Asset Pricing Anomalies and Time-Varying Expected Returns

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Abstract

I analyze the expected (as opposed to realized) returns associated with twelve well cited asset pricing anomalies using two different methods of detecting time-variation in expected returns. First, I jointly estimate the expected equity premium and the time-varying market betas of anomaly portfolios in a conditional CAPM framework and I find that nine of the twelve anomaly spread portfolios exhibit significantly higher conditional market betas in periods when the equity premium is at its highest. Second, using a regime switching model with time varying transition probabilities to estimate the joint distribution of returns on groups of up to five anomalies at a time, I find that the spread portfolios of six out of the twelve anomalies have significantly higher expected returns in recessionary and high-volatility states of the world. Overall, my findings support the hypothesis that some portion of the cross-sectional variation in average returns associated with all but the momentum and reversal anomalies is attributable to variation in risk. The strongest support is received by the size and book-to-market anomalies, while the remaining anomalies fall somewhere in between.

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1 Introduction

Over the past three decades, the empirical asset pricing literature has provided strong evidence supporting the hypothesis that average stock returns are predictable in the cross section. It appears that we can reliably predict which firms will have higher stock returns over the short to medium run using readily available firm-level characteristics such as market capitalization (Banz (1981)), book-to-market value of equity (Fama and French (1992)), past stock returns (Jegadeesh and Titman (1993), Lehmann (1990)), accruals (Sloan (1996)), and various measures of firm growth (e.g. Titman, Wei and Xie (2004), Cooper, Gulen and Schill (2008) or profitability (Fama and French (2006), Novy-Marx (2013)).[1] The puzzling finding however, is that none of these patterns of cross-sectional predictability can be explained by the leading risk-based asset pricing models, which is why they are often referred to as "anomalies".[2]

The mere existence and apparent ubiquity of these asset pricing anomalies is disconcerting, as it implies that at least one of the following holds: (1) the existing asset pricing models fail to capture a significant portion of the cross-sectional variation in firm-level risk and (2) average stock returns are not entirely driven by risk. Both of these scenarios have significant implications for many areas of financial markets, affecting, among others, investors' optimal portfolio allocation decisions, firms' cost of capital calculations, creditors' decisions to lend and the performance evaluation of fund managers. It comes as no surprise then, that an extensive research effort has been dedicated to understanding the robustness of, and possible driving forces behind these anomalies.

[1]The appendix contains a more thorough discussion of these, and several other predictability results studied in this paper.

[2]The asset pricing models I refer to here are the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) and the Fama and French (1993) three factor model, though whether the latter can be considered a risk-based model is still a matter of debate.

An initial line of debate in this line of literature was championed by Lo and MacKinlay (1990) and was centered around the possibility that the anomalies are the outcome of random chance or data snooping (i.e. the result of academics and practitioners continually searching for variables that can predict stock returns in the same dataset, for decades). However, the sheer magnitude of the t-statistics associated with many of the anomalies, coupled with several successful out-of-sample tests (Jegadeesh and Titman (2001), Griffin et al. (2003)) have caused this argument to significantly lose traction. As a result, the cross-sectional predictability of stock returns seems to be generally accepted as a statistically robust result and the debate now centers on whether the anomalies are a result of risk (not captured by existing models) or mispricing or both.

In general terms, all mispricing-based explanations are based on the idea that investors expectations are "wrong" in one way or another, in the sense that they systematically deviate from rational expectations (Cochrane (2011)). Results from the psychology literature are often invoked to justify the viability of such mistakes, and various market frictions are sometimes proposed to explain why the anomaly profits are not arbitraged away (e.g. Lakonishok et al. (1994), Sloan (1996), Barberis et al. (1998)). On the other hand, risk-based explanations fall in one of two camps. One group of studies attempts to provide economic models which tie firm risk to one or more of the anomaly characteristics mentioned above, but takes the stochastic discount factor as given (e.g. Berk et al. (1999), Gomes et al. (2003), Carlson et al. (2004)). The second group of studies proposes alternative methods of measuring risk but does not directly attempt to link risk to firm characteristics (e.g. Cochrane (1996), Jagannathan and Wang (1996), Brennan et al. (2004))

In this paper, I contribute to the body of work of the latter group of studies by exploring several methods of accounting for time variation in risk and expected returns, which the standard risk models fail to do. Focusing on twelve widely cited asset pricing anomalies, I investigate to what extent each of them is associated with cross-sectional variation in risk. Specifically, I investigate the anomalies related to firm size (Banz (1981)), book-to-market (Fama and French (1992)), momentum (Jegadeesh and Titman (1993)), short term reversal (Lehmann (1990)), asset growth (Cooper et al. (2008)), net stock issuance (Daniel and Titman (2006)), capital investment (Titman et al. (2004)), net operating assets (Hirshleifer et al. (2004)), accruals (Sloan (1996)), gross profitability (Novy-Marx (2013)), net profitability (Fama and French (2006)) and distress probability (Ohlson (1980)). Using two different methods of detecting time-series variation in conditional expected returns for each anomaly, I show evidence that these expected returns tend to increase during periods in which the expected equity premium is high and during periods in which economic conditions are poor. Below, I elaborate on my findings and their implications for the risk associated with anomaly portfolios.

In my first set of tests, following Petkova and Zhang (2005), I use a conditional version of the CAPM to simultaneously estimate the (time varying) expected market premium, the market betas of each anomaly (both as linear functions of observed macroeconomic variables) and the sensitivity of their market betas to the market premium. I find that the spread portfolios of anomalies associated with size, asset growth, capital investment, equity issuance, gross and net profitability and distress probability have significantly higher market betas in periods of high market premium (i.e. they are riskier in "bad times").[3]

While these conditional CAPM tests do suggest that many of the anomalies studied here expose the investor to significant business cycle risk, I find that this is not enough to entirely account for the large average returns associated with most of the anomaly hedge portfolios.

[3]Petkova and Zhang (2005) focus on the book-to-market anomaly.

Except for size, book-to-market and short term reversal, all of the other anomalies still exhibit significantly positive abnormal returns with respect to the conditional CAPM. This evidence is consistent with the finding in Lewellen and Nagel (2006) that, for the conditional CAPM to explain the anomalies, we would need implausibly large time-series variation in market betas. Nevertheless, the purpose of this study is not to completely rule out mispricing, but to investigate to what extent the anomalies are due to risk.

The conditional CAPM tests are restrictive from at least three points of view. First, they assume that the relationship between conditional (market) risk loadings and risk premia is linear. Second, they do not take into account the effect of time-varying conditional volatility on the risk-return relationship. Third, they restrict the stochastic discount factor to be a linear combination of the market factor and scaled versions of it. In the second part of the paper, I relax these assumptions by modeling the joint conditional distribution of (spread) returns on up to five anomaly portfolios using a regime switching model with time varying transition probabilities. In this setting, conditional expectations and conditional volatilities are both dependent on a latent binomial state variable with Markovian dynamics. To facilitate the interpretation of the two states as periods of good and bad economic conditions, I let the probabilities of transitioning from one state to another be (non-linear) functions of the lagged Leading Economic Index which is constructed by The Conference Board based on macroeconomic variables shown to have predictive power over future GDP growth.

Estimating this model on several groups of up to five anomalies, I find that in all cases, one of the states (henceforth state 1) is associated with significantly higher conditional return volatilities for all anomalies included in the model.[4] In addition, in all models estimated, a positive shock to the Leading Economic Index significantly decreases the probability of

[4]Joint estimation using more than five anomalies was made impossible by the large number of parameters involved in such models.

staying in state 1. Moreover, the estimated smoothed probabilities of being in state 1 follow a significantly countercyclical pattern, based on the ex-post NBER recession indicator. Taken together, this evidence suggests that the model does a reasonable job at capturing recessionary and high-volatility states of the economy.

With this result in mind, I use the model to analyze the behavior of expected anomaly returns over the business cycle. Specifically, I calculate conditional expected returns on the spread portfolio for each anomaly and I compare their average during periods with high likelihood of being in state 1 with their average over the rest of the sample period. I find that for the size, book-to-market, asset growth, capital investment, equity issuance, accruals and net operating assets anomalies, the spread portfolio has significantly higher expected returns when the likelihood of being in the bad state of the economy (state 1) is high. Assuming that risk premia are higher in such bad states of the world, this evidence supports the notion that the aforementioned anomalies have a significant risk component. Once again, this does not completely rule out mispricing, since expected returns could still have a non-risk component. However these results do put the burden on any study attempting to explain anomalies with mispricing arguments to also provide an explanation for why this mispricing would produce countercyclical variation in expected anomaly returns.

This paper is related to a recent strand of literature which attempts to analyze several asset pricing anomalies together, as opposed to individual anomalies in isolation (Fama and French (2008), Stambaugh et al. (2012), Hou et al. (2012)). Most notably, Stambaugh et al. (2012) study almost the same group of anomalies as I do and provide evidence that a significant part of anomaly returns is due to behavioral forces, in particular, market sentiment, coupled with short sale constraints. In contrast, the analysis of the time series properties of expected anomaly returns in this study suggests that returns of many asset pricing anomalies are also consistent with a risk explanation.

The Markov switching model used in this paper is similar to the one used by Perez-Quiros and Timmermann (2000) which in turn borrows from Gray (1996). However, this paper differs from Perez-Quiros and Timmermann (2000) in a couple of important aspects. First, they focus on the asymmetric response of small and large companies to changes in credit market conditions, while I am interested in studying how conditional expected returns of anomaly spread portfolios vary over time. Second, and as a consequence of the first point, Perez-Quiros and Timmermann (2000) model the joint distribution of returns of the long and short leg of the size anomaly, while I am interested in the way different anomalies interact, and thus model the joint distribution of groups of several different anomalies.

The rest of the paper is organized as follows. Section 2 describes the data used throughout my tests. Section 3 contains standard univariate and multivariate tests of the asset pricing anomalies. Section 4 contains the conditional CAPM tests, Section 5 presents the tests using the regime switching model and Section 6 concludes.

2 Data

This section describes the firm-level and macroeconomic-level data used to construct the variables employed in this study. The discussion of the set of asset pricing anomalies analyzed in this paper and the outline the methodology used to construct each set of anomaly portfolios are relegated to the appendix. In the interest of readability, I chose to discuss the more complex methodologies associated with the conditional CAPM and recime switching models in their respective sections.

The firm-level data needed to construct the asset pricing anomalies are taken from Wharton's CRSP and COMPUSTAT databases. Data on monthly return, price and number of shares outstanding are taken from CRSP, and returns are corrected for delisting bias as suggested by Shumway (1997).[5] All annual and quarterly accounting variables are taken from the CRSP & COMPUSTAT merged database. Following the literature, I keep only the firms with CRSP share codes 10 and 11 listed on the NYSE, AMEX and NASDAQ, and I exclude financials (SIC between 6000 and 6999) and utilities (SIC between 4900 and 4999).

When merging the three databases, for each firm, the data on annual variables from the fiscal year ending in calendar year $t-1$ are aligned with the data on monthly variables from June of calendar year t. Similarly, the data on quarterly variables from the fiscal quarter ending in calendar quarter $t-1$ are aligned with the data on monthly variables from the last month of calendar quarter t. This is standard procedure in the literature and is meant to account for the fact that accounting data is released with a lag. This merging technique is used to ensure that the accounting data has reached the public at the moment when returns are measured.

I use several economy-wide variables in my tests. Specifically, using data from the Federal Reserve Bank of St. Louis, I measure the risk-free rate as the yield on the three month Treasury bill, the term spread as the difference in yields between a ten year and a one year government bond, and the default spread as the difference in yields between corporate bonds with an Aaa Moody's rating and ones with a Baa Moody's rating. The dividend yield on the S&P 500 is taken from Robert Shiller's website.[6] Finally, I use Kenneth French's website for data on the Fama and French (1993) three factors: the market premium, the size factor (SMB) and the value factor (HML).[7]

[5] This adjustment does not materially affect any of the results.

