that in our main specification, leads to severely biased coefficients in small T large N settings such as ours. The biases are similar to the familiar Stambaugh bias that arises in standard time-series VARs with return forecasting regressions. To avoid this statistical issue and to mimic reasonable investor learning, we include rolling means of firm or industry clean surplus earnings and book-to-market ratios in the VARs. Because we use data up until time t to compute the mean at time t, including these quasi-fixed effects does not induce a mechanical small-sample correlation between the shocks and the explanatory variables, which would arise with actual fixed effects. We apply shrinkage to these rolling means to increase the precision of our estimates. Tables 9 and 10 show the resulting variance decompositions. The case with industry rolling means is $Spec4$, and the case with firm-specific rolling means is $Spec5$. Overall, the inclusion of these variables does not materially alter the

[7] In unreported tests, we explore specifications that include additional market-level and anomaly-level variables, such as aggregate versions of anomaly characteristics and spreads in valuations across anomaly portfolios.

anomaly decomposition results relative to our baseline specification ($Spec0$).

8 Conclusion

Despite decades of research on forecasting short-term stock returns, there is no widely accepted explanation for observed cross-sectional patterns in stock returns. We provide new evidence on the sources of anomaly portfolio returns by aggregating firm-level cash flow and discount rate estimates from a panel VAR system. Our aggregation approach enables researchers to study the components of portfolio returns, while avoiding the biases inherent in analyzing the cash flows and discount rates of rebalanced portfolios.

We contribute three novel findings to our understanding of stock return anomalies. First, cash flow variation is the primary driver of anomaly returns. Second, discount rate shocks amplify the impact of cash flow shocks on anomaly returns as these shocks are strongly negatively correlated. This correlation is driven by news about long-run cash flows. Third, cash flow and discount rate shocks to anomalies exhibit little relation with shocks to the market. In fact, discount rate shocks to the market are slightly *negatively* correlated with discount rate shocks to the anomaly MVE portfolio, casting doubt on theories in which time-varying aggregate risk aversion or sentiment plays a prominent role. Based on this evidence, the most promising theories of anomalies are those that emphasize the importance of firm-level long-run cash flow shocks as drivers of changes in firm risk or errors in investors' expectations. In future research, we hope to explain why anomaly cash flows—unlike industry cash flows—are priced by analyzing the economic sources of correlation in firm cash flows.

References

Ang, Andrew, Robert Hodrick, Yuhang Xing, and Xioayan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Babenko, Ilona, Oliver Boguth, Yuri Tserlukevich, 2016, Idiosyncratic cash flows and systematic risk, *Journal of Finance* 81, 425–455.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645–1680.

van Binsbergen, Jules, and Ralph Koijen, 2010, Predictive regressions: A present value approach, *Journal of Finance* 65, 1439–1471.

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

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

Campbell, John, and Luis Viceira, 2002, *Strategic Asset Allocation* (Clarendon Lectures in Economics, Cambridge, MA).

Campbell, John, and T. Vuolteenaho, 2004, Bad Beta, Good Beta, *American Economic Review* 94, 1249–1275.

Chen, Long and Xinlei Zhao, 2009, Return Decomposition. *Review of Financial Studies* 22 (12), 5213–5249.

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

Cooper, Michael, Huseyin Gulen, and Michael Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609–1651.

Davis, James, Eugene Fama, and Kenneth French, 2000, Characteristics, covariance, and average returns: 1929-1997, *Journal of Finance* 55, 389–406.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 2001, Overconfidence, Arbitrage, and Equilibrium Asset Pricing, *Journal of Finance* 56, 921–965.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605–1643.

De Long, Bradford, Andrei Shleifer, Lawrence Summers, and Robert Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703–738.

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

Fama, Eugene, and Kenneth French, 1995, Size and Book-to-Market Factors in Earnings and Returns, *Journal of Finance* 50, 131–155.

Fama, Eugene, and Kenneth French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

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

Hansen, Lars, John Heaton, Junghoon Lee, and Nikolai Roussanov, 2007, Chapter 61: Intertemporal substitution and risk aversion, in James J. Heckman and Edward E. Learner, eds.: *Handbook of Econometrics*, Volume 6A (Elsevier, Amsterdam).

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Kelly, Bryan, and Seth Pruitt, 2013, Market expectations in the cross-section of present values, *Journal of Finance* 68, 1721–1756.

Kozak, Serhiy, and Shrihari Santosh, 2017, Why Do Discount Rates Vary?, University of Michigan working paper.

Larrain, Borja, and Motohiro Yogo, 2008, Does firm value move too much to be justified by subsequent changes in cash flow? *Journal of Financial Economics* 87, 200–226.

Lettau, Martin, and Stijn van Nieuwerburgh, 2008, Reconcling the return predictability evidence, *Review of Financial Studies* 21, 1607–1652.

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

Lyle, Matthew R., and Charles C.Y. Wang, 2015, The cross section of expected holding period returns and their dynamics: A present value approach, *Journal of Financial Economics* 116, 505–525.

Nickell, Stephen, 1981, Biases in Dynamic Models with Fixed Effects, *Econometrica* 49, 1417–1426.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Ohlson, James, 1995, Earnings, book values, and dividends in equity valuation, *Contemporary Accounting Research* 11, 661–687.

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *Review of Financial Studies* 22, 435–480.

Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *Journal of Finance* 63, 921–945.

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

Stambaugh, Robert, 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

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

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

Appendix A: Cash Flows vs. Discount Rates of Trading Strategies

Here we show that the cash flows and discount rates of rebalanced portfolios, such as anomaly portfolios, can differ substantially from those of the underlying firms in the portfolios. We provide examples below in which firms have constant cash flows, but all variation in returns to the rebalanced portfolio comes from cash flow shocks.

We first consider a stylized behavioral model of stock returns and cash flows. Assume that all firms pay constant dividends:

$$D_{i,t} = \bar{d}. \tag{23}$$

Assume that investors in each period erroneously believe that any given firm's dividend is permanently either $d_L < \bar{d}$ or $d_H > \bar{d}$. We define the firms associated with low (high) dividend beliefs to be value (growth) firms. The pricing of these firms satisfies:

$$P^{\text{value}} = \frac{d_L}{R-1}, \tag{24}$$

$$P^{\text{growth}} = \frac{d_H}{R-1}, \tag{25}$$

where R is the gross risk-free rate. Each period, with probability q, investors switch their beliefs about each stock's dividends either from d_L to d_H or from d_H to d_L. Investors believe their beliefs will last forever, whereas in reality they will switch with probability q in each period.

Now consider a value fund that invests only in stocks that investors currently believe will pay dividends of d_L. Further assume that there are only two firms in the economy—a firm that currently is a growth firm and a firm that currently is a value firm. When beliefs switch, the growth firm becomes a value firm and vice versa. This switch therefore induces trading in the value fund as the fund has to sell firms that become growth firms and buy the new value firms.

Such trading has a significant impact on the fund's dividends. Suppose that the fund initially holds one share of the value stock, which implies that its initial wealth is $W_0 = P^{\text{value}}$. Assume investors do not switch beliefs in the next period. In this case, the fund's gross return is:

$$
\begin{aligned}
R_1^{\text{value}} &= \frac{P^{\text{value}} + \bar{d}}{P^{\text{value}}} \\
&= 1 + \frac{\bar{d}}{P^{\text{value}}}.
\end{aligned} \tag{26}
$$

Period 1 cum-dividend wealth is

$$
W_1^{cum} = P^{\text{value}} + \bar{d}, \tag{27}
$$

where ex-dividend wealth is P^{value} and dividend is $d_1 = \bar{d}$. Assume that beliefs switch in period 2. Then:

$$
\begin{aligned}
R_2^{\text{value}} &= \frac{(R-1)\left(\frac{d_H}{R-1} + \bar{d}\right)}{d_L} \\
&= \frac{d_H + (R-1)\,\bar{d}}{d_L} \\
&= \frac{d_H}{d_L} + \frac{\bar{d}}{P^{\text{value}}}.
\end{aligned} \tag{28}
$$

So fund wealth becomes:

$$
W_2^{cum} = P^{\text{value}} \frac{d_H}{d_L} + \bar{d}.
$$

Ex-dividend wealth is $W_2^{ex} = P^{\text{value}} \frac{d_H}{d_L}$, and the dividend is $d_2 = \bar{d}$ once again. The dividend price ratio of the strategy is now:

$$
\frac{W_2^{ex}}{d_2} = \frac{P^{\text{value}}}{\bar{d}} \frac{d_H}{d_L} > \frac{P^{\text{value}}}{\bar{d}}. \tag{29}
$$

The higher price-dividend ratio reflects high expected dividend growth next period.

Importantly, the fund now reinvests its capital gain into the current value stock and is able to purchase more than one share. Assuming beliefs do not switch in period 3, the fund's wealth increases to:

$$
\begin{aligned}
W_3^{cum} &= P^{\text{value}} \frac{d_H}{d_L} \left(1 + \frac{\bar{d}}{P^{\text{value}}} \right) \\
&= P^{\text{value}} \frac{d_H}{d_L} + \frac{d_H}{d_L} \bar{d}.
\end{aligned} \tag{30}
$$

Now ex-dividend wealth is $W_3^{ex} = P^{\text{value}} \frac{d_H}{d_L}$ and $d_3 = \bar{d} \times d_H/d_L$, implying that dividend growth during this period is high as $d_3/d_2 = d_H/d_L > d_2/d_1 = 1$. The price-dividend ratio of the strategy is now:

$$
\frac{W_3^{ex}}{d_3} = \frac{P^{\text{value}} \frac{d_H}{d_L}}{\bar{d} \times d_H/d_L} = \frac{P^{\text{value}}}{\bar{d}}, \tag{31}
$$

meaning that the price-dividend ratio returns to its original value.

In summary, dividend growth of the dynamic value strategy varies over time, but expected returns to the strategy are constant and given by:

$$
\begin{aligned}
E(R^{\text{value}}) &= 1 - q + q \frac{d_H}{d_L} + \frac{\bar{d}}{P^{\text{value}}} \\
&= 1 - q + q \frac{d_H}{d_L} + \frac{\bar{d}}{d_L}(R - 1).
\end{aligned} \tag{32}
$$

A symmetric argument applies to the analogous growth strategy, which also has time-varying dividend growth and constant expected returns. We conclude that return variation in the dynamic trading strategies arises solely because of cash flow shocks even though all firms in the economy incur only discount rate shocks. Firm-level return variation is driven by changes in firms' expected returns, not their dividends—which are constant.

There are no discount rate shocks to the returns of these dynamic strategies when viewed from the perspective of an investor who invests in the value or growth funds. However, unexpected returns to such funds are in fact, under the objective measure of the econometrician, due to discount rate shocks to the underlying firms. The firms' actual expected returns vary, whereas their dividend growth does not.

This feature of rebalanced portfolios is not limited to the case of time-varying mispricing.

Consider a rational model in which value firms have riskier cash flows than growth firms. If time-variation in a firm's cash flow risk causes it to switch between being a value firm and a growth firm, the rational model delivers the same insights as the behavioral model discussed above.

In this example, we assume firms' log dividend growth is:

$$\Delta d_{i,t+1} = -\frac{1}{2}\sigma^2 + \sigma\left(\rho_{s_{i,t}}\varepsilon_{m,t+1} + \sqrt{1-\rho^2_{s_{i,t}}}\varepsilon_{i,t+1}\right), \tag{33}$$

where $\varepsilon_{m,t+1}$ and $\{\varepsilon_{i,t+1}\}_i$ are uncorrelated standard normally distributed shocks representing aggregate and firm-specific dividend shocks, respectively. Firm exposure to aggregate dividend shocks is:

$$\rho_{s_{i,t}} = \begin{cases} \rho^H & \text{if } s_{i,t} = 1 \\ \rho^L & \text{if } s_{i,t} = 0 \end{cases}, \tag{34}$$

where $s_{i,t}$ follows a two-state Markov process where $\Pr\{s_{i,t+1} = 1|s_{i,t} = 0\} = \Pr\{s_{i,t+1} = 0|s_{i,t} = 1\} = \pi$. For ease of exposition, set $\rho^L = 0$ and $\rho^H = 1$. Initially, half of firms are in state 1, while the other half are in state 0. If a regime change occurs, all firms currently in state 1 switch to state 0, and vice versa.

The log stochastic discount factor is:

$$m_{t+1} = -\frac{1}{2}\gamma^2\sigma^2 - \gamma\sigma\varepsilon_{m,t+1}, \tag{35}$$

where we implicitly assume a zero risk-free rate and where $\gamma > 0$ represents risk aversion. These assumptions imply that the conditional mean and volatility of cash flow growth is constant. However, firm risk varies with $s_{i,t}$, which determines the covariance of cash flows with the pricing kernel, causing time-varying firm risk premiums.

Solving for the price-dividend ratio as a function of the state yields:

$$\begin{aligned} PD(s_{i,t}) &= E_t\left[e^{-\frac{1}{2}\gamma^2\sigma^2-\gamma\sigma\varepsilon_{m,t+1}-\frac{1}{2}\sigma^2+\sigma\left(\rho_{s_{i,t}}\varepsilon_{m,t+1}+\sqrt{1-\rho^2_{s_{i,t}}}\varepsilon_{i,t+1}\right)}\left(1+PD(s_{i,t+1})\right)\right] \\ &= e^{-\gamma\sigma^2\rho_{s_{i,t}}}\left(1+\pi PD(s_{i,t+1}\neq s_{i,t}) + (1-\pi)PD(s_{i,t+1}=s_{i,t})\right). \end{aligned} \tag{36}$$

Denote the price-dividend ratio in state j as PD_j. The price-dividend relation above is a system with two equations and two unknowns with the solution:

$$PD_1 = \frac{1}{e^{\gamma\sigma^2} - 1} \tag{37}$$

$$PD_0 = 1/\pi + \frac{1}{e^{\gamma\sigma^2} - 1} \tag{38}$$

These equations show that price-dividend ratios are higher in state 0 when dividend risk is low than in state 1 when dividend risk is high, implying that expected returns are higher in state 0 as expected dividend growth is constant across states. Firms' expected net returns are:

$$E_t\left[R_{i,t+1}|s_{i,t} = 0\right] - 1 = 0, \tag{39}$$

$$E_t\left[R_{i,t+1}|s_{i,t} = 1\right] - 1 = 2(e^{\gamma\sigma^2} - 1). \tag{40}$$

Since $PD_0 > PD_1$, we see that $E_t\left[R_{i,t+1}|s_{i,t} = 1\right] > E_t\left[R_{i,t+1}|s_{i,t} = 0\right]$. Thus, firms' price-dividend ratios fluctuate because of shocks to discount rates, not cash flows. Although there are cash flow shocks in returns arising from the contemporaneous dividend shock $\left(\sigma\left(\rho_{s_{i,t}}\varepsilon_{m,t+1} + \sqrt{1-\rho_{s_{i,t}}^2}\varepsilon_{i,t+1}\right)\right)$, dividends are unpredictable and therefore do not induce time-variation in the price-dividend ratio.

Now consider a value mutual fund that in each period buys firms that are currently in the low valuation state 1. With probability π, value firms held by the fund will switch to the high valuation state 0, meaning that they become growth firms. The fund sells all firms in each period and reinvests the proceeds in firms that are in the low valuation state 1. The fund pays out all firm dividends as they occur. The expected return to this strategy is constant and equal to $E_t\left[R_{i,t+1}|s_{i,t} = 1\right] - 1 = 2(e^{\gamma\sigma^2} - 1)$, even though all firms' expected returns vary over time.

We now analyze the growth of the value fund's dividends in each period. The first source of fund dividend growth is growth in the underlying firms' dividends, which satisfy:

$$\frac{D_{i,t+1}}{D_{i,t}} = e^{-\frac{1}{2}\sigma^2 + \sigma\varepsilon_{m,t+1}}. \tag{41}$$

The second source of fund dividend growth is growth in the number of shares of value firms held by the fund. If value firms switch to growth firms, the fund will reap a capital gain and be able to buy more shares of the new value firms in the following period. Define the indicator variable $\mathbf{1}_{s_{i,t} \neq s_{i,t-1}}$ as equal to 1 if there was a regime shift from period $t-1$ to period t and 0 otherwise. Accounting for both sources of growth, fund dividend growth is:

$$\frac{D_{t+1}^{Fund}}{D_t^{Fund}} = \mathbf{1}_{s_{i,t} \neq s_{i,t-1}} \frac{PD_0}{PD_1} e^{-\frac{1}{2}\sigma^2 + \sigma\varepsilon_{m,t+1}} + \left(1 - \mathbf{1}_{s_{i,t} \neq s_{i,t-1}}\right) e^{-\frac{1}{2}\sigma^2 + \sigma\varepsilon_{m,t+1}}, \tag{42}$$

where the term $\frac{PD_0}{PD_1} = 1 + \frac{e^{\gamma\sigma^2} - 1}{\pi}$ represents the capital gain from the prior period. Dividends are predictably high after high capital gains and low after low capital gains. The predictability in dividend growth leads to a time-varying price-dividend ratio for the mutual fund, even though its expected return is constant. Thus, discount rate shocks to the underlying value firms are cash flow shocks for the mutual fund implementing a value trading strategy.

Appendix B: Relation to Equilibrium Models

The VAR offers a parsimonious, reduced-form model of the cross-section of expected cash flows and discount rates at all horizons. Here we demonstrate that the VAR specification is related to standard asset pricing models. In well-known models such as Campbell and Cochrane's (1999) habit formation model and Bansal and Yaron's (2004) long-run risk model, the log stochastic discount factor is conditionally normally distributed and satisfies:

$$m_{t+1} = -r_{f,t} - \frac{1}{2}\left\|\lambda_t\right\|^2 + \lambda_t' \eta_{t+1}, \tag{43}$$

where λ_t is a $K \times 1$ vector of conditional risk prices, η_{t+1} is a $K \times 1$ vector of standard normal shocks, and $r_{f,t}$ is the risk-free rate. With conditionally normal log returns, applying the Law of One Price yields the following expression for the conditional expected log return of firm i:

$$\begin{aligned} E_t\left[r_{i,t+1}\right] &= r_{f,t} - \frac{1}{2}v_{i,t} + cov_t\left(m_{t+1}, r_{i,t+1}\right) \\ &= r_{f,t} - \frac{1}{2}v_{i,t} + \beta_{i,t}'\lambda_t, \end{aligned} \tag{44}$$

where $v_{i,t} \equiv var_t\left(r_{i,t+1}\right)$ is firm return variance, and $\beta_{i,t}^{(k)} = \frac{cov_t\left(\lambda_t^{(k)}\eta_{t+1}^{(k)}, r_{i,t+1}\right)}{var_t\left(\lambda_t^{(k)}\eta_{t+1}^{(k)}\right)}$ and $\beta_{i,t} = \left[\beta_{i,t}^{(1)} \ \ \beta_{i,t}^{(2)} \ \ ... \ \ \beta_{i,t}^{(K)}\right]'$ represent firm betas.