[6] http://www.econ.yale.edu/ shiller/data.htm

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

3 Standard Tests of Asset Pricing Anomalies

I begin my analysis by verifying that the anomalies described in the previous section are robust in my sample period. The standard procedure toward this end is to show that the spread portfolio associated with each anomaly provides significantly positive average returns over the whole sample, both using realized returns as well as risk adjusted returns. I pursue several tests of this nature below.

A few clarifications are in order before proceeding to the main tests of this section. First, due to restricted data availability on the quarterly COMPUSTAT file, the quarterly ROA and O-score anomalies are calculated starting in June 1972. All the other anomalies are calculated starting in June 1965. The sample extends to June of 2012.

Second, I provide summary statistics for each sorting variable in Table 1. One interesting observation emerging from this table is that there is a significant degree of variability in each one of the anomaly variables. This implies that the long and short portfolios contain firms that differ greatly with respect to the variable on which they were sorted, not only from each other but also from the rest of the firms not included in the hedge portfolio.

Finally, to verify that we do not have instances in which two or more anomaly characteristics are so highly correlated that they basically produce the same hedge portfolios, in Table 2 I present the matrix of correlation coefficients for all pairs of sorting variables. The correlations are generally small, with two notable, but not surprising exceptions: the growth-related variables (asset growth, capital investment, equity issuance, accruals and net operating assets) have correlations of up to 0.58 and the distress probability variable (O-score) is strongly negatively correlated with firm size and net profitability. While these results imply that there may be significant informational overlap between some of the sorting variables, they also suggest that each anomaly characteristic is likely to contain a nonnegligible amount of unique information.

In Table 3 I analyze the performance of the long, short and spread anomaly portfolios over the entire sample period. Panels A and B present results based on equal-weighted and value-weighted raw (realized) returns. The first three columns show sample averages and t-statistics of the time series of monthly portfolio returns. The results show that all anomalies except for the value-weighted size and short-term reversal are associated with significantly positive realized stock returns. For equal-weighted portfolios, average realized returns on the spread portfolio range from 0.178% per month for the O-score anomaly to 1.377% per month for the momentum anomaly. The value-weighted spread portfolios produce returns between 0.35% per month for the size anomaly and 1.388% per month for the momentum anomaly.

Columns 4 though 7 in Table 3 apply only to the spread portfolio. The annualized Sharpe ratios in column 4 suggest that the anomaly mean returns are high relative to their standard deviation. As an additional way to assess the performance of the spread portfolios, in the last three columns of the table I calculate the cumulative annual returns for each anomaly, from July of year t to June of year $t+1$, for each year t in the sample and report the percentage of years in which this annual return was positive as well as the mean and median of the annual returns during periods when they are negative. A visual depiction of the annual anomaly returns is provided in Figures 7.1 and 7.2.

The results show that the anomalies produce positive returns in a large proportion of the years. On the other hand, the last two columns of Table 3 show that, when they do lose money, many of the anomalies produce very large negative returns. For example, while the momentum anomaly promises the highest average returns of all anomalies, it loses money in about a quarter of the years in the sample, averaging negative returns of about 15% to 18%

in those years. This piece of evidence is suggestive of the fact that the positive performance of the anomalies over the entire sample masks considerable time series variation in returns, which commands further investigation if we are to understand the risks associated with these investment strategies. The three main tests in this paper are designed specifically to explore this issue.

Panel C of Table 3 reports risk adjusted returns for the spread anomaly portfolios, where the risk adjustment is made using either the CAPM (first two columns), the Fama and French (1993) three factor model (columns three and four), or a four factor model obtained by augmenting the Fama and French (1993) model with a "momentum factor" as in Carhart (1997) (the last two columns). These risk adjustments are made by regressing the time series of monthly return of each spread portfolio on a constant and the risk factors proposed by the asset pricing model employed. The numbers reported in the table are the intercepts from these regressions and their t-statistics. In line with the previous literature, the results show that, except for size and BM, the anomalies produce significantly positive risk-adjusted returns over the full sample.

4 Tests Based on the Conditional CAPM

One potential reason why the CAPM and the Fama and French (1993) models fail to explain the cross-sectional variation in average returns associated with the anomaly variables is that these models do not account for the fact that both risk premia as well as risk loadings may vary over time and, importantly, may covary with each other. To see why this is the case, consider a conditional version of the CAPM:

$$E_t[R_{i,t+1}] = \gamma_t \beta_{i,t} \tag{1}$$

where

$$\beta_{i,t} \equiv Cov_t[R_{i,t+1}, R_{m,t+1}]/Var_t[R_{m,t+1}] \tag{2}$$

is the time-varying risk loading of asset i on the market and $\gamma_t = E_t[R_{m,t+1}]$ is the time-varying expected market premium. Following Jagannathan and Wang (1996), taking conditional expectations of equation 1 yields

$$E[R_{i,t+1}] = \bar{\gamma}\bar{\beta}_i + Cov[\gamma_t, \beta_{i,t}] = \bar{\gamma}\bar{\beta}_i + Var[\gamma_t]\varphi_i \tag{3}$$

where $\bar{\gamma} \equiv E[\gamma_t]$ is the average market excess return, $\bar{\beta}_i \equiv E[\beta_{i,t}]$ is asset i's average market beta, and $\varphi_i \equiv Cov[\beta_{i,t}, \gamma_t]/Var[\gamma_t]$ is a measure of how much the conditional market premium and the conditional market beta covary with each other.

It can easily be seen from equation 3 that for any given anomaly, the difference in average returns between the long and short portfolio can still be consistent with risk even if the long portfolio does not have a higher average risk loading than the short portfolio ($\bar{\beta}_i$), as long as the long portfolio has a conditional risk loading $\beta_{i,t}$ that covaries more with the conditional market premium γ_t (i.e. a higher φ_i).

Petkova and Zhang (2005) propose a methodology to jointly estimate the three key ingredients in the above argument (the conditional market premium (γ_t), the conditional market beta ($\beta_{i,t}$), and beta-premium sensitivity (φ_i)) in order to test whether the conditional CAPM can explain the value premium. I apply their methodology to all of the twelve anomalies studied in this paper.

Following closely the notation in Petkova and Zhang (2005), I estimate the expected market premium using a regression of realized excess market returns ($R_{m,t+1}$) on lagged values of several standard macroeconomic variables used in the time-series predictability literature:

$$R_{m,t+1} = \delta_0 + \delta_1 DIV_t + \delta_2 DEF_t + \delta_3 TERM_t + \delta_4 TB_t + \epsilon_{m,t+1} \tag{4}$$

These variables are the dividend yield on the S&P 500 index (DIV), the default premium (DEF), the term premium ($TERM$) and the yield on the one month Treasury bill (TB), all measured as described in Section 2. The estimate of the expected market premium is given by the fitted value from the above regression:

$$\hat{\gamma}_t = \hat{\delta}_0 + \hat{\delta}_1 DIV_t + \hat{\delta}_2 DEF_t + \hat{\delta}_3 TERM_t + \hat{\delta}_4 TB_t \tag{5}$$

To estimate the conditional market beta for any particular anomaly hedge portfolio, I regress the monthly returns of that portfolio ($R_{i,t+1}$) on a constant and the contemporaneous realized excess market return, letting the market beta depend linearly on the lagged value of same predictor variables used in estimating the expected market premium:

$$R_{i,t+1} = \alpha_i + (\beta_{i,0} + \beta_{i,1} DIV_t + \beta_{i,2} DEF_t + \beta_{i,3} TERM_t + \beta_{i,4} TB_t) R_{m,t+1} + \varepsilon_{i,t+1} \tag{6}$$

The conditional market betas are calculated using the estimated coefficients from equation 6:

$$\hat{\beta}_{i,t} = \hat{\beta}_{i,0} + \hat{\beta}_{i,1} DIV_t + \hat{\beta}_{i,2} DEF_t + \hat{\beta}_{i,3} TERM_t + \hat{\beta}_{i,4} TB_t \tag{7}$$

Finally, the beta-premium sensitivity of each portfolio is estimated by regressing its estimated conditional market beta on the estimated conditional market premium:

$$\hat{\beta}_{i,t} = c_i + \varphi_i \hat{\gamma}_t + \eta_{i,t} \tag{8}$$

Since both the $\hat{\beta}_{i,t}$ and the $\hat{\gamma}_t$ variables in equation 8 are estimated using the same instruments, the measurement errors embedded in them are likely to be correlated, which would bias our inferences. To address this issue, Petkova and Zhang (2005) propose estimating the three quantities of interest $\hat{\gamma}_t$, $\hat{\beta}_{i,t}$ and φ_i simultaneously via the generalized method of moments (GMM), using the set of orthogonality conditions from equations 4, 6 and 8 as moment conditions:

$$E[(R_{m,t+1} - \mathbf{Z}_t\boldsymbol{\delta})\mathbf{Z}_t'] = 0 \tag{9}$$

$$E[[R_{i,t+1} - \alpha_i - (\mathbf{Z}_t R_{m,t+1})\mathbf{b}_i](\imath\ \mathbf{Z}_t R_{m,t+1})'] = 0 \tag{10}$$

$$E[(\mathbf{Z}_t\mathbf{b}_i - c_i - \varphi_i\mathbf{Z}_t\boldsymbol{\delta})(\imath\ \mathbf{Z}_t\boldsymbol{\delta})'] = 0 \tag{11}$$

where $\mathbf{Z}_t \equiv [\imath\ \mathrm{DIV}_t\ \mathrm{DEF}_t\ \mathrm{TERM}_t\ \mathrm{TB}_t]$ is the set of instruments ($\imath$ is a vector of ones), $\boldsymbol{\delta} = [\delta_0\ \delta_1\ \delta_2\ \delta_3\ \delta_4]'$ is the set of coefficients from equation 4, and $\mathbf{b}_i \equiv [b_{i,0}\ b_{i,1}\ b_{i,2}\ b_{i,3}\ b_{i,4}]'$ is the set of coefficient from equation 6.

Before moving on to the results based on this GMM procedure, in the first three columns of Table 4, I report some non-parametric estimates of the correlation between conditional betas and the conditional market premium. To do so, I split the periods in my sample according to their estimated market premia ($\hat{\gamma}_t$) and designate the highest 20% as "Trough" and the lowest 20% as "Peak". The first two columns of the table present averages of the conditional market beta estimates ($\hat{\beta}_{i,t}$) of the spread portfolio, calculated separately over periods in "Trough" and in "Peak". Most important for my analysis is the difference between these averages, which is reported in column three. Consistent with the idea that the anomalies become riskier during bad economic conditions, the results in this column show that many of the anomaly spread portfolios have significantly higher market betas during periods of high market premia ("Trough") than during periods with low market premia ("Peak"). For equal-weighted portfolios (Panel A), this is the case for the anomalies based on size, BM, equity issuance, gross profitability and ROA. For value-weighted portfolios, this is the case for all but the momentum, reversal, accruals and NOA anomalies.

Columns four through six in Table 4 contain the beta-premium sensitivities (φ_i) for the long, short and spread portfolios obtained from the GMM estimation. While the signs on these estimates are consistent with the ones found using the non-parametric procedure described above, the t-statistics are almost always insignificant.[8] Moreover, in the last column of the table, I present the GMM estimates of the abnormal returns of each spread portfolio (α_i in equation 6). While these abnormal returns are always lower than the ones obtained from the static CAPM, in most cases they remain statistically significant. The only exceptions are the equal-weighted size and O-score anomalies and the value-weighted size and BM anomalies. My results are consistent with Petkova and Zhang (2005) and Lewellen and Nagel (2006), as they suggest that the conditional CAPM goes in the right direction in explaining the cross-sectional variation in average returns but does not completely explain it away.