We make simplifying assumptions to relate this setup to the VAR specification. Define firm risk premiums as $z_{i,t}^{(k)} \equiv \beta_{i,t}^{(k)}\lambda_t^{(k)}$ and $z_{i,t} = \left[z_{i,t}^{(1)} \ \ z_{i,t}^{(2)} \ \ ... \ \ z_{i,t}^{(K)}\right]'$. Suppose that risk premiums, variances, and the risk-free rate evolve according to:

$$z_{i,t+1} = \bar{z} + A_z\left(z_{i,t} - \bar{z}\right) + \Sigma_{z,t}\varepsilon_{i,t+1}^{z}, \tag{45}$$

$$v_{i,t+1} = \bar{v} + A_v\left(v_{i,t} - \bar{v}\right) + \sigma_{v,t}\varepsilon_{i,t+1}^{v}, \tag{46}$$

$$r_{f,t+1} = \bar{r}_f + A_{r_f}\left(r_{f,t} - \bar{r}_f\right) + \sigma_{r,t}\varepsilon_{t+1}^{r_f}, \tag{47}$$

for all firms i. Assume firm log return on equity is also conditionally normal:

$$e_{i,t+1} = \mu + x_{i,t} + \sigma_{e,t}\varepsilon_{i,t+1}^{e}, \tag{48}$$

$$x_{i,t+1} = A_x x_{i,t} + \Sigma_{x,t}\varepsilon_{i,t+1}^{x}, \tag{49}$$

where $x_{i,t}$ is an $L \times 1$ vector of latent state variables determining expected return on equity. All shocks can be correlated.

Assuming the clean-surplus model described earlier, firm book-to-market ratios are given by:

$$bm_{i,t} = a_0 + a_1' r_{f,t} + a_2' z_{i,t} + a_3' x_{i,t} + a_4 v_{i,t}. \tag{50}$$

Define the $(2K + L + 1) \times 1$ vector $s_{i,t} = \left[r_{f,t}' \ \ z_{i,t}' \ \ v_{i,t}...x_{i,t}'\right]'$ to consist of the stacked state variables. We assume there exist $(2K + L + 1)$ observed characteristics, $\xi_{i,t}$, that span $s_{i,t}$:

$$\xi_{i,t} = A_1 + A_2 s_{i,t}, \tag{51}$$

where A_2 is invertible. With the characteristic spanning assumption, firms' book-to-market become a function of the observed characteristics, resulting in a VAR representation of the present-value relation. In sum, the VAR specification concisely summarizes the dynamics of expected cash flows and discount rates, even when both consist of multiple components fluctuating at different frequencies. The VAR yields consistent estimates even though there is heteroskedasticity across firms and time.

When analyzing long-short portfolios, we obtain the anomaly cash flow (discount rate) shock as the difference in the cash flow (discount rate) shocks between the long and short portfolios. Taking the value anomaly as an example, suppose the long value portfolio and short growth portfolio have the same betas with respect to all risk factors except the value factor (say, $\lambda_t^{(2)}$). According to Equation (44), discount rate shocks to this long-short portfolio can only arise from three sources: 1) shocks to the spread in the factor exposure between value and growth firms ($\beta^{(2)}_{\text{value},t} - \beta^{(2)}_{\text{growth},t}$); 2) shocks to the price of risk of the value factor ($\lambda_t^{(2)}$); or 3) shocks to the difference in return variance between the two portfolios. The third possibility arises because we analyze log returns. Similarly, cash flow shocks to this long-short portfolio only reflect these portfolios' differential exposure to cash flow factors.

Table 1 - Summary Statistics

Table 1: Panel A shows summary statistics for firm-level returns, cash flows, and characteristics. The first column lists the variables as defined in the text. The second column reports the number of firm-year observations, n. The remaining columns report the mean, standard deviation and various percentiles of the firm-year distribution for each variable. Panel B provides the correlation matrix for the firm accounting characteristics. The sample spans the years 1964 through 2015.

Panel A:	N	Mean	SD	P1	P10	P50	P90	P99
AnnRet	68,639	12.66	50.70	−81.06	−39.82	7.69	65.60	175.00
Rf	68,639	5.35	3.12	0.12	0.31	5.55	8.61	13.96
Volat	63,561	38.69	16.94	15.34	21.83	35.11	58.75	102.45
SizeWt	68,639	0.31	1.06	0.00	0.01	0.06	0.55	5.38
$\ln\text{ROE}^{\text{CS}}$	65,275	11.29	32.27	−86.64	−11.90	10.23	36.33	117.96
lnBM	67,296	−0.72	0.83	−3.04	−1.78	−0.66	0.29	0.98
lnME	68,590	4.89	1.31	2.90	3.37	4.65	6.73	8.62
lnProf	66,361	21.27	26.92	−72.50	6.39	23.33	39.14	77.92
lnInv	67,475	16.10	28.27	−31.35	−4.87	9.91	42.83	132.75

Panel B:	1	2	3	4
lnBM (1)	1.00			
lnME (2)	−0.28	1.00		
lnProf (3)	−0.11	0.19	1.00	
lnInv (4)	−0.19	−0.03	0.02	1.00
lnMom (5)	−0.25	0.16	0.06	−0.07

Table 2 - Return and Earnings Forecasting Regressions

Table 2: The table shows forecasting regressions of firms' annual real log returns (lnRet), log annual real clean-surplus earnings ($lnROE^{CS}$), and log book-to-market (lnBM) on one-year-lagged value of a set of characteristics: lnBM, log profitability (lnProf), log asset growth (lnInv), log market equity (lnME), log 6-month momentum percentile (lnMom6), realized variance (lnRV), and the log one-year real risk-free rate (lnRf). The first five characteristics are also interacted with lnBM in a manner explained in the main text. The sample spans the years 1964 through 2015. Standard errors clustered by year and firm appear in parenthesis. N denotes the number of observations. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

	lnRet	lnROE^{CS}	lnBM
Lag lnRet	0.011	0.127**	0.121+
	(0.080)	(0.025)	(0.072)
Lag lnROE^{CS}	−0.036	−0.040*	−0.004
	(0.035)	(0.017)	(0.029)
Lag lnBM	0.051*	−0.109**	0.875**
	(0.021)	(0.009)	(0.023)
Lag lnProf	0.043**	0.069**	0.0266
	(0.014)	(0.009)	(0.018)
Lag lnInv	−0.051**	0.003	0.057**
	(0.014)	(0.005)	(0.011)
Lag lnME	−0.019	−0.003	0.017+
	(0.018)	(0.005)	(0.010)
Lag lnMom6	0.019	−0.005	−0.026+
	(0.018)	(0.006)	(0.015)
Lag lnRV	−0.030	−0.006	0.025
	(0.021)	(0.007)	(0.019)
Lag lnd_bm_bm	0.013	−0.018**	0.005
	(0.012)	(0.005)	(0.013)
Lag lnd_prof_bm	−0.009	0.022**	0.032**
	(0.007)	(0.003)	(0.007)
Lag lnd_inv_bm	0.004	−0.010**	−0.015**
	(0.004)	(0.003)	(0.005)
Lag lnd_me_bm	−0.007	0.014**	0.022**
	(0.007)	(0.004)	(0.008)
Lag lnd_mom_bm	0.011+	−0.015**	−0.027**
	(0.006)	(0.003)	(0.008)
Lag lnRf	0.002	0.013	0.011
	(0.028)	(0.008)	(0.024)
R^2	0.045	0.241	0.698
N	49,755	49,755	49,755

Table 3 - Characteristic Forecasting Regressions

Table 3: Panel A shows annual forecasting regressions of firm characteristics on their own lag as well as the firm's lagged book-to-market ratio. The characteristics are log profitability (lnProf), log asset growth (lnInv), log market equity (lnME), log three-year issuance (lnIssue), and realized variance (lnRV), as well as interactions with lnBM as explained in the main text. Panel B reports the regression coefficients of the aggregate variable, the log one-year real risk-free rate (lnRf), which is regressed only on its own lag. The sample spans the years 1964 through 2015. Standard errors clustered by year and firm appear in parenthesis. N denotes the number of observations. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

Panel A:	Own Lag	Lag lnBM	R^2	N
lnProf	0.734**	−0.080**	46.7%	49,708
	(0.052)	(0.018)		
lnInv	0.157**	−0.301**	15.7%	49,720
	(0.026)	(0.026)		
lnME	0.978**	0.022	91.1%	49,749
	(0.005)	(0.014)		
lnMom6	0.048*	0.056*	0.3%	49,748
	(0.019)	(0.027)		
lnRV	0.688**	−0.056*	48.9%	49,408
	(0.068)	(0.035)		
Lag lnd_bm_bm	0.566**	−0.307**	60.7%	49,755
	(0.025)	(0.039)		
Lag lnd_prof_bm	0.666**	0.118**	51.7%	49,755
	(0.020)	(0.013)		
Lag lnd_inv_bm	0.258**	0.163**	11.0%	49,755
	(0.013)	(0.018)		
Lag lnd_me_bm	0.685**	0.149**	54.9%	49,755
	(0.021)	(0.017)		
Lag lnd_mom_bm	0.022	0.157**	2.0%	49,755
	(0.027)	(0.014)		

Panel B:	Own Lag	R^2	N
Lag lnRf	0.603**	36.3%	51
	(0.200)		

Table 4 - Variance Decompositions

Table 4: The table displays the variance decomposition of firm-level and market-level real returns into CF and DR components. "Panel VAR" means that the CF and DR shocks are retrieved from our main panel VAR, while "Time-series VAR", which only is releevant for the market portfolio, refers to a VAR run directly at the market level, using market returns, earnings and book-to-market ratios. surplus earnings, returns, and book-to-market ratio. The sample spans the years 1964 through 2015. Standard errors appear in parentheses. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

	$var\,(DR)$	$var\,(CF)$	$var\,(Cross)$	$-2cov\,(DR, CF)$	$corr\,(DR, CF)$	$corr\,(Pred, Act)$
Firm-level returns						
Panel VAR						
Fraction of $var\,(r)$	0.225^{+}	0.533^{**}		0.243^{**}	-0.351^{*}	
	(0.122)	(0.115)		(0.075)	(0.162)	
Market returns						
Panel VAR						
Fraction of $var\,(r_m)$	0.178	0.552^{**}	0.008^{**}	0.308^{+}	-0.492	0.985^{**}
	(0.119)	(0.191)	(0.003)	(0.213)	(0.452)	(0.002)
Time-series VAR						
Fraction of $var\,(r_m)$	0.281	0.248		0.471^{**}	-0.892^{**}	
	(0.236)	(0.187)		(0.144)	(0.249)	

Table 5 - Anomaly Variance Decompositions

Table 5: Panel A of the table shows decompositions of the variance of log anomaly returns into cash flow (CF) and discount rate (DR) components. The anomaly return is the difference between the log return of the top quintile portfolio and the log return of the bottom quintile portfolio, where the quintile sort is based on the relevant characteristic. Panel B shows variance decompositions of log returns to alternative mean-variance efficient (MVE) portfolios: the first is the in-sample MVE portfolio based on the quintile long-short anomaly portfolios only, the second includes also the market portfolio. The sample spans the years 1964 through 2015. Standard errors appear in parentheses. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

	$var\,(DR)$	$var\,(CF)$	$var\,(Cross)$	$-2cov\,(DR, CF)$	$corr\,(DR, CF)$	$corr\,(Pred, Act)$
Panel A: Individual long-short anomaly portfolios						
Book-to-market:						
Fraction of $var\,(r_{bm})$	0.180	0.536^{**}	0.022^{*}	0.316^{**}	-0.509^{**}	0.958^{**}
	(0.116)	(0.169)	(0.011)	(0.122)	(0.195)	(0.041)
Profitability:						
Fraction of $var\left(r_{prof}\right)$	0.232^{+}	0.529^{**}	0.042^{+}	0.326^{**}	-0.466^{**}	0.884^{**}
	(0.137)	(0.165)	(0.022)	(0.128)	(0.166)	(0.072)
Size:						
Fraction of $var\,(r_{size})$	0.170	0.399^{*}	0.028^{+}	0.343^{**}	-0.659^{**}	0.910^{**}
	(0.121)	(0.174)	(0.017)	(0.113)	(0.154)	(0.059)
Momemtum:						
Fraction of $var\,(r_{mom})$	0.157	0.436^{**}	0.024^{**}	0.361^{**}	-0.690^{**}	0.955^{**}
	(0.106)	(0.167)	(0.010)	(0.114)	(0.143)	(0.042)
Investment:						
Fraction of $var\,(r_{inv})$	0.177^{+}	0.563^{**}	0.029^{*}	0.366^{**}	-0.579^{**}	0.945^{**}
	(0.098)	(0.167)	(0.015)	(0.128)	(0.163)	(0.047)
Panel B: MVE portfolios						
MVE portfolio, ex market:						
Fraction of $var(r_{mve}^{ex\ mkt})$	0.142	0.440^{**}	0.026^{**}	0.373^{**}	-0.747^{**}	0.924^{**}
	(0.097)	(0.173)	(0.010)	(0.118)	(0.134)	(0.056)
MVE portfolio, incl. market:						
Fraction of $var\left(r_{mve}^{all}\right)$	0.131	0.580^{**}	0.025^{*}	0.322^{*}	-0.583^{+}	0.932^{**}
	(0.092)	(0.182)	(0.011)	(0.152)	(0.323)	(0.053)

Table 6 - Correlations between Anomaly and Market Return Components

Table 6: Panel A of the table shows correlations between market cash flow and discount rate shocks and the anomaly cash flow and discount rate shocks. Panel B shows correlations between market cash flow and discount rate shocks and the cash flow and discount rate shocks of the mean-variance efficient (MVE) portfolio, where the latter is constructed as the in-sample MVE portfolio based on the quintile long-short anomaly portfolios *only* – thus, the market portfolio is not included in the MVE portfolio construction. The sample spans the years 1964 through 2015. Standard errors appear in parentheses. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

	Market CF		Market DR	
	Anomaly CF	Anomaly DR	Anomaly CF	Anomaly DR
Panel A:				
Book-to-market	−0.12	−0.20	0.38*	0.12
	(0.21)	(0.16)	(0.16)	(0.21)
Profitability	−0.10	0.20	0.06	−0.45**
	(0.17)	(0.20)	(0.21)	(0.14)
(-) Investment	−0.06	−0.02	0.35*	−0.02
	(0.21)	(0.17)	(0.16)	(0.17)
(-) Size	−0.08	−0.36*	−0.08	0.27
	(0.19)	(0.18)	(0.18)	(0.22)
Momentum	0.08	0.06	−0.14	−0.12
	(0.16)	(0.18)	(0.15)	(0.17)
Panel B:				
MVE portfolio, ex. market	−0.01	0.06	0.14	−0.27
	(0.16)	(0.20)	(0.15)	(0.17)

Table 7 - Anomaly Variance Decompositions:
Short- and Long-run Cash Flow Shocks

Table 7: The table shows correlations between short-run and long-run cash flow shocks, as well as the correlation between short- and long-run cash flow shocks and discount rate shocks. The anomaly return is the difference between the log return of the top quintile portfolio and the log return of the bottom quintile portfolio, where the quintile sort is based on the relevant characteristic. The sample spans the years 1964 through 2015. Standard errors appear in parentheses. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

	$Corr\,(CF_{short-run}, CF_{long-run})$	$Corr\,(DR, CF_{short-run})$	$Corr\,(DR, CF_{long-run})$
Book-to-market:	-0.43^{**}	0.11	-0.55^{**}
	(0.16)	(0.16)	(0.18)
Profitability:	-0.55^{**}	-0.16	-0.28
	(0.12)	(0.16)	(0.20)
Size:	-0.15	0.17	-0.77^{**}
	(0.15)	(0.15)	(0.11)
Investment:	-0.32^{*}	-0.04	-0.57^{**}
	(0.15)	(0.17)	(0.14)
Momentum:	-0.49^{**}	-0.03	-0.59^{**}
	(0.13)	(0.17)	(0.18)
Market:	0.09	0.04	-0.58
	(0.25)	(0.32)	(0.46)

Table 8 - Correlations of CF and DR shocks with aggregate metrics

Table 8: The table shows contemporaneous correlations between the market and anomaly portfolios' cash flow and discount rate shocks and various aggregate metrics: 1-year log real per capita consumption growth, 1-year real per capita GDP growth, the 1-year difference in the log labor share, 3-year consumption and GDP growth (current and future 2 years), one year log difference in Baker and Wurgler's sentiment index, the 1-year different in the Baa-Aaa yield spread, the 1-year change in the term spread, the one-year change in the 3-month T-bill rate, and the cumulated one year shock to the Broker-Dealer leverage factor of Adrien, Etula, and Muir (2014). A bold number implies significant at the 5 percent level, a number in italics implies significance at the 10 percent level. The sample spans the years 1964 through 2015. Standard errors appear in parentheses. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