5 Tests Based on the Markov-Switching Model

In this section, I investigate if anomaly spread portfolios become riskier during bad states of the world by modeling the conditional distribution of anomaly returns using a regime switching model with Markovian dynamics, similar in spirit to Hamilton (1989). The goal is to design the model so as to induce the latent state variable to capture switches between periods of good and bad economic conditions, and to test if conditional expected anomaly returns are different across these two states of the world. Under the reasonable assumption that risk premia increase during poor economic conditions and in the absence of theories

[8]The only exception is the BM spread portfolio which, consistent with Petkova and Zhang (2005), has a conditional market beta which is significantly positively related to the expected market premium.

which predict mispricing patterns with a countercyclical behavior, this would allow us to conclude that anomalies are at least to a significant extent due to (time-varying) risk.

The joint conditional expectation of the long and short portfolios is modeled as a function of the same lagged economic variables used to predict the market premium in the previous conditional CAPM tests, but the coefficients on these variables are now allowed to depend on a latent state $s_t \in \{1, 2\}$:

$$\mathbf{R}_t = \boldsymbol{\beta}_{0,s_t} + \boldsymbol{\beta}_{1,s_t} DIV_{t-1} + \boldsymbol{\beta}_{2,s_t} DEF_{t-1} + \boldsymbol{\beta}_{3,s_t} TERM_{t-1} + \boldsymbol{\beta}_{4,s_t} RF_{t-1} + \boldsymbol{\varepsilon}_t \tag{12}$$

where $\mathbf{R}_t = (R_t^L, R_t^S)'$ is the vector of realized returns on the long (L) and short (S) portfolios at time t, and $\boldsymbol{\beta}_{k,s_t} = (\beta^L_{k,s_t}, \beta^S_{k,s_t})'$ are the state dependent sensitivities of expected returns with respect to the macroeconomic variable $k \in \{DIV, DEF, TERM, TB\}$.

The joint conditional volatility of the long and short portfolio returns is also modeled as a function of the latent state variable s_t, allowing this state to possibly capture transitions between periods of high and low stock return volatility:

$$\boldsymbol{\varepsilon}_t \sim N(0, \Omega_{s_t}) \tag{13}$$

with

$$\Omega_{s_t} = \begin{bmatrix} \sigma^2_{L,s_t} & \xi_{s_t}\sigma_{L,s_t}\sigma_{S,s_t} \\ \xi_{s_t}\sigma_{L,s_t}\sigma_{S,s_t} & \sigma^2_{S,s_t} \end{bmatrix} \tag{14}$$

where σ^2_{L,s_t} and σ^2_{L,s_t} are the conditional variances of the returns on the long and short portfolios and ξ_{s_t} is their conditional correlation (also state dependent).

To further facilitate the interpretation of the latent state s_t as periods of high and low marginal utility of consumption, I deviate from the classical model of Hamilton (1989) and, following Gray (1996) and Perez-Quiros and Timmermann (2000), I allow state transition probabilities to depend on the Leading Economic Index (LEI) provided by The Conference Board, which is particularly designed to predict changes in economic business conditions. Specifically, the transition probabilities are given by:

$$p_t = prob(s_t = 1|s_{t-1} = 1) = \Phi(\pi_0 + \pi_1 \Delta LEI_{t-2}) \tag{15}$$

$$q_t = prob(s_t = 2|s_{t-1} = 2) = \Phi(\pi_0 + \pi_2 \Delta LEI_{t-2}) \tag{16}$$

where ΔLEI_{t-2} is the log annual change in the Leading Economic Indicator, lagged twice. The parameters in the conditional mean, volatility and transition probability equation are estimated via MLE, using a modified version of the Hamilton (1989) filter as shown by Gray (1996).

The results give us at least three reasons to believe that the model indeed captures good and bad states of the economy. First, for all anomalies, one of the states (henceforth state 1) is always associated with significantly higher volatility parameters for both the long and short portfolios. Second, for almost all anomalies, the transition probability parameter π_1 is negative, suggesting that when the Leading Economic Index predicts improving business conditions, the likelihood of staying in the high volatility state decreases significantly [9]. Third, using the model's parameter estimates, I calculate the probabilities of being in state 1 at every point in the sample (often referred to as the smoothed probabilities), and find that it exhibits strong countercyclical properties, based on the ex-post NBER recession indicator. A visual depiction of this latter result is presented in Figures 3 and 4. Overall, these three pieces of evidence suggest that state 1 is a mixture of a high-volatility state and a recessionary state. For brevity and for lack of a better term, I will henceforth refer to it as the "bad state".

Given this result, I test whether expected anomaly returns are higher in periods with

[9] These results are not tabulated

higher probabilities of being the state 1 (the bad state). To do so, I first calculate expected returns for both the long and short portfolios as

$$E_{t-1}[R_t^i] = E_{t-1}[\hat{\beta}^i_{0,s_t}] + \sum_{k=1}^{4} E_{t-1}[\hat{\beta}^i_{k,s_t}] M_{k,t-1} \tag{17}$$

where i stands for either the long or the short portfolio and the $M_{k,t-1}, k \in \{1, 2, 3, 4\}$ are the four macroeconomic variables in the conditional mean equation. It is important to note that the conditional expectiations in equation 17 are calculated using predictive, not filtered or smoothed probabilities, meaning that they depend only on the information available at time $t-1$. These probabilities are easily obtained as a byproduct of the Hamilton (1989) filter. Once the expected returns on the long and short portfolio are calculated, I take the difference between them to obtain the expected returns on the spread portfolio.

To get a sense for the cyclical attributes of these estimated expected returns, in Figures 5 and 6, I superimpose them onto the NBER recessions indicator. A quick glance at these graphs suggests that for most anomalies, the expected return on the spread portfolio increases considerably in most recessions, especially for value-weighted anomalies (Figure 6). This is consistent with the idea that anomaly spread portfolios are more risky in poor economic conditions.

Next, I perform a more formal test of the casual observations from Figures 5 and 6. To this end, I split the sample into periods in which the smoothed probability of being in state 1 is over 50% ("HI") and periods in which it is below 50% ("LO") and calculate averages of the estimated expected spread portfolio returns, separately for "HI" and "LO" periods. Table 8 presents these averages for equal-weighted and value-weighted anomaly portfolios (column 1, 2, 4 and 5), as well as the difference between them (columns 3 and 6).

The results confirm the existence of significant time series variation in anomaly expected returns. In periods with a high likelihood of being in the bad state ("HI"), many anomalies experience expected returns that are two to three times larger than in the periods when the bad state is not likely. Using equal-weighted portfolios this holds for the anomalies based on size, reversal, capital investment and NOA. Using value-weighted portfolios, this holds for the anomalies based on size, BM, asset growth, capital investment, accruals, and NOA. Once again, if one is willing to entertain the assumption that risk premia are larger during bad economic conditions, this evidence suggests that the anomaly portfolios are exposed to significant business cycle risk.

A potential concern with the previous set of results is that we have not yet imposed the restriction that the bad state occurs simultaneously for all anomalies. Hence, in principle, each anomaly could be identifying different types of states. For example, given that the coefficient on the Leading Economic Index in the transition probability equation is not always negative and significant, it may the case that for some anomalies, the states identified may not have a business cycle component and may just be high- and low - volatility states. To impose the restriction that all anomalies are identifying the same state, we would need to jointly estimate the above Markov switching model using all the anomalies together. Unfortunately the number of parameters involved in doing so quickly becomes unmanageable, even if we restrict ourselves to fewer predictive variables in the conditional mean equation. As a consequence, I will restrict myself to a joint estimation which uses several, but not all of the anomalies at the same time.

To begin with, I estimate a version of the above Markov switching model based on spread-portfolio returns of four anomalies: size, book-to-market, asset growth and gross profitability. I chose the size and book-to-market anomalies because of their prolific use as part of the Fama and French (1993) three-factor model and the asset growth and gross profitability anomalies because of the new evidence by Hou, Xue and Zhang (2012) that and investment factor and a profitability factor perform well in explaining the cross-section of stock returns.[10] To be specific, I estimate a model in which the transition probabilities are still given by equations 15 and 16, and the conditional means and conditional volatilities are given by:

$$\mathbf{R}_t = \boldsymbol{\beta}_{0,s_t} + \boldsymbol{\beta}_{1,s_t} DIV_{t-1} + \boldsymbol{\varepsilon}_t \tag{18}$$

$$\boldsymbol{\varepsilon}_t \sim N(0, \Omega_{s_t}) \tag{19}$$

where $\mathbf{R}_t = (R_t^{SZ}, R_t^{BM}, R_t^{AG}, R_t^{GP})'$ is the vector of realized returns on the spread-portfolios for the size (SZ), book-to-market (BM), asset growth (AG) and gross profitability (GP) anomalies while Ω_{s_t} is the 4x4 variance-covariance matrix of these spread-portfolio returns in state $s_t \in \{1, 2\}$. Notice also how the set of predictive variables in the conditional mean equation was reduced to the dividend yield in order to keep the number of parameters to a manageable.[11] I chose the dividend yield as it is arguably the most often used variable in the time-series return predictability literature.

The results from estimating the above model are shown in Table 6. The bottom part of the table contains the parameter estimates for the transition probabilities. The negative and significant coefficient on the Leading Economic Index (LEI) in state 1 suggests that the two regimes have a business cycle component with state 1 being a recessionary state. In addition, the last two columns in the top part of the table indicate that the volatility parameters were estimated very precisely and that state 1 is associated with significantly higher return volatilities than state 2. Thus, once again we can conclude that state 1 is a mixture of a recessionary state and a high-volatility state.

[10] The investment factor in Hou et al. (2012) is based on asset growth and their profitability factor is based on ROE. It should be noted that all my results remain qualitatively similar if I use CAPX and ROA instead of asset growth and gross profitability for the joint estimation.

[11] Even in this restricted model, we have to estimate 40 parameters.

Moving on to the parameters in the conditional mean equation, we notice a couple of interesting findings. First, for size and book-to-market, the coefficients on the dividend yield are positive and larger in the bad state. Even though the coefficients are only significant in the good state, using a Likelihood Ratio test I confirm that the coefficients are significantly different going from one state to the other, for both size and book-to-market, with a p-value of less than 0.001. This implies that both the size and book-to-market spread portfolios are significantly more sensitive to changes in the dividend yield during recessionary/high-volatility periods than during expansionary/low-volatility periods. Coupled with the evidence that variation in the dividend yield is almost entirely driven by movement in risk premia (e.g. Cochrane (2011)) this suggests that the size and book-to-market anomalies expose investors to business-cycle risk. On the other hand, this result does not hold for the asset growth and gross profitability spread returns, which casts some doubt on the suggestion by Hou et al. (2012) to use investment and profitability spread portfolios as risk factors.

In my final set of tests, I incorporate each of the remaining eight anomalies into the above model, one by one. As a result, I estimate eight different Markov switching models, each based on five anomalies, with size, book-to-market, asset growth and gross profitability being common to all eight models. This commonality is meant to increase the likelihood that we are detecting the same states across models, while the fact that each model uses five anomalies jointly assures us that at least those five anomalies experience switches between states at the same time. The goal is to test whether our previous finding that expected anomaly returns are higher in bad states of the world (Table 5), holds under this more robust setting.

As a way of verifying whether our eight models truly capture the same regimes, I first calculate the time-series of smoothed probabilities of being in state 1, for each of the eight models described above. I find that the pair-wise correlations between these probabilities range from 0.82 to 0.93 which suggests that while not perfectly identical, the regimes identified by the new Markov switching models exhibit a very high degree of overlap.

In Table 7 I present the parameters of interest from the transition probability equation and the conditional volatility equation for each model. Each row corresponds to one of the eight Markov switching models described above, and the first column lists the anomalies that we cycle through to form each of these models. For example, the row labeled "Momentum" presents estimates from the model base on size, book-to-market, asset growth, gross profitability and momentum. Columns two and three contain the parameter estimates for the Leading Economic Index (LEI) which governs the transition probabilities. In every one of the eight models, the coefficient on LEI in state 1 is negative and significant (though marginal when using Accruals), implying that an increase in expectations about future GDP has a strongly negative impact on the likelihood of remaining in state 1.