	1yr Cons. growth	1yr GDP growth	Change labor share	3yr Cons. growth	3yr GDP growth	Change in sentiment	Change Baa-Aaa spread	Change in Term Spread	Change risk-free rate	B-D Lev. Factor
CF correlations:										
Market:	**0.37**	**0.37**	**−0.44**	**0.32**	**0.31**	0.03	**−0.47**	**−0.28**	0.12	**0.31**
Book-to-market:	−0.06	−0.05	−0.10	−0.04	−0.04	0.17	−0.02	0.09	0.05	0.22
(-) Investment:	−0.22	−0.22	0.02	−0.06	−0.05	0.09	0.01	0.23	0.09	0.20
Profitability:	0.15	0.13	0.20	0.17	0.16	−0.16	0.13	−0.01	−0.18	0.02
(-) Size:	−0.06	−0.07	0.01	0.15	0.16	0.04	−0.05	0.11	−0.04	0.20
Momentum:	0.19	0.20	*-0.24*	0.19	0.20	0.00	−0.18	−0.03	−0.07	0.06
MVE ex market:	0.17	0.18	*-0.23*	0.22	0.23	0.05	−0.15	0.07	−0.14	*0.24*
MVE all:	**0.34**	**0.35**	**−0.43**	**0.35**	**0.35**	0.06	**−0.44**	−0.08	−0.05	**0.40**
DR correlations:										
Market:	0.02	0.03	0.07	−0.19	−0.18	0.14	0.20	−0.07	0.18	0.09
Book-to-market:	0.09	0.08	0.22	−0.05	−0.05	0.05	**0.27**	−0.03	0.12	−0.01
(-) Investment:	0.08	0.10	0.12	−0.17	−0.17	0.14	0.21	−0.14	0.12	−0.04
Profitability:	−0.03	−0.05	−0.09	−0.01	−0.01	0.06	−0.20	−0.11	0.12	**−0.32**
(-) Size:	−0.07	−0.06	0.07	−0.16	−0.16	−0.10	0.15	0.00	0.00	−0.19
Momentum:	**−0.28**	**−0.29**	0.22	0.04	0.04	**−0.31**	0.04	0.16	−0.10	−0.15
MVE ex market:	*-0.26*	**−0.28**	**0.34**	−0.02	−0.02	**−0.27**	0.14	0.08	0.02	**−0.33**
MVE all:	−0.16	−0.17	**0.34**	−0.18	−0.18	−0.03	**0.28**	−0.04	0.21	−0.20

Table 9 - Market Variance Decompositions in Alternative Specifications

Table 9: The table shows variance decompositions of market log returns into cash flow (CF) and discount rate (DR) components, derived from alternative specifications of the firm-level panel VAR, as explained in the text. Spec1 refers to the simplest VAR specification without interaction terms. Spec2 refers to the specification that includes the aggregate book-to-market ratio. Spec3 refers to the specification that in addition includes interaction terms. Spec4 and Spec5 refer to specifications including industry-and firm-specific rolling means, respectively. The sample spans the years 1964 through 2015. Standard errors appear in parentheses. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

		$var(DR)$	$var(CF)$	$var(Cross)$	$-2cov(DR, CF)$	$corr(DR, CF)$	$corr(Pred, Act)$
$Spec1$	Fraction of $var(r_m)$	0.207	0.642**	0.010*	0.194	−0.266	0.987**
		(0.139)	(0.226)	(0.005)	(0.278)	(0.466)	(0.023)
$Spec2$	Fraction of $var(r_m)$	1.073	0.318	0.008	−0.344	0.294	0.987**
		(1.076)	(0.231)	(0.015)	(1.206)	(0.817)	(0.023)
$Spec3$	Fraction of $var(r_m)$	1.498	0.551	0.040	−0.876	0.482	0.987**
		(2.876)	(0.842)	(0.173)	(3.389)	(1.067)	(0.023)
$Spec4$	Fraction of $var(r_m)$	0.177	0.550**	0.007^{+}	0.182	−0.292	0.988**
		(0.123)	(0.195)	(0.004)	(0.242)	(0.476)	(0.022)
$Spec5$	Fraction of $var(r_m)$	0.204	0.559**	0.007*	0.200	−0.297	0.987**
		(0.138)	(0.212)	(0.003)	(0.256)	(0.473)	(0.022)

Table 10 - Anomaly Variance Decompositions in Alternative Specifications

Table 10: The table shows decompositions of the variance of log long-short anomaly returns into cash flow (CF) and discount rate (DR) components. The variance-decompositions are derived from alternative specifications of the firm-level panel VAR, as explained in the text. Spec1 refers to the simplest VAR specification without interaction terms. Spec2 refers to the specification that includes the aggregate book-to-market ratio. Spec3 refers to the specification that in addition includes interaction terms. Spec4 and Spec5 refer to specifications including industry-and firm-specific rolling means, respectively. The sample spans the years 1964 through 2015. Standard errors appear in parentheses. The marks '+', '*', and '**' indicate signficance at the 10, 5, and 1 percent levels, respectively.

		$var(DR)$	$var(CF)$	$var(Cross)$	$-2cov(DR,CF)$	$corr(DR,CF)$	$corr(Pred,Act)$
Book-to-market:							
Spec1	Fraction of $var(r_{bm})$	0.166^{+}	0.477^{**}	0.017^{*}	0.354^{**}	-0.628^{**}	0.967^{**}
		(0.100)	(0.152)	(0.008)	(0.121)	(0.190)	(0.040)
Spec2	Fraction of $var(r_{bm})$	0.087	0.705^{**}	0.030	0.253^{*}	-0.512^{*}	0.968^{**}
		(0.078)	(0.272)	(0.033)	(0.123)	(0.228)	(0.036)
Spec3	Fraction of $var(r_{bm})$	0.104	1.140	0.095	-0.040	0.057	0.967^{**}
		(0.087)	(0.818)	(0.251)	(0.377)	(0.517)	(0.036)
Spec4	Fraction of $var(r_{bm})$	0.152^{+}	0.413^{**}	0.015^{*}	0.312^{**}	-0.624^{**}	0.971^{**}
		(0.090)	(0.133)	(0.007)	(0.114)	(0.184)	(0.034)
Spec5	Fraction of $var(r_{bm})$	0.171^{+}	0.425^{**}	0.015^{*}	0.350^{**}	-0.649^{**}	0.967^{**}
		(0.107)	(0.155)	(0.007)	(0.121)	(0.204)	(0.036)
Profitability:							
Spec1	Fraction of $var(r_{prof})$	0.179^{+}	0.487^{**}	0.033^{**}	0.360^{**}	-0.610^{**}	0.892^{**}
		(0.107)	(0.154)	(0.013)	(0.121)	(0.159)	(0.068)
Spec2	Fraction of $var(r_{prof})$	0.122	0.663^{**}	0.044	0.275^{*}	-0.480^{*}	0.900^{**}
		(0.098)	(0.243)	(0.038)	(0.137)	(0.214)	(0.066)
Spec3	Fraction of $var(r_{prof})$	0.320	0.735^{*}	0.060	0.010	-0.010	0.914^{**}
		(0.223)	(0.329)	(0.133)	(0.323)	(0.336)	(0.061)
Spec4	Fraction of $var(r_{bm})$	0.177^{+}	0.403^{**}	0.026^{**}	0.328^{**}	-0.614^{**}	0.914^{**}
		(0.103)	(0.133)	(0.011)	(0.115)	(0.162)	(0.060)
Spec5	Fraction of $var(r_{bm})$	0.203	0.430^{**}	0.026^{**}	0.334^{**}	-0.566^{**}	0.903^{**}
		(0.138)	(0.161)	(0.010)	(0.122)	(0.203)	(0.066)
Size:							
Spec1	Fraction of $var(r_{size})$	0.160	0.386^{*}	0.021	0.362^{**}	-0.727^{**}	0.937^{**}
		(0.111)	(0.155)	(0.010)	(0.115)	(0.171)	(0.050)
Spec2	Fraction of $var(r_{size})$	0.080	0.617^{**}	0.031	0.279^{*}	-0.625^{**}	0.937^{**}
		(0.083)	(0.283)	(0.024)	(0.128)	(0.194)	(0.050)
Spec3	Fraction of $var(r_{size})$	0.285	0.967	0.081	-0.112	0.107	0.943^{**}
		(0.379)	(0.686)	(0.160)	(0.569)	(0.452)	(0.047)
Spec4	Fraction of $var(r_{bm})$	0.150	0.340^{**}	0.023^{*}	0.317^{**}	-0.702^{**}	0.935^{**}
		(0.103)	(0.138)	(0.010)	(0.108)	(0.172)	(0.050)
Spec5	Fraction of $var(r_{bm})$	0.141	0.389^{**}	0.020^{*}	0.327^{**}	-0.699^{**}	0.903^{**}
		(0.106)	(0.167)	(0.010)	(0.107)	(0.161)	(0.062)
Investment:							
Spec1	Fraction of $var(r_{inv})$	0.169^{+}	0.530^{**}	0.022^{**}	0.374^{**}	-0.625^{**}	0.950^{**}
		(0.087)	(0.161)	(0.007)	(0.126)	(0.166)	(0.045)
Spec2	Fraction of $var(r_{inv})$	0.086	0.883^{*}	0.054	0.212	-0.386	0.951^{**}
		(0.066)	(0.389)	(0.063)	(0.179)	(0.351)	(0.044)
Spec3	Fraction of $var(r_{inv})$	0.087	0.991	0.095	0.142	-0.241	0.953^{**}
		(0.051)	(0.872)	(0.276)	(0.328)	(0.638)	(0.043)
Spec4	Fraction of $var(r_{bm})$	0.162^{+}	0.425^{**}	0.015^{**}	0.341^{**}	-0.651^{**}	0.958^{**}
		(0.083)	(0.133)	(0.005)	(0.115)	(0.169)	(0.041)
Spec5	Fraction of $var(r_{bm})$	0.182^{+}	0.438^{**}	0.019^{**}	0.351^{**}	-0.620^{**}	0.955^{**}
		(0.100)	(0.174)	(0.007)	(0.121)	(0.176)	(0.042)