The last two columns of Table 7 present the conditional volatility parameters of only the anomaly that is new to each model. For example, the last two columns on the first row tell us that when we estimated the Markov switching model using size, book-to-market, asset growth, gross profitability and momentum, the variance estimates for momentum returns were 0.0157 in state 1 and 0.0016 in state 2. For brevity, the variance estimates of the four anomalies which are common to all models are not presented, but we can report that once again, across the board, conditional return volatilities are significantly higher in state 1 and state 2. Taken together, these pieces of evidence support the idea that state 1 is a recessionary, high-volatility state in each one of the eight models estimated.

Finally, in Table 8, we repeat the tests from Table 5 which compare the expected returns of each anomaly across the two states. Similarly to Table 7, each row in Table 8 contains estimates from a different jointly-estimated Markov switching model. After estimating each model, we calculate the time series of expected returns for each anomaly in the model (using equation 17). Then the sample period is split into months during which the predictive probability of being in state 1 is higher than 50% ("HI") and periods during which it is lower ("LO") and average expected returns are calculated for both of these periods, for each anomaly. The table reports differences between these average expected returns during "HI" and during "LO" times ("HI"-"LO"). As an example, the first row of the table suggests that when we estimate the model using momentum, size, book-to-market, asset growth and gross profitability, the average expected returns when state 1 is likely is 1.558% per month lower than when state 1 is not likely. The analogous number for the size anomaly in this first model would be 1.352% and so on.

Looking first at the four anomalies that are common to all of the eight models (columns three through six), we notice that expected returns on size, book-to-market and asset growth are all significantly higher when the bad state is more likely than when it is not, regardless of what the fifth anomaly in the model is. In contrast, the expected returns of the gross profitability anomaly do not depend significantly on what the state is projected to be. Focusing now on the anomalies that change across models (column 2), we find that expected returns for the capital investment, accruals and NOA anomalies are significantly higher when the bad state is more likely but this is not the case for the momentum, reversal, issuance, ROA and O-score anomalies. Overall, these findings are consistent with the ones from the anomaly-by-anomaly estimation (Table 5) and they suggest that the size, book-to-market, asset growth, capital investment, accruals and NOA anomalies are riskier during the recessionary, high-volatility state.

6 Conclusion

In this paper I analyze twelve well cited patterns of cross-sectional predictability in stock returns which do not seem to be explained by variation in risk. In particular, I use several recent methodological advances in the field of empirical asset pricing to analyze the expected (as opposed to realized) returns associated with these so called asset pricing anomalies.

In an initial set of tests, I use the methodology proposed by Petkova and Zhang (2005) to jointly estimate the expected equity premium and the time-varying market betas of spread portfolios associated with each anomaly. I find that eight of the twelve value-weighted anomaly spread portfolios (all but momentum, reversal, accruals and NOA) exhibit significantly higher conditional market betas in periods when the equity premium is at its highest. However, this is not enough to capture all of the cross-sectional variation in average return associated with the anomaly portfolios.

Second, I use a regime switching model with time varying transition probabilities to estimate the joint distribution of returns on the long and short portfolio for each anomaly in an attempt to use the information in the conditional expectations and volatilities of the anomaly portfolios to identify states of the world with good and bad economic conditions. I find that the model robustly identifies a high volatility state and show evidence that the value-weighted spread portfolios of seven out of the twelve anomalies (size, book-to-market, asset growth, capital investment, equity issuance, accruals, NOA) have significantly higher expected returns when the likelihood of being in the high volatility state is highest.

Finally, in order to alleviate the concern that different anomalies may be identifying different states, I use the same type of regime switching model to estimate the joint distribution of groups of five anomalies at a time. I find that six out of the above seven anomalies (size, book-to-market, asset growth, capital investment, accruals, NOA) exhibit countercyclical expected returns. Overall, my results support the hypothesis that a significant portion of the cross-sectional variation in average returns associated with all but the momentum and reversal anomalies is attributable to variation in risk. The evidence is particularly strong for the size and book-to-market anomalies and more mixed for the remaining eight anomalies.

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A Constructing Anomaly Portfolios

My portfolio formation procedure is fairly standard. One important issue is that the firm characteristics on which I focus in this paper come at different frequencies. The momentum and short-term reversal variables are measured monthly. For these anomalies, I form portfolios at the end of every month t, hold them for one month and then rebalance them at the end of month $t+1$. The net profitability and distress probability variables are measured quarterly. For these two anomalies, I form portfolios at the end of every calendar quarter t, using values from the fiscal quarter ending in calendar quarter $t-1$. These portfolios are held for three months and are rebalanced at the end of calendar quarter $t+1$. The rest of the variables: market capitalization, book-to-market, capital investment, net equity issuance, asset growth, net operating assets, accruals, and gross profitability are all measured annually. For these anomalies, I form portfolios at the end of June in each calendar quarter t, based on values from the fiscal year ending in calendar year $t-1$. The portfolios are held for twelve months and rebalanced at the end of June in calendar quarter $t+1$.

In each formation period I sort firms into deciles based on how they rank with respect to the anomaly variable in question. Firms ranking above the 90^{th} percentile are assigned to decile 10 and firms ranking below the 10^{th} percentile are assigned to decile 1. However, since some of the anomaly variables are positively correlated with average return and others are negatively correlated with average returns, constructing the spread portfolio for some anomalies requires buying firms in decile 10 and shorting firms in decile 1, while for others it requires the opposite. To alleviate any confusion in this regard, throughout the paper I refer to the extreme decile portfolios not as "decile 1" and "decile 10" but as the "long" and "short" portfolios, depending on whether the anomaly hedging strategy calls for buying or shorting that particular portfolio. Explicitly, for the book-to-market, momentum, gross profitability and net profitability, the long portfolio is decile 10 and the short portfolio is decile 1, while for the rest of the anomalies it is the opposite. Naturally then, using this alternative terminology, the hedge portfolio is always constructed by buying the long portfolio and shorting the short portfolio.

A.1 Size

Early studies, going back as far as Banz (1981), Reinganum (1981) and Basu (1983), have shown that firms with small market capitalization experience significantly higher average stock returns than firms with large market capitalization without having significantly higher market betas. The sorting variable for this anomaly is measured as the natural logarith of the firm's stock price times the number of shares outstanding at the end of June.

A.2 Book-to-market

Investment professionals as well as a academics have long pointed out that firms with low prices relative to fundamental measures of value such as earnings, cash flows or book equity significantly outperform firms with high price to value ratios.[12] Further work by Fama and French (1993) shows that the predictive power of all of these valuation ratios seems to be captured parsimoniously by the ratio of book to market value of equity (henceforth BM). More importantly, firms with high BM (also referred to as 'value' firms) earn significantly higher stock returns than firms with low BM ('growth' firms) without exposing the investor to significantly higher market risk. This failure of the (static) CAPM is often referred to as the 'value' anomaly.

The BM ratio in calendar year t is measured as the book value of equity in fiscal year ending in $t-1$ divided by the market value of equity in December of $t-1$. The book

[12]See for example Graham et al. (1934), Dreman (1977), Basu (1977) and Fama and French (1992)

value of equity is measure as total assets minus total liabilities minus deferred taxes and investment tax credit (if available) minus the value of preferred stock(if available). The value of preferred stock is measured as either the liquidating value, redemption value of carrying value of preferred stock, in order of availability.

A.3 Momentum and Reversal

Several studies have shown that, in the short to medium term (one to twelve months), past stock returns have predictive power over future stock returns. Most prominently, Jegadeesh and Titman (1993) document what has later been termed the "momentum effect" in stock prices. This refers to the finding that firms with the highest stock returns in the past three to twelve months have significantly higher risk adjusted stock returns in the subsequent one to twelve months than firms with the lowest past returns. This finding has arguably received the most research attention out of all the asset pricing anomalies and has faired very well against a battery of robustness tests (Fama and French (2008), Griffin et al. (2003)).

There are several methods of constructing hedge portfolios based on this finding, depending on how far back we want look to measure past stock returns and how often we rebalance the portfolio. Additionally, one must also decide on whether to include a gap between the period used to measure past stock returns and the holding period, so as to insure that results are not driven by non-synchronous trading and other market microstructure considerations (Jegadeesh and Titman (1993)). Following Fama and French (2008), I construct momentum portfolios at the end of every month t by sorting firms into deciles based on their cumulative stock returns during months $t-12$ to $t-1$ (hence, I do skip a month between the holding period and the measurement period). The portfolios are held for one month and then rebalanced.

In contrast to the aforementioned evidence that in the medium run, past returns are positively related to future returns, Jegadeesh (1990) and Lehmann (1990) find that in the short run (one month), past returns are negatively related to future returns. Consequently, the hedge portfolio associated with this "reversal effect" is formed at the end of each month t by sorting stocks into deciles based on their return during that month.

A.4 Capital investment

Titman et al. (2004) and Xing (2008) find that several measures of past capital investment are negatively related to future risk-adjusted stock returns. I measure past capital investment at the end of June in each calendar year t, as the change in property plant and equipment from fiscal year ending in $t-2$ to fiscal year ending in $t-1$, divided by the firm's total assets at the end of the fiscal year ending in $t-2$.

A.5 Equity issuance

Based on prior evidence that firm-level stock repurchases are followed by high stock returns (Ikenberry et al. (1995)) and stock issues are followed by low stock returns (Loughran and Ritter (1995)), Daniel and Titman (2006) and Pontiff and Woodgate (2008) show evidence that the change in firms' total number of share outstanding is negatively related to their future stock returns. I measure firms' net stock issuance at the end of June in each calendar year t as the log change in their split-adjusted shares outstanding from the fiscal year ending in $t-2$ to fiscal year ending in $t-1$.

A.6 Net operating assets

Hirshleifer et al. (2004) find that a measure of net operating assets, measured as total operating assets minus total operating liabilities scaled by the average total assets over the past two years, is strongly negatively associated with future stock returns. More precisely, their net operating assets variable is calculated in June of calendar year t as

$$NOA_t = \frac{OA_{t-1} - OL_{t-1}}{(TA_{t-1} + TA_{t-2})/2}$$

with

$$OA_{t-1} = TA_{t-1} - CSI_{t-1}$$

$$OL_{t-1} = TA_{t-1} - DCL_{t-1} - LTD_{t-1} - MI_{t-1} - PS_{t-1} - CE_{t-1}$$

where, dropping the subscripts, NOA is net operating assets, OA is operating assets, OL is operating liabilities, TA is total assets, CSI is cash and short-term investments, DCL is debt in current liabilities, LTD is long-term debt, MI is minority interest, PS is preferred stock and CE is common equity.

A.7 Asset growth

Motivated by the aforementioned evidence that various measures of firm growth seem to be negatively related to future stock returns, Cooper et al. (2008) investigate whether an all-encompassing measure of growth in total assets also has predictive power in the cross-section of stock returns. They find that indeed, the percentage growth in firm total assets from fiscal year ending in $t-2$ to fiscal year ending in $t-1$ is strongly negatively associated to the firm's stock returns from July t to June $t+1$. Moreover, they convincingly show that the predictive power of the asset growth variable can not be attributed to any one component of total assets, total liabilities or shareholder's equity, which includes the previous three anomaly variables.

A.8 Accruals

Sloan (1996) finds evidence that firms with high accruals earn significantly lower risk-adjusted stock returns than firms with low accruals. The accrual variable is measured in June of calendar year t as the change in noncash working capital minus the change in depreciation, all scaled by the average total assets over the past two years:

$$ACC_t = \frac{(\Delta CA_{t-1} - \Delta CSH_{t-1}) - (\Delta CL_{t-1} - \Delta STD_{t-1} - \Delta TP_{t-1}) - \Delta DEP_{t-1}}{(TA_{t-1} + TA_{t-2})/2}$$

where, dropping the subscripts, ACC is accruals, CA is current assets, CSH is cash, CL is current liabilities, STD is short term debt, TP is taxes payable, DEP is depreciation, TA is total assets and Δ is the change operator, with all changes being taken from fiscal year ending in $t-2$ to fiscal year ending in $t-1$.

A.9 Profitability

Recent studies have shown that two different measures of firm profitability are significantly positively related to future stock returns. Novy-Marx (2013) uses an annual measure of gross profitability while Fama and French (2006) use a quarterly measure of net profitability (henceforth ROA) and they show that more profitable firms have significantly higher future stock returns than less profitable firms. The gross profitability portfolios of Novy-Marx (2013) are formed at the end of June of every calendar quarter t using decile cutoffs based on

$$GP_t = \frac{S_{t-1} - COGS_{t-1}}{TA_{t-1}}$$

where GP is gross profitability, S is sales, $COGS$ is cost of goods sold, and TA is total assets. The net profitability portfolios of Fama and French (2006) are formed at the end of every calendar quarter t, using decile cutoffs based on

$$ROA_t = \frac{NI_{t-1} - PD_{t-1} + DT_{t-1}}{TA_{t-1}}$$

where ROA is return on assets, NI is net income, PD is preferred dividends, DT is deferred taxes and TA is total assets, all of them taken from the quarterly COMPUSTAT file.

A.10 Distress probability

Dichev (1998) uses measures of bankruptcy risk proposed by Ohlson (1980) and Altman (1968) to proxy for firms' likelihoods of financial distress. He finds that firms with higher distress probabilities earn significantly lower average stock returns. To build portfolios based on this anomaly, at the end of each calendar quarter t, I measure firms' O-score (Ohlson (1980)) as

$$\begin{aligned} Oscore_t = -1.32 - 0.407 \log\left(\frac{TA_{t-1}}{CPI_{t-1}}\right) + 6.03\frac{TD_{t-1}}{TA_{t-1}} - 1.43\frac{WC_{t-1}}{TA_{t-1}} \\ +0.076\frac{CL_{t-1}}{CA_{t-1}} - 1.72D1_{t-1} - 2.37\frac{NI_{t-1}}{TA_{t-1}} - 1.83\frac{PI_{t-1}}{TL_{t-1}} \\ +0.285D2_{t-1} - 0.521\frac{NI_t - NI_{t-1}}{|NI_{t-1}| + |NI_{t-2}|} \end{aligned}$$

where TA is total assets, CPI is the consumer price intex, TD is the book value of debt (long term debt plus debt in current liabilities), WC is working capital (current assets (CL) minus current liabilities (CL)), $D1$ is an indicator equal to one if total liabilities exceeds total assets, NI is net income, PI is funds provided by operations, TL is total liabilities, and $D2$ is an indicator equal to one if net income is negative for the last two quarters. The $t-1$ subscripts on all of these variables indicates that they are measured in the fiscal quarter ending in calendar quarter $t-1$.

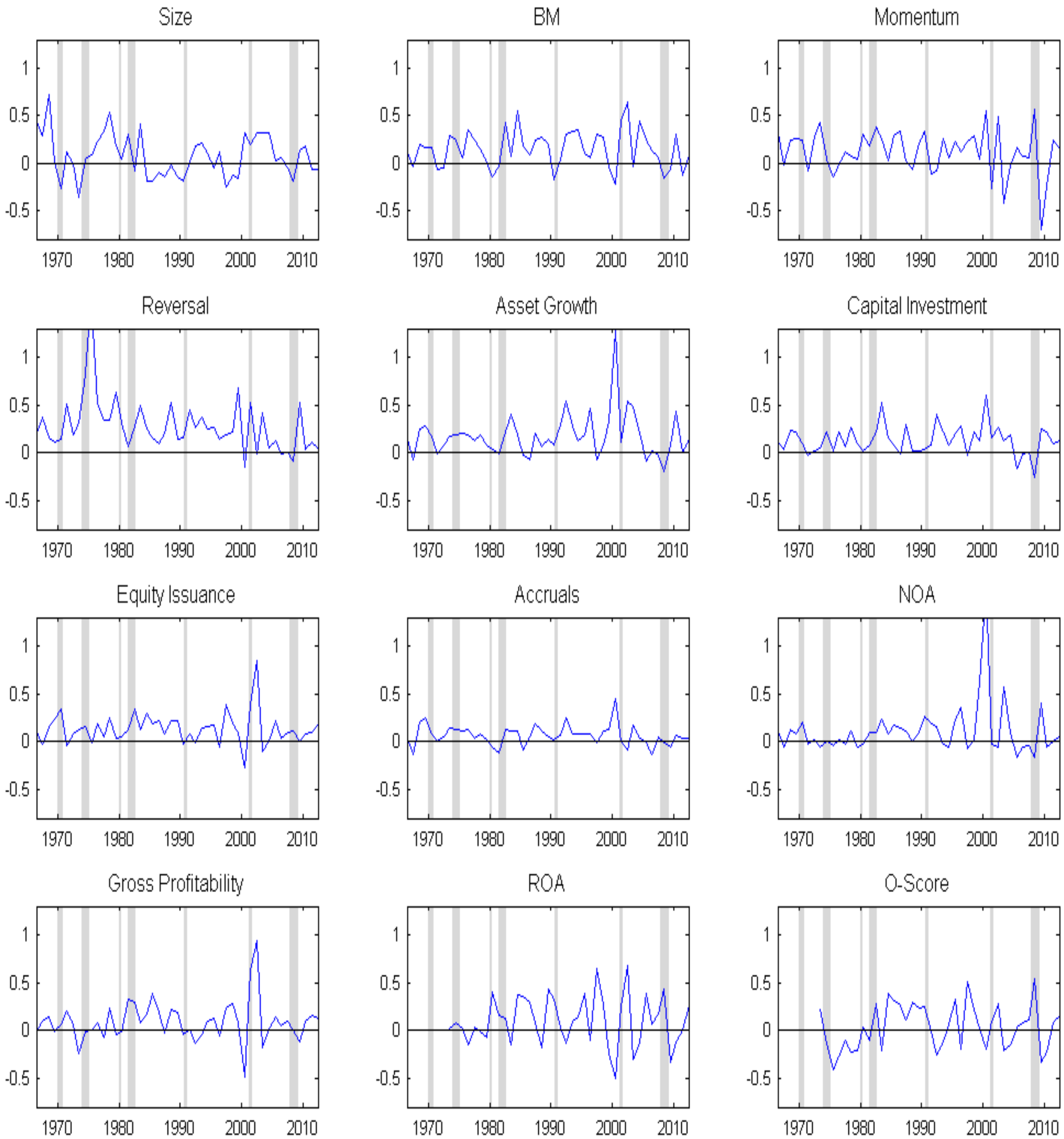

Figure 1. Annual Equal-Weighted Anomaly Returns

For each anomaly, this figure plots the cumulative annual returns derived from the monthly equal-weighted returns of the spread portfolio (long - short). Specifically, for each year t (on the x-axis), I plot the buy-and-hold equal-weighted returns obtained on the spread portfolio over the period spanning July of year $t-1$ to June of year t.

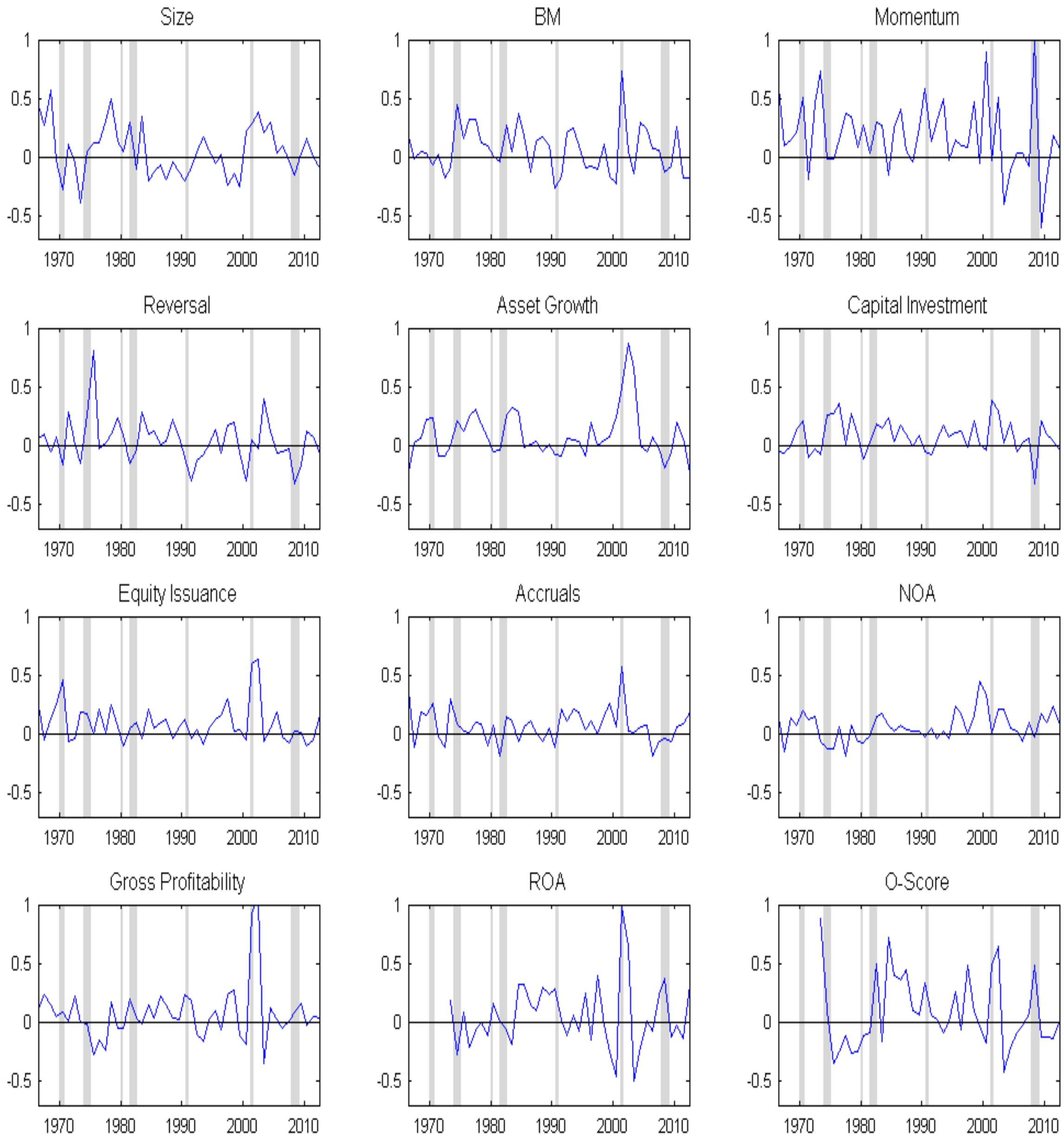

Figure 2. Annual Value-Weighted Anomaly Returns

For each anomaly, this figure plots the cumulative annual returns derived from the monthly value-weighted returns of the spread portfolio (long - short). Specifically, for each year t (on the x-axis), I plot the buy-and-hold value-weighted returns obtained on the spread portfolio over the period spanning July of year $t-1$ to June of year t.