Figure 1 - Cumulative Return Forecasting Coefficients

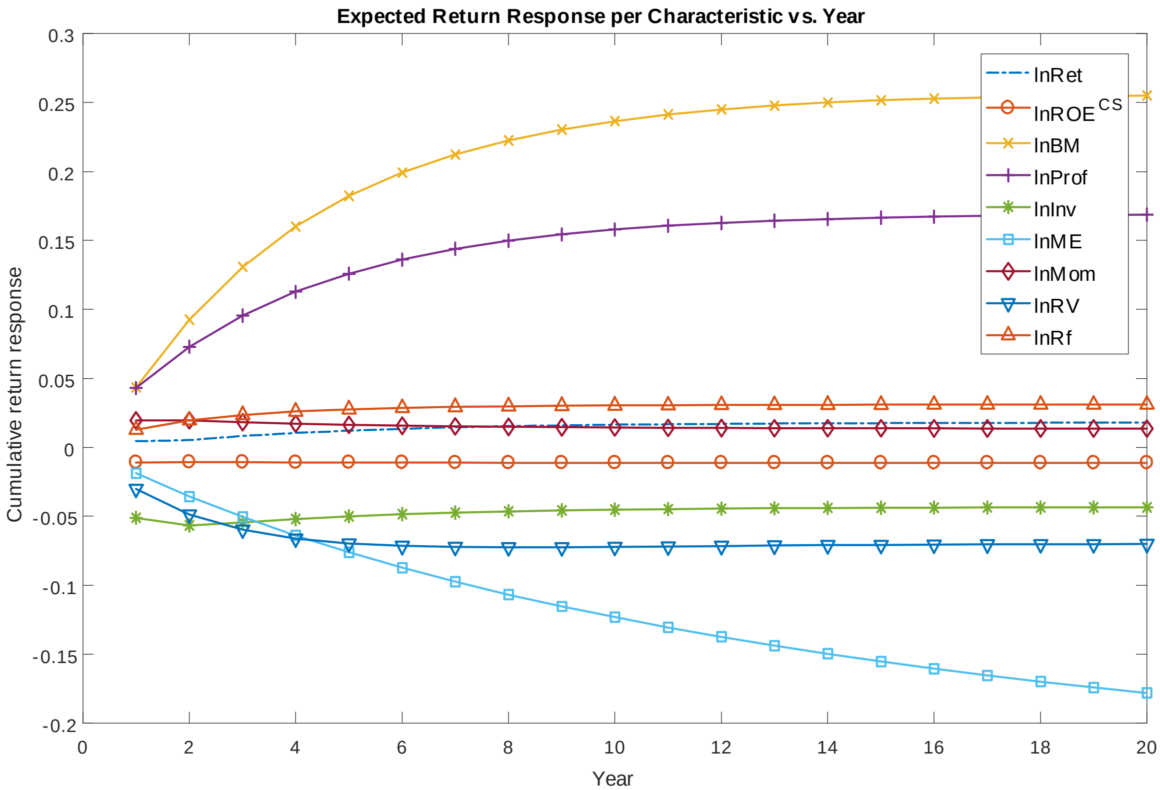


Figure 1: The plot shows the cumulative coefficients of real log return forecasts based on each characteristic (y-axis) for forecasting horizons of 1 to 20 years (x-axis), as implied by the panel VAR. When computing the cumulative coefficient, the coefficient for horizon j is multiplied by κ^j, where $\kappa = 0.96$ as in the text. Thus, the cumulative coefficient for each horizon represents the discount rate component of log book-to-market ratio for that horizon.

Figure 2 - Cumulative Earnings Forecasting Coefficients

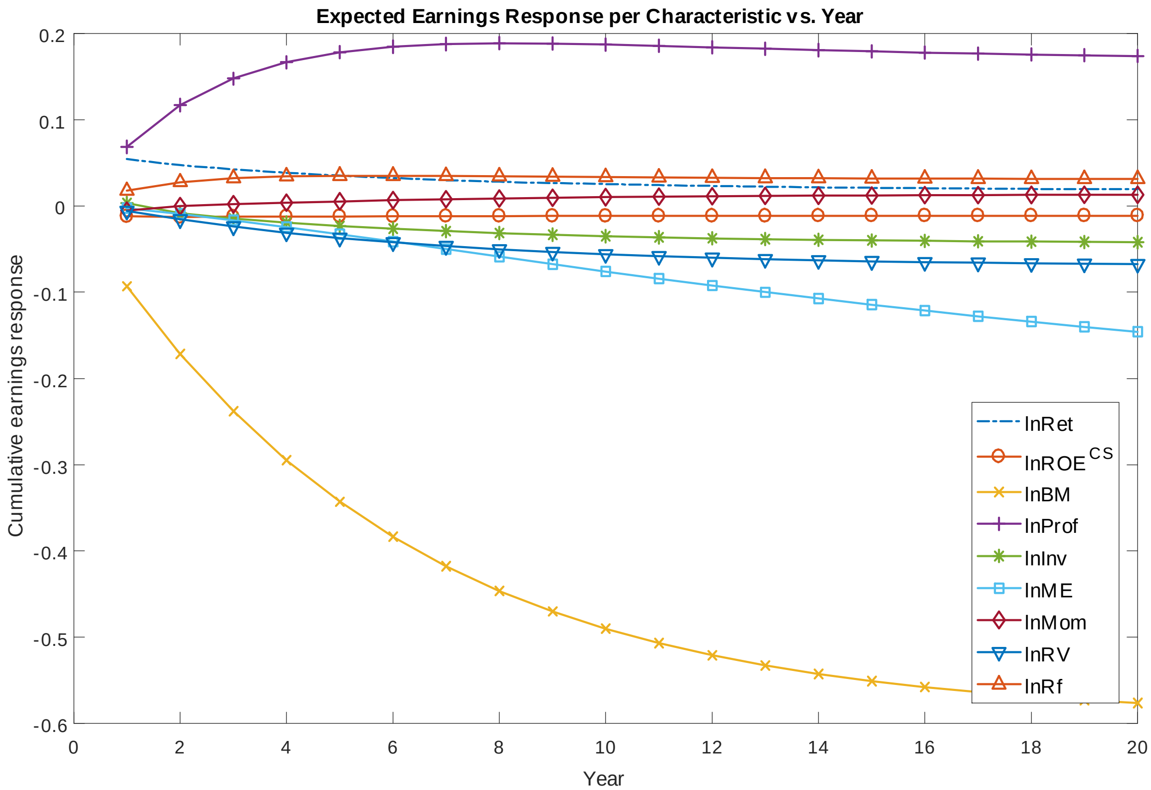


Figure 2: The plot shows the cumulative coefficients of real log earnings forecasts based on each characteristic (y-axis) for forecasting horizons of 1 to 20 years (x-axis), as implied by the panel VAR. When computing the cumulative coefficient, the coefficient for horizon j is multiplied by κ^j, where $\kappa = 0.96$ as in the text. Thus, the cumulative coefficient for each horizon represents the cash flow component of log book-to-market ratio for that horizon.

Figure 3 - Predicting 10-year Market Earnings and Returns

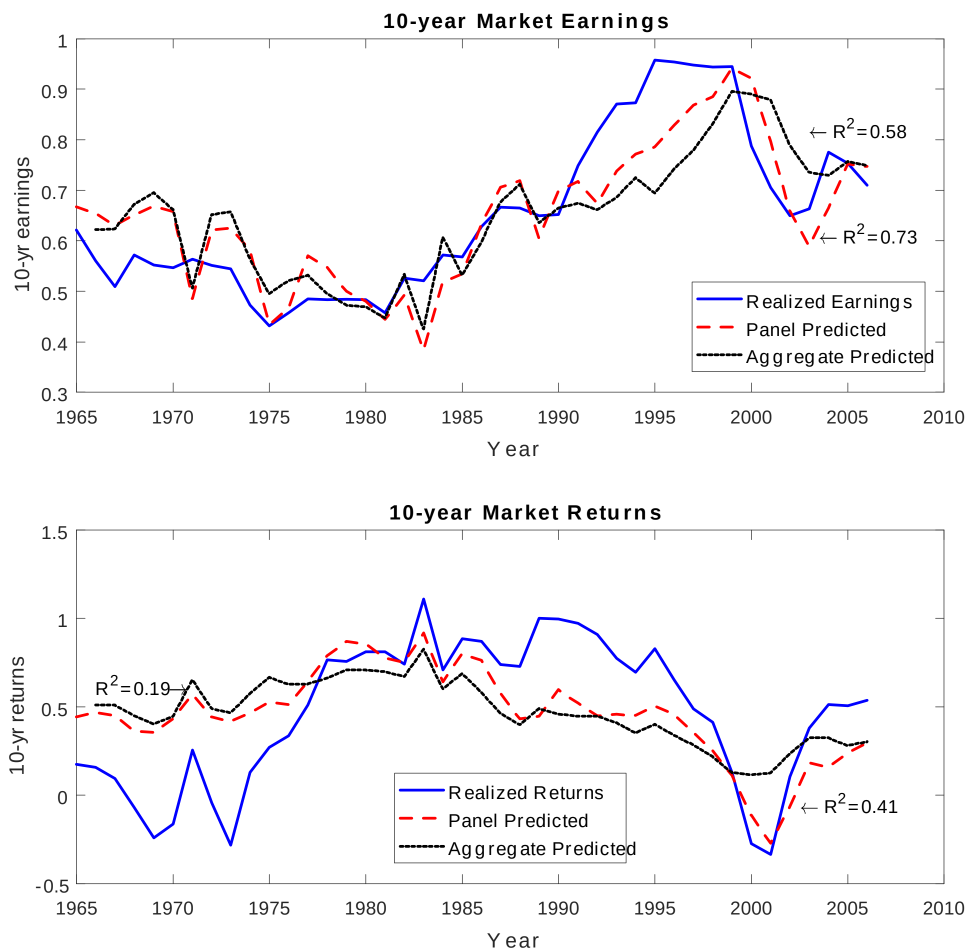


Figure 3: The top plot shows realized versus predicted 10-year log clean surplus earnings of the market portfolio. The solid blue line corresponds to realized earnings, while the dashed red and dotted black lines represent predicted earnings from the panel VAR and market-level VAR, respectively. The year on the x-axis is the year of the prediction -e.g., year 2005 corresponds to the 10-year realized earnings in 2006-2015. The bottom plot shows the corresponding for 10-year log real market returns.