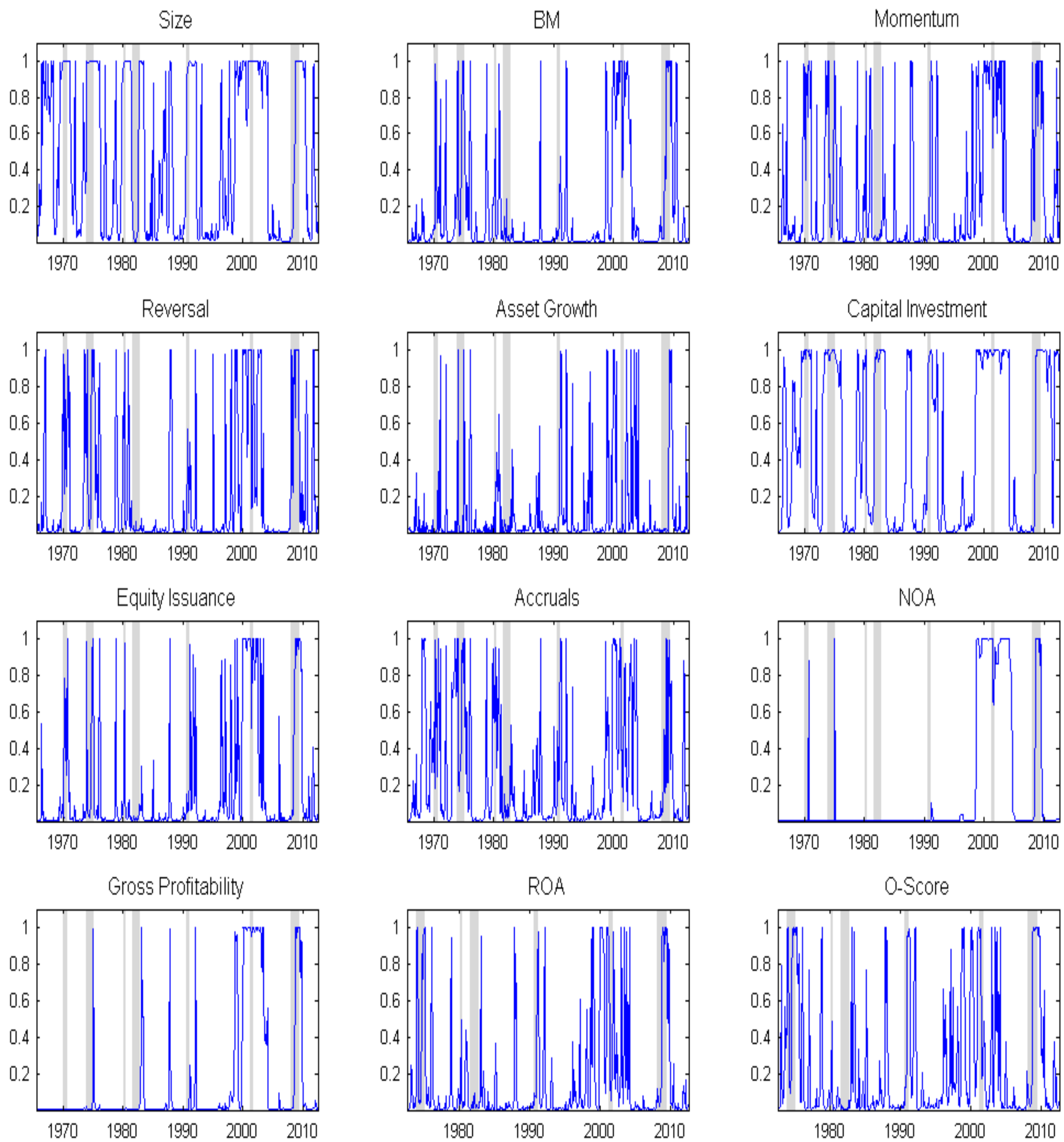

Figure 3. Smoothed Probabilities of Being in State 1 (Equal-Weighted)

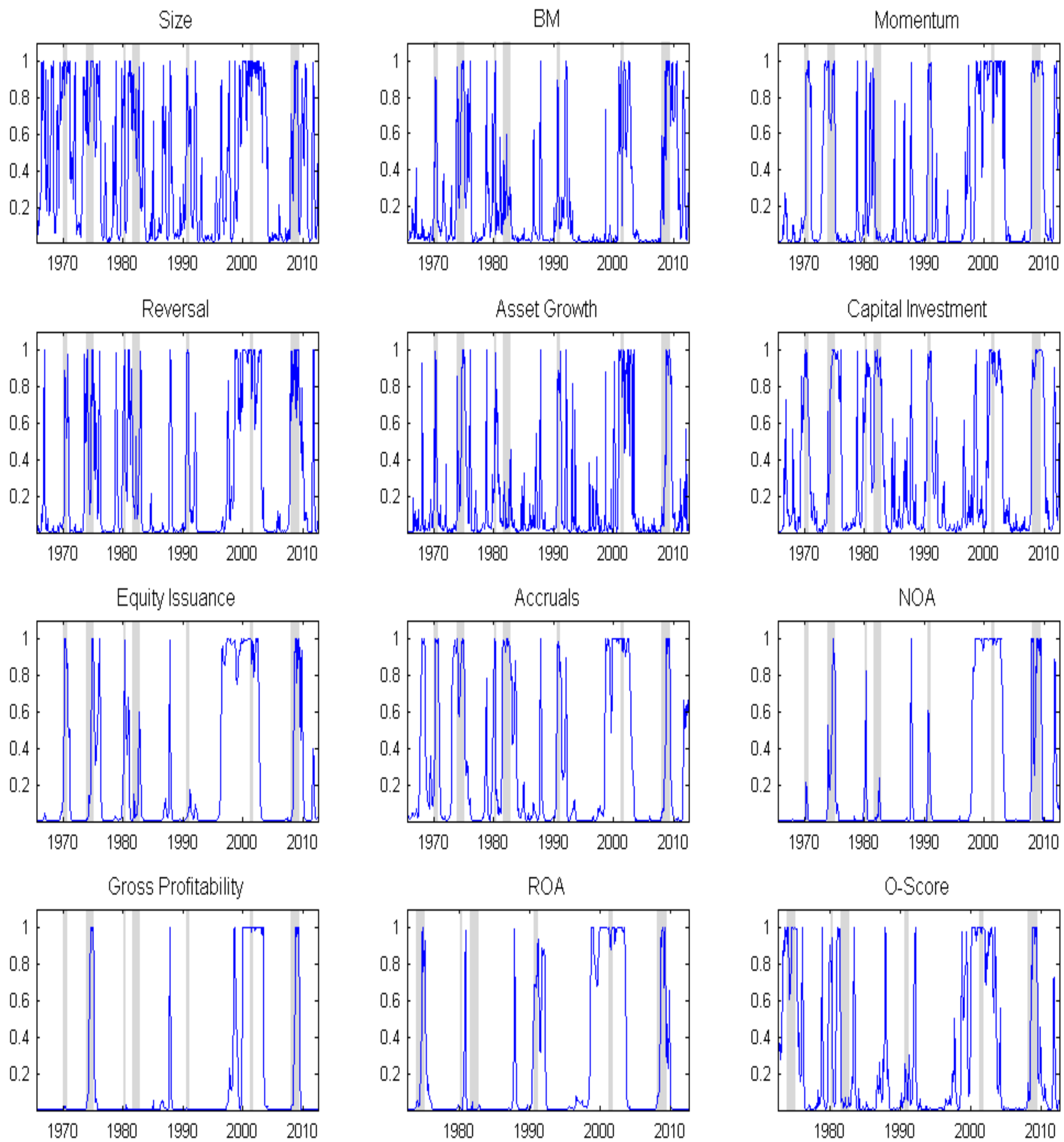

Figure 4. Smoothed Probabilities of Being in State 1 (Value-Weighted)

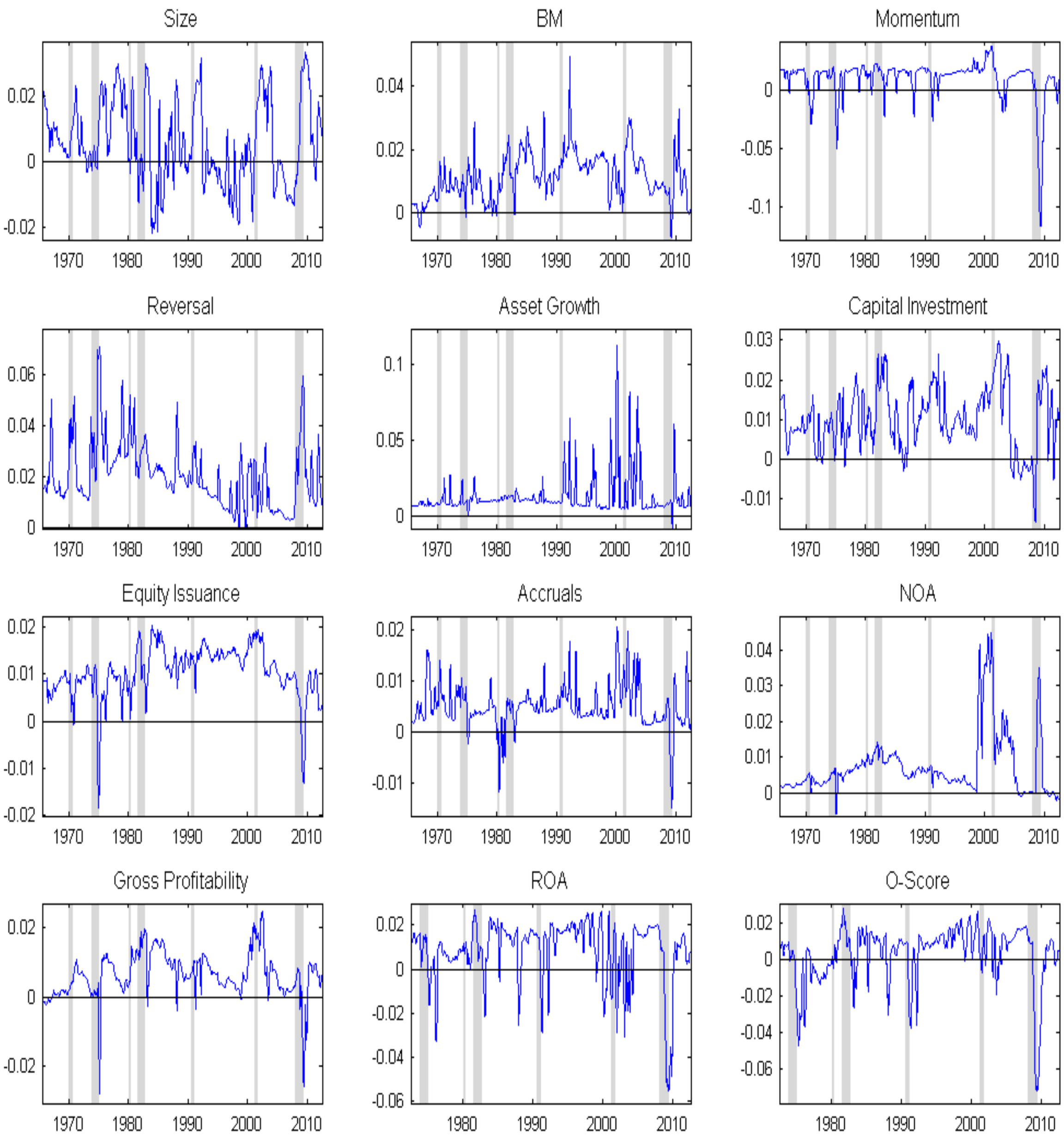

Figure 5. Conditional Expected Anomaly Returns (Equal-Weighted)

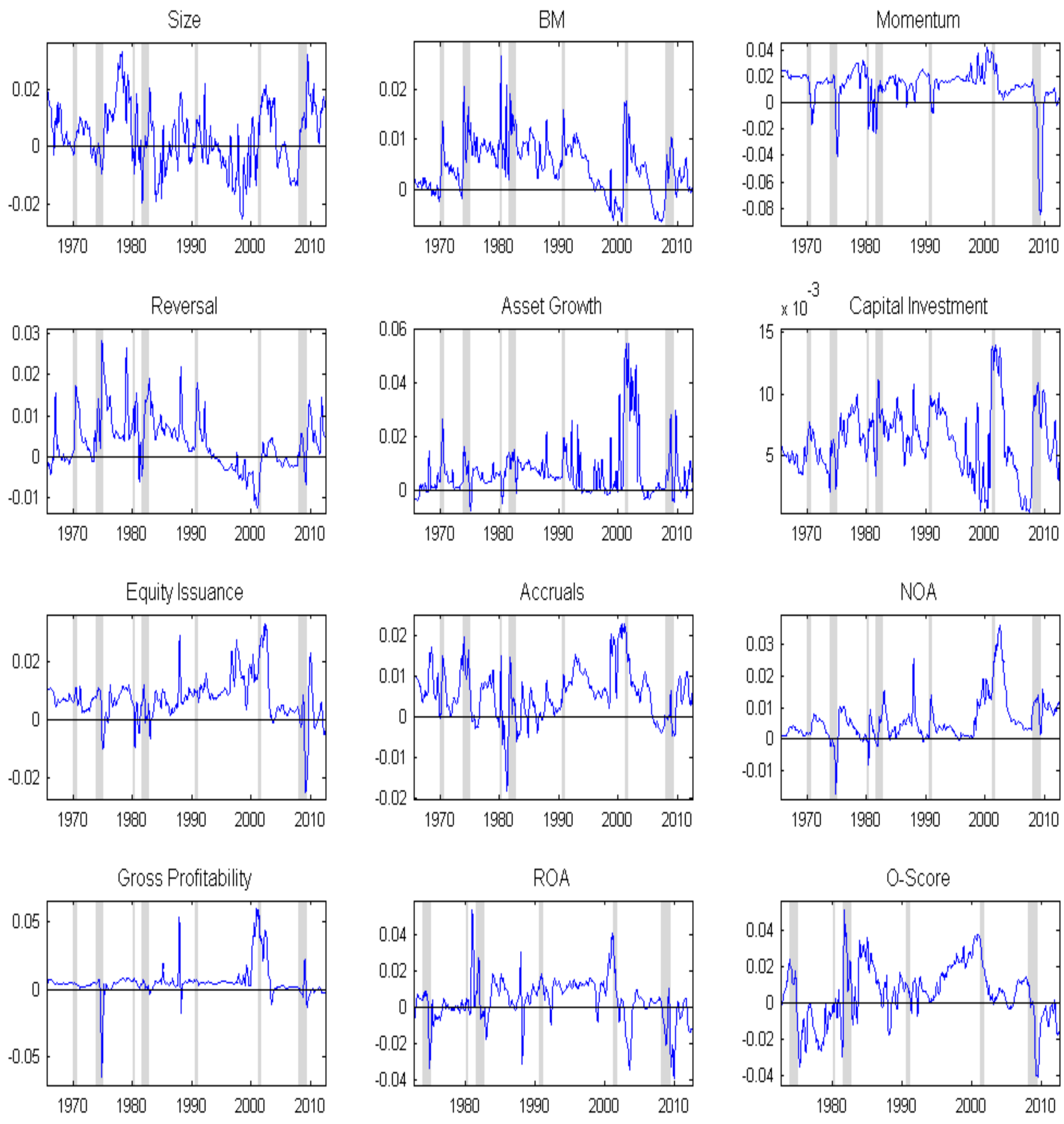

Figure 6. Conditional Expected Anomaly Returns (Value-Weighted)

Table 1. Summary Statistics

This table presents summary statistics for the variables used to construct the asset pricing anomalies. The sample period is July, 1972 to June, 2012 for the quarterly variables (*ROA* and *Oscore*) and July, 1965 to June, 2012 for all the other variables. *Momentum* and *Reversal* are calculated in each month t as follows: *Momentum* is the cumulative buy-and-hold return from month $t-12$ to month $t-2$. *Reversal* is the return in month t. *ROA* and *Oscore* are calculated (using quarterly data) at the end of each calendar quarter t as follows: *ROA* is net income minus preferred dividends plus deferred taxes in fiscal quarter ending in $t-1$ divided by beginning of (fiscal) quarter total assets. *Oscore* is measured as specified in Model 1 of Table 4 in Ohlson (1980) using data from fiscal quarter ending in $t-1$ (see text for details). *Size* is calculated each June as the natural log of firm market cap, in millions (using CRSP data). The rest of the variables are calculated (using annual data) in June of each calendar year t as follows: *BM* is the ratio of book value of equity in fiscal year ending in $t-1$ divided by market cap in December $t-1$. *Asset Growth* is the growth in total assets from fiscal year ending in $t-2$ to fiscal year ending in $t-1$. *Capital Investment* is the change from fiscal year ending in $t-2$ to fiscal year ending in $t-1$ in the ratio of property, plant and equipment divided to lagged total assets. *Equity Issuance* is the change in the natural log of shares outstanding (split-adjusted) from fiscal year ending in $t-2$ to fiscal year ending in $t-1$. *Accruals* is the change in noncash working capital minus the change in depreciation, all scaled by the average total assets over the past two years (see text for details). *NOA* is total operating assets minus total operating liabilities scaled by the average total assets over the past two years. *Gross Profitability* is sales minus cost of goods sold divided by total assets in fiscal year ending in $t-1$. p25 and p75 stand for the 25^{th} and 75^{th} percentile of each variable.

	N	**Mean**	**p25**	**Median**	**p75**	**Std. Dev**
Size	165,438	4.544	2.940	4.383	6.033	2.144
BM	156,112	0.851	0.321	0.625	1.110	0.854
Momentum	1,969,566	0.161	-0.244	0.042	0.364	0.825
Reversal	1,981,979	0.013	-0.078	0.002	0.083	0.242
Asset Growth	147,964	0.152	-0.019	0.077	0.206	0.390
Capital Investment	147,806	0.042	-0.007	0.014	0.059	0.116
Equity Issuance	158,187	0.041	0.000	0.004	0.029	0.119
Accruals	141,408	0.038	-0.052	0.020	0.115	0.329
NOA	145,548	0.623	0.508	0.673	0.785	0.245
Gross Profitability	156,416	0.374	0.189	0.344	0.522	0.280
ROA	531,439	-0.006	-0.008	0.009	0.022	0.064
Oscore	491,226	-1.253	-2.433	-1.523	-0.382	1.723

Table 2. Correlations Between Anomaly Variables

This table presents pair-wise correlation coefficients for the variables used to construct the asset pricing anomalies. The sample period is July, 1972 to June, 2012 (constrained by the availability of the quarterly variables (*ROA* and *Oscore*). Since the variables come at different frequencies, I use only the data in June of each year t to measure the correlation coefficients. *Momentum* and *Reversal* are calculated in each month t as follows: *Momentum* is the cumulative buy-and-hold return from month $t-12$ to month $t-2$. *Reversal* is the return in month t. *ROA* and *Oscore* are calculated (using quarterly data) at the end of each calendar quarter t as follows: *ROA* is net income minus preferred dividends plus deferred taxes in fiscal quarter ending in $t-1$ divided by beginning of (fiscal) quarter total assets. *Oscore* is measured as specified in Model 1 of Table 4 in Ohlson (1980) using data from fiscal quarter ending in $t-1$ (see text for details). *Size* is calculated each June as the natural log of firm market cap, in millions (using CRSP data). The rest of the variables are calculated (using annual data) in June of each calendar year t as follows: *BM* is the ratio of book value of equity in fiscal year ending in $t-1$ divided by market cap in December $t-1$. *Asset Growth* is the growth in total assets from fiscal year ending in $t-2$ to fiscal year ending in $t-1$. *Capital Investment* is the change from fiscal year ending in $t-2$ to fiscal year ending in $t-1$ in the ratio of property, plant and equipment divided to lagged total assets. *Equity Issuance* is the change in the natural log of shares outstanding (split-adjusted) from fiscal year ending in $t-2$ to fiscal year ending in $t-1$. *Accruals* is the change in noncash working capital minus the change in depreciation, all scaled by the average total assets over the past two years (see text for details). *NOA* is total operating assets minus total operating liabilities scaled by the average total assets over the past two years. *Gross Profitability* is sales minus cost of goods sold divided by total assets in fiscal year ending in $t-1$.

	BM	**Mom**	**Rev**	**AG**	**Inv**	**Iss**	**Acc**	**NOA**	**GP**	**ROA**	**O**
Size	-0.14	0.05	0.00	0.02	0.01	-0.06	-0.02	-0.01	-0.01	0.13	-0.34
BM		-0.11	0.03	-0.14	-0.08	-0.13	-0.03	0.19	-0.07	0.02	0.03
Momentum (Mom)			0.05	0.01	-0.03	-0.04	0.00	-0.02	0.07	0.19	-0.15
Reversal (Rev)				0.00	-0.01	-0.03	0.00	0.01	0.03	0.06	-0.04
Asset Growth (AG)					0.58	0.43	0.24	0.26	-0.05	0.08	-0.05
Capital Investment (Inv)						0.24	0.11	0.35	-0.07	0.06	0.02
Equity Issuance (Iss)							0.08	0.05	-0.16	-0.22	0.15
Accruals (Acc)								0.21	0.05	0.06	-0.03
NOA									0.02	0.26	0.08
Gross Profitability (GP)										0.30	-0.20
ROA											-0.56

Table 3. Unconditional Anomaly Performance

For all anomalies, portfolios are based on decile cutoffs of the entire sample at formation time. For *Momentum* and *Reversal* portfolios are formed every month and are held for a single month. For *ROA* and *O-Score* portfolios are formed at the end of every calendar quarter and are held for three months. For the rest of the anomalies, portfolios are formed in June of every year and are held for 12 months. The sample period is July, 1972 to June, 2012 for the quarterly variables (*ROA* and *Oscore*) and July, 1965 to June, 2012 for all the other variables. Please see the text for a detailed description of the calculation of each variable. Panel A and Panel B present results using raw portfolio returns, equal-weighted for Panel A and value-weighted for Panel B. The first four columns in these two panels show the average raw returns for the long, short and spread portfolios, as well as the annualized Sharpe Ratio for the spread portfolio. For the last three columns I calculate the cumulative buy-and-hold returns from July, t to June $t+1$ for each year t and present the percentage of these years when this cumulative return is positive (column 5), as well as the mean and median return in the years when this return is negative. Panel C contains equal-weighted and value-weighted abnormal returns for the spread portfolio of each anomaly. Abnormal returns are measured with respect to the CAPM (first two columns), the Fama and French (1993) three factor model (columns three and four) as well as a four factor model which augments the Fama and French (1993) model with a 'momentum factor' as in Carhart (1997). All four factors are from Kenneth French's website. The point estimates in Panel C as well as the ones in the first four columns of panels A and B are in percentage points. t-statistics are presented in parentheses.

Panel A: Average Monthly Raw Returns on Equal-Weighted Portfolios

	Long (L)	**Short (S)**	**Spread (L-S)**	**Sharpe Ratio**	**% Yrs. Positive**	**Mean Neg. Yrs.**	**Median Neg. Yrs.**
Size	0.963	0.406	0.557	0.365	0.595	-0.142	-0.146
	(3.34)	(2.03)	(2.51)			(-6.76)	(-5.39)
BM	1.367	0.234	1.133	0.913	0.744	-0.096	-0.067
	(4.84)	(0.73)	(6.26)			(-5.03)	(-4.01)
Momentum	1.393	0.43	0.963	0.516	0.744	-0.182	-0.104
	(4.78)	(1.1)	(3.54)			(-3.11)	(-2.49)
Reversal	1.872	-0.176	2.048	1.377	0.914	-0.067	-0.054
	(5.01)	(-0.63)	(9.45)			(-1.93)	(-1.54)
Asset Growth	1.352	0.023	1.329	1.137	0.808	-0.063	-0.071
	(3.62)	(0.07)	(7.8)			(-3.31)	(-2.64)
Capital Investment	1.223	0.192	1.03	1.139	0.872	-0.082	-0.031
	(3.82)	(0.65)	(7.81)			(-2)	(-1.6)
Equity Issuance	1.174	0.113	1.06	0.933	0.829	-0.068	-0.037
	(4.95)	(0.34)	(6.4)			(-2.22)	(-1.77)
Accruals	0.87	0.358	0.512	0.807	0.787	-0.071	-0.07
	(2.68)	(1.1)	(5.54)			(-4.49)	(-3.59)
NOA	1.044	0.252	0.792	0.681	0.617	-0.056	-0.051
	(3.16)	(0.92)	(4.67)			(-5.49)	(-4.38)
Gross Profitability	1.079	0.408	0.671	0.566	0.659	-0.094	-0.043
	(4.01)	(1.2)	(3.88)			(-2.97)	(-2.37)
ROA	1.022	0.186	0.835	0.427	0.675	-0.186	-0.142
	(3.51)	(0.4)	(2.7)			(-5.18)	(-4.13)
O-Score	0.66	0.325	0.335	0.178	0.575	-0.197	-0.203
	(2.47)	(0.75)	(1.13)			(-8.71)	(-6.95)