Figure 4 - Predicting 10-year Value Anomaly Earnings and Returns

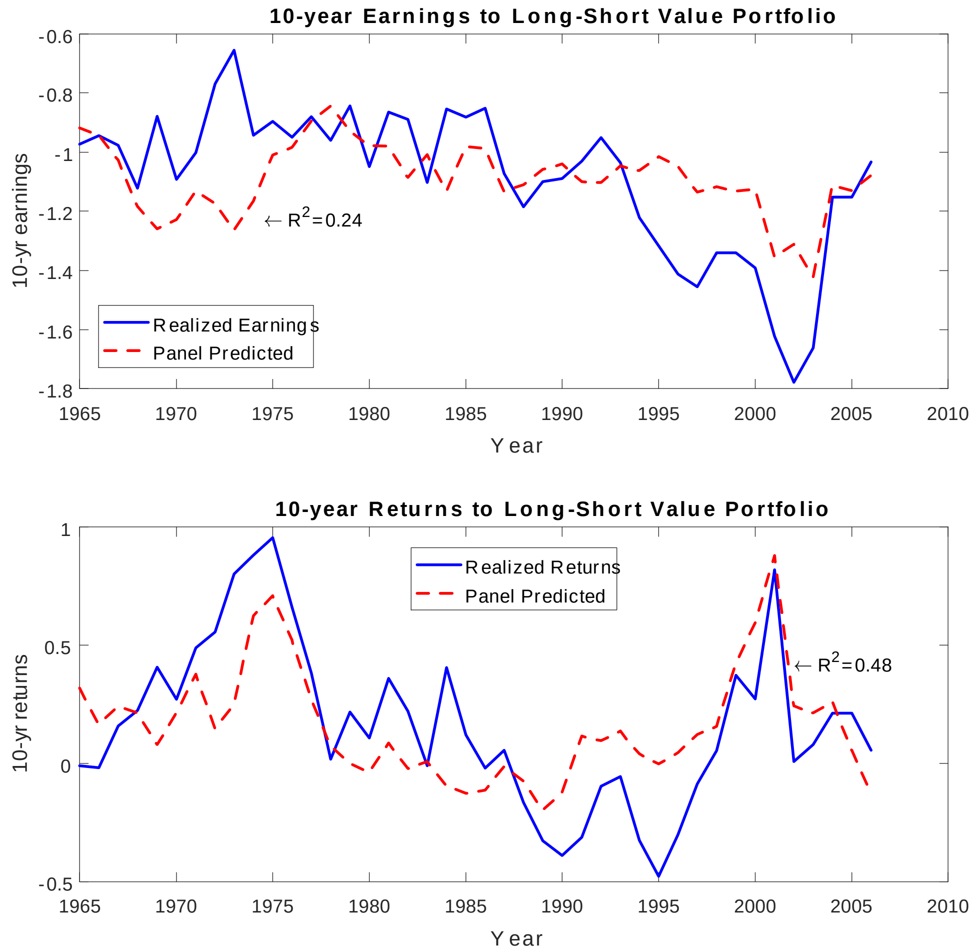


Figure 4: The top plot shows realized versus predicted 10-year log clean-surplus earnings of the long-short portfolio formed by sorting on book-to-market ratios. The solid blue line corresponds to realized earnings, while the dashed red line represent predicted earnings from the panel VAR. The year on the x-axis is the year of the prediction-e.g., year 2005 corresponds to the 10-year realized earnings in 2006-2015. The bottom plot shows the corresponding for 10-year real log returns to the long-short value portfolio.

Figure 5 - Predictive Power of Valuation Components

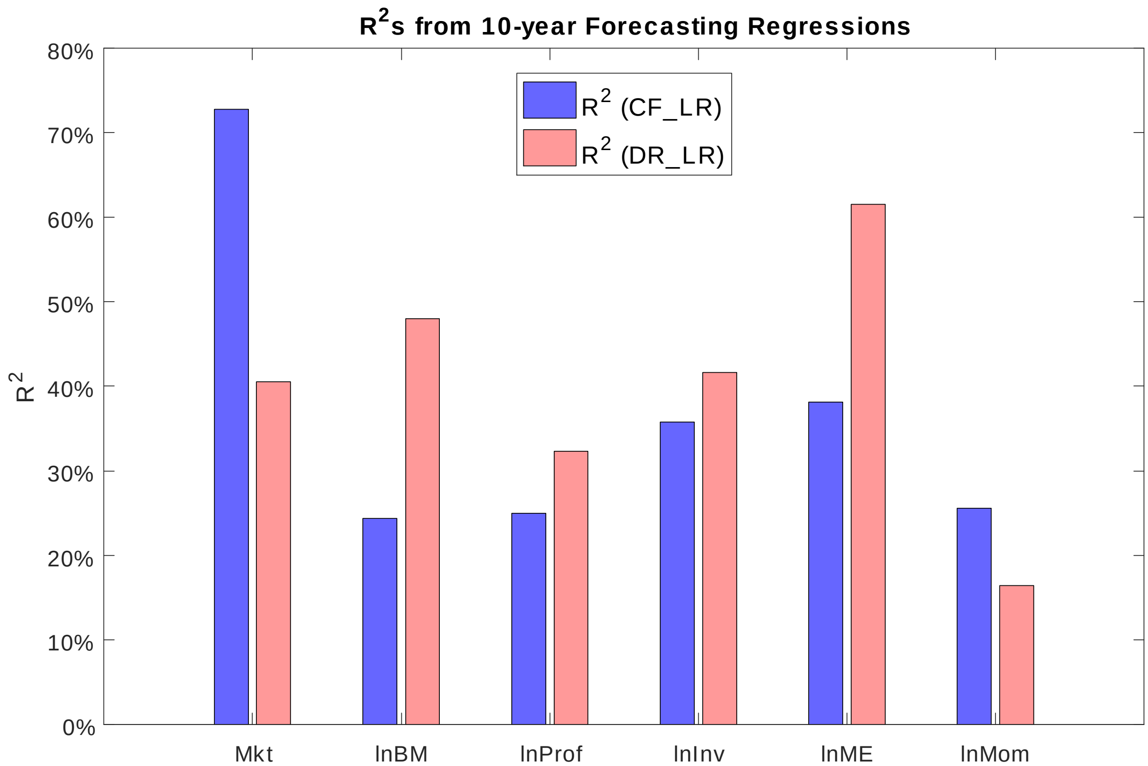
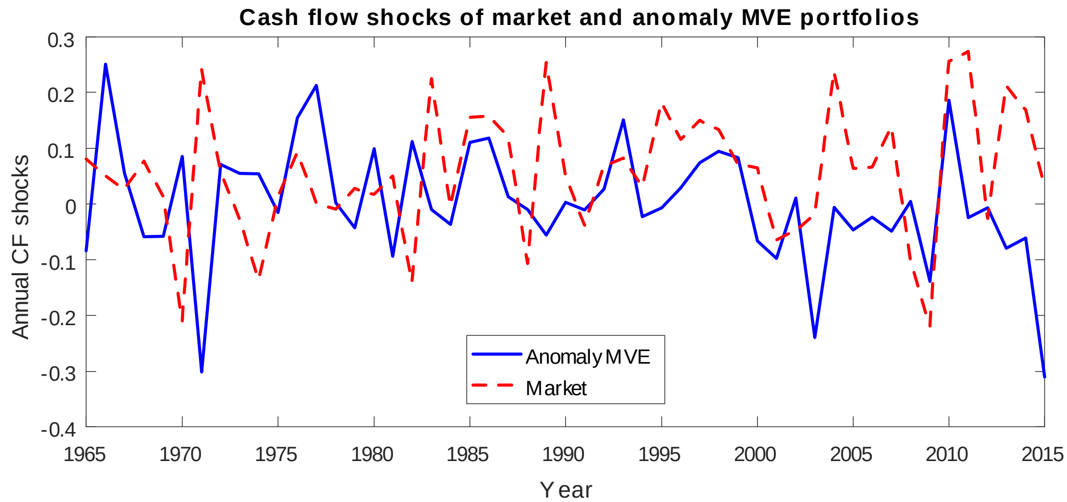


Figure 5: The figure shows the R2 statistics from regressions forecasting either 10-year earnings or returns of portfolios. The blue (left) bars represent the predictive power of regressions of 10-year log clean-surplus earnings on the cash flow components of firms' log book-to-market ratios (CF_LR) aggregated to the relevant portfolio level. The light red (right) bars represent the predictive power of regressions of 10-year log real returns on the discount rate components of firms' log book-to-market ratios (DR_LR). The portfolios are the market portfolio (Mkt), as well as top quintile minus bottom quintile portfolios sorted on book-to-market (B/M), profitability (Prof), investment (Inv), size (ME), and issuance (Issue). See the main text for details regarding the construction of the test portfolios and the corresponding cash flow and discount rate components. The sample spans the years 1964 through 2015.

Figure 6 - Market CF and DR shocks vs. anomaly MVE CF and DR shocks



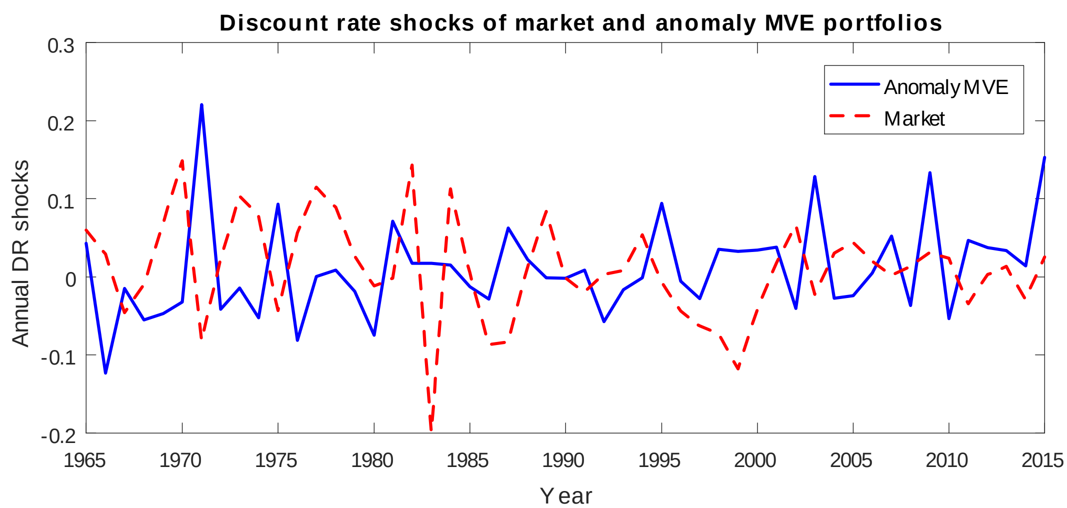


Figure 6: Panel A shows the cash flow shocks from the market and the anomaly mean-variance efficient (MVE) portfolio. The latter is constructed using only the long-short anomaly portfolios and in-sample MVE weights. Panel B shows the same for discount rate shocks. The sample is annual, from 1965 through 2015.

Figure 7 - Predicting 10-year Market Earnings and Returns in Alternative Specifications

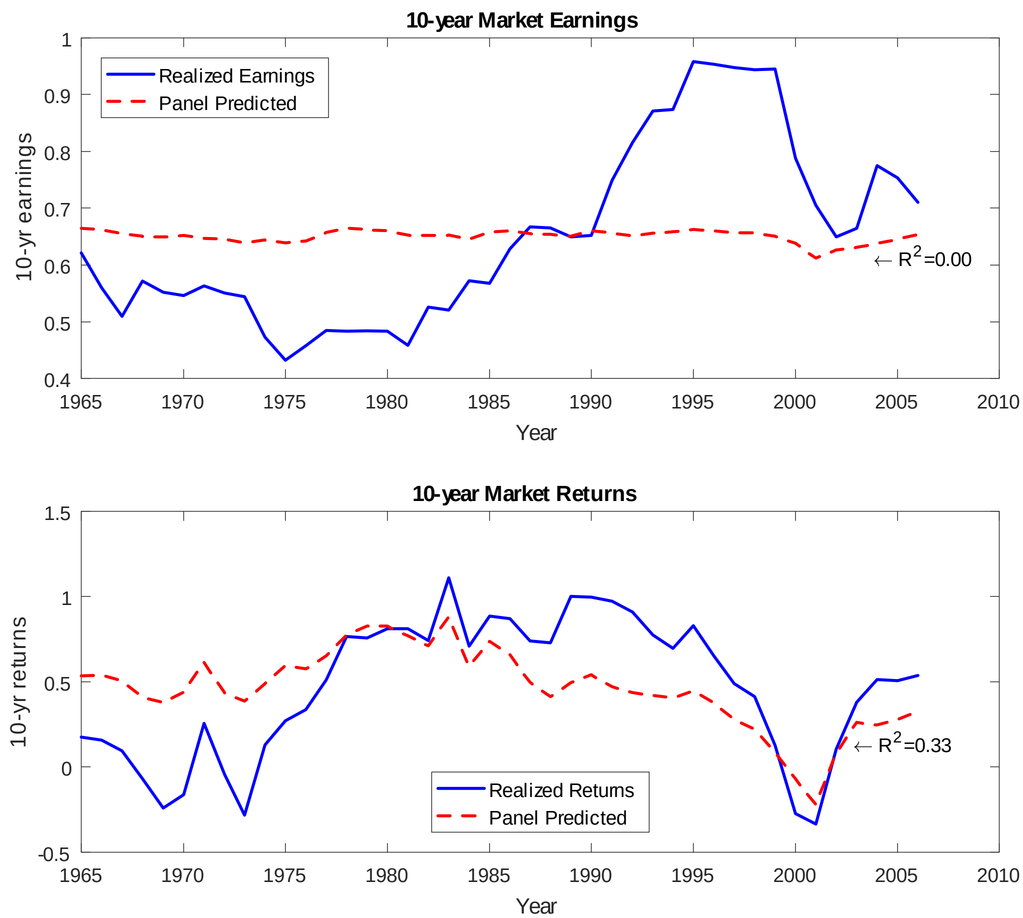


Figure 7: The top plot shows realized versus predicted 10-year log clean surplus earnings of the market portfolio. The solid blue line corresponds to realized earnings, while the red, dashed line represent predicted earnings from an alternative specification of the panel VAR (v2, where the aggregate book-to-market ratio is included in the VAR). The year on the x-axis is the year of the prediction -e.g., year 2005 corresponds to the 10-year realized earnings in 2006-2015. The bottom plot shows the corresponding for 10-year log real market returns.

Figure 8 - Predictive Power of Valuation Components in Alternative Specifications

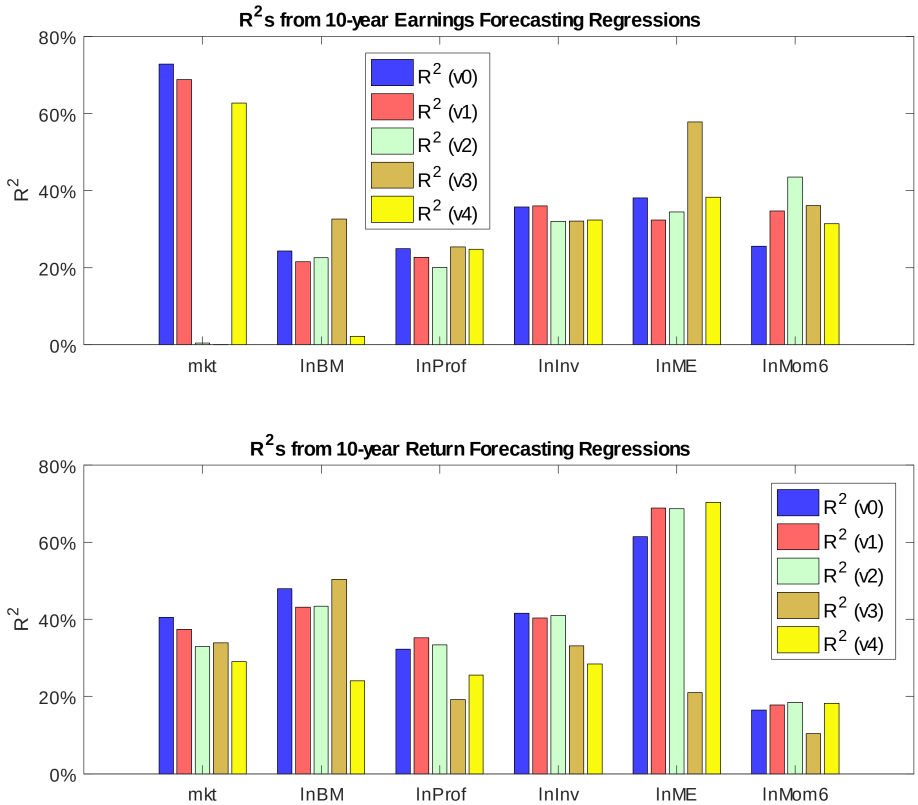


Figure 8: The figure shows the R^2 statistics from regressions forecasting either 10-year earnings (top plot) or returns (bottom plot) of portfolios. The dark blue (left) bars represent the predictive power of regressions using long-run cash flow or discount rate components of the log book-to-market ratios from the main panel VAR specification. The red bars correspond to specification v1 (simplest VAR, without interaction terms), the light green bars correspond to specification v2 (adding the aggregate book-to-market ratio to the panel VAR). The light brown bars correspond to specification v3 (adding both aggregate lnBM and interaction terms, as explained in the text). Finally, the yellow, rightmost bars correspond to specificaiton v4 (adding look-ahead-bias-free industry fixed effects). The portfolios are the market portfolio (Mkt), as well as top quintile minus bottom quintile portfolios sorted on book-to-market (B/M), profitability (Prof), investment (Inv), size (ME), and 6-month Momentum (Mom6). See the main text for details regarding the construction of the test portfolios and the corresponding cash flow and discount rate components. The sample spans the years 1964 through 2015.