Table 3. Unconditional Anomaly Performance (continued)

Panel B: Average Monthly Raw Returns on Value-Weighted Portfolios							
	Long (L)	**Short (S)**	**Spread (L-S)**	**Sharpe Ratio**	**% Yrs. Positive**	**Mean Neg. Yrs.**	**Median Neg. Yrs.**
Size	0.723	0.373	0.35	0.243	0.553	-0.14	-0.128
	(2.61)	(2.02)	(1.67)			(-6.51)	(-5.2)
BM	0.841	0.36	0.48	0.35	0.617	-0.132	-0.13
	(3.32)	(1.62)	(2.4)			(-8.68)	(-6.93)
Momentum	1.079	-0.31	1.388	0.669	0.723	-0.151	-0.086
	(4)	(-0.89)	(4.59)			(-3.14)	(-2.51)
Reversal	0.549	0.196	0.353	0.223	0.574	-0.115	-0.071
	(1.72)	(0.82)	(1.53)			(-5.48)	(-4.37)
Asset Growth	0.876	0.16	0.715	0.562	0.659	-0.083	-0.068
	(3.01)	(0.54)	(3.85)			(-4.69)	(-3.74)
Capital Investment	0.844	0.216	0.627	0.646	0.702	-0.072	-0.051
	(3.35)	(0.82)	(4.43)			(-3.36)	(-2.68)
Equity Issuance	0.843	0.096	0.747	0.697	0.702	-0.057	-0.051
	(4.28)	(0.37)	(4.78)			(-8.45)	(-6.74)
Accruals	0.655	0.056	0.599	0.597	0.744	-0.093	-0.08
	(2.4)	(0.18)	(4.1)			(-5.95)	(-4.75)
NOA	0.671	0.06	0.61	0.48	0.723	-0.074	-0.057
	(2.32)	(0.25)	(3.29)			(-4.73)	(-3.78)
Gross Profitability	0.71	0.135	0.575	0.396	0.68	-0.121	-0.101
	(3.24)	(0.45)	(2.72)			(-4.59)	(-3.67)
ROA	0.512	0.08	0.431	0.232	0.55	-0.167	-0.128
	(2.1)	(0.19)	(1.47)			(-5.3)	(-4.23)
O-Score	0.465	-0.129	0.594	0.331	0.525	-0.16	-0.124
	(2.11)	(-0.32)	(2.1)			(-6.58)	(-5.25)

Table 3. Unconditional Anomaly Performance (continued)

Panel C: Abnormal Returns						
	CAPM Alpha (EW)	**CAPM Alpha (VW)**	**3 Factor Alpha (EW)**	**3 Factor Alpha (VW)**	**4 Factor Alpha (EW)**	**4 Factor Alpha (VW)**
Size	0.52	0.265	0.125	-0.146	0.207	-0.146
	(2.34)	(1.28)	(0.98)	(-1.87)	(1.6)	(-1.84)
BM	1.276	0.476	0.73	-0.269	0.687	-0.207
	(7.51)	(2.37)	(7.04)	(-2.73)	(6.5)	(-2.07)
Momentum	1.031	1.505	1.245	1.727	0.107	0.339
	(3.79)	(5.03)	(4.61)	(5.79)	(0.7)	(2.84)
Reversal	1.915	0.187	1.813	0.118	2.205	0.463
	(9.14)	(0.85)	(8.64)	(0.53)	(11.08)	(2.14)
Asset Growth	1.375	0.774	1.156	0.412	1.082	0.367
	(8.1)	(4.2)	(7.3)	(2.48)	(6.71)	(2.16)
Capital Investment	1.06	0.663	0.907	0.454	0.825	0.361
	(8.04)	(4.69)	(7.43)	(3.37)	(6.68)	(2.65)
Equity Issuance	1.208	0.877	1.043	0.762	0.852	0.539
	(7.92)	(6.03)	(7.7)	(5.56)	(6.41)	(4.06)
Accruals	0.535	0.669	0.511	0.606	0.488	0.498
	(5.8)	(4.66)	(5.46)	(4.23)	(5.11)	(3.44)
NOA	0.745	0.547	0.912	0.836	0.891	0.735
	(4.41)	(2.97)	(6.1)	(4.88)	(5.83)	(4.22)
Gross Profitability	0.715	0.688	0.671	0.795	0.579	0.517
	(4.14)	(3.34)	(3.92)	(3.87)	(3.32)	(2.55)
ROA	0.885	0.629	0.949	0.791	0.503	0.524
	(2.86)	(2.25)	(3.26)	(3.14)	(1.8)	(2.09)
O-Score	0.402	0.84	0.765	1.081	0.474	0.825
	(1.36)	(3.23)	(2.98)	(5.89)	(1.87)	(4.62)

Table 4. Conditional Asset Pricing Tests

All periods in the sample are split according to their estimated market premia and the highest 20% are deignated as "Trough" and the lowest 20% as "Peak". The first two columns of the table present averages of the conditional market beta estimates of the spread portfolio, calculated separately over periods in "Trough" and in "Peak". The differences between these averages are reported in column three. Columns four through six contain the beta-premium sensitivities for the long, short and spread portfolios obtained from the GMM estimation in section 4. The last column presents the GMM estimates of the abnormal returns of each spread portfolio. Panel A and Panel B contain results based on equal-weighted and value-weighted anomaly portfolios respectively. All the point estimates in the first three and the last column are in percentage points. t-statistics are in parentheses.

Panel A: Conditional CAPM for Equal-Weighted Portfolios

	Fitted Beta (Spread)			**Beta-Premium Sensitivity**			**CCAPM Alpha**
	Trough	**Peak**	**Diff**	**Long**	**Short**	**Spread**	**Spread**
Size	0.137	0.042	0.095	3.514	2.521	0.992	0.523
	(5.08)	(1.96)	(3.91)	(0.47)	(0.83)	(0.12)	(1.54)
BM	0.113	-0.802	0.915	20.738	-18.547	39.284	1.114
	(1.77)	(-23.05)	(13.67)	(1.76)	(-1.68)	(2.21)	(4.66)
Momentum	-0.393	-0.001	-0.393	-14.705	2.681	-17.387	1.085
	(-2.41)	(-0.02)	(-2.4)	(-1.89)	(0.17)	(-1.08)	(3.95)
Reversal	0.308	0.342	-0.034	-5.443	-3.293	-2.151	1.932
	(6.01)	(19.7)	(-0.65)	(-0.39)	(-0.52)	(-0.17)	(6.55)
Asset Growth	-0.094	-0.126	0.031	-3.597	-5.676	2.078	1.364
	(-2.75)	(-2.7)	(0.68)	(-0.32)	(-0.7)	(0.29)	(5.25)
Capital Investment	-0.067	-0.085	0.018	4.51	3.04	1.47	1.049
	(-3.43)	(-2.66)	(0.6)	(0.45)	(0.39)	(0.28)	(5.73)
Equity Issuance	-0.084	-0.669	0.585	13.067	-10.321	23.388	1.106
	(-1.46)	(-17.41)	(8.72)	(1.37)	(-0.84)	(1.41)	(7.54)
Accruals	-0.109	0.009	-0.119	0.01	2.902	-2.893	0.543
	(-3.63)	(0.27)	(-2.8)	(0.00)	(0.33)	(-0.39)	(4.22)
NOA	-0.215	0.454	-0.67	-18.818	6.343	-25.161	0.841
	(-7.7)	(8.2)	(-12.24)	(-1.35)	(0.76)	(-1.38)	(2.95)
Gross Profitability	0.089	-0.375	0.463	0.884	-15.235	16.119	0.643
	(0.9)	(-7.19)	(4.21)	(0.16)	(-0.81)	(0.97)	(3.52)
ROA	0.031	-0.371	0.401	-0.34	-21.455	21.114	0.788
	(0.24)	(-3.72)	(2.66)	(-0.07)	(-0.74)	(0.75)	(2.9)
O-Score	-0.289	-0.087	-0.202	-3.711	1.842	-5.553	0.398
	(-2.76)	(-4.13)	(-1.92)	(-0.62)	(0.11)	(-0.43)	(1.24)

Table 4. Conditional Asset Pricing Tests (continued)

Panel B: Conditional CAPM for Value-Weighted Portfolios							
	Fitted Beta (Spread)			Beta-Premium Sensitivity			CCAPM Alpha
	Trough	**Peak**	**Diff**	**Long**	**Short**	**Spread**	**Spread**
Size	0.266	0.124	0.142	2.596	-0.675	3.27	0.257
	(10.44)	(5.16)	(6.04)	(0.34)	(-0.35)	(0.35)	(0.77)
BM	0.428	-0.427	0.855	32.757	-4.084	36.84	0.325
	(4.52)	(-6.41)	(8.37)	(1.93)	(-0.71)	(1.7)	(1.39)
Momentum	-0.654	-0.018	-0.636	-15.906	12.402	-28.309	1.594
	(-2.44)	(-0.24)	(-2.36)	(-2.15)	(0.77)	(-1.34)	(6.21)
Reversal	0.446	0.358	0.087	-1.983	-5.915	3.932	0.18
	(6.24)	(19.99)	(1.22)	(-0.19)	(-1.14)	(0.3)	(0.79)
Asset Growth	0.066	-0.412	0.478	15.84	-7.327	23.167	0.663
	(2.18)	(-10.28)	(10.41)	(1.52)	(-0.84)	(1.65)	(2.55)
Capital Investment	0.039	-0.252	0.291	18.15	4.693	13.457	0.598
	(1.61)	(-10.1)	(9.19)	(1.66)	(1.05)	(1.46)	(3.79)
Equity Issuance	-0.218	-0.464	0.246	11.346	1.919	9.427	0.827
	(-2.41)	(-17.82)	(2.63)	(1.28)	(0.31)	(0.73)	(5.31)
Accruals	-0.177	-0.116	-0.062	-6.496	-4.136	-2.36	0.683
	(-3.93)	(-4.63)	(-1.28)	(-1.02)	(-0.88)	(-0.36)	(3.88)
NOA	-0.097	0.373	-0.471	-22.901	-2.444	-20.457	0.624
	(-1.71)	(10.42)	(-7.81)	(-1.04)	(-0.28)	(-1.22)	(2.83)
Gross Profitability	0.059	-0.742	0.801	10.454	-16.602	27.056	0.564
	(0.33)	(-10.56)	(4.12)	(1.89)	(-0.66)	(0.97)	(2.53)
ROA	-0.156	-0.785	0.628	-6.148	-30.212	24.064	0.536
	(-0.92)	(-7.1)	(3.22)	(-1.15)	(-0.97)	(0.81)	(2.01)
O-Score	-0.433	-0.716	0.283	-5.325	-19.155	13.83	0.774
	(-4.29)	(-19.83)	(2.69)	(-1.51)	(-1.13)	(0.89)	(2.05)

Table 5. Expected Anomaly Returns Based on the Markov Switching Model

The sample period is split into periods in which the smoothed probability of being in the recessionary/high-volatility state estimated in Section 5 is over 50% ("HI") and periods in which it is below 50% ("LO"). The table reports averages of estimated expected spread portfolio returns, calculated separately for "HI" and "LO" periods (columns 1,2, 4 and 5). Columns 3 and 6 report the differences between these averages. All point estimates are in percentage points. t-statistics are in parentheses.

	Equal-Weighted			**Value-Weighted**		
	HI	**LO**	**HI-LO**	**HI**	**LO**	**HI-LO**
Size	1.133	0.279	0.853	0.558	0.162	0.395
	(6.05)	(1.61)	(3.67)	(3.99)	(0.93)	(1.91)
BM	1.345	1.172	0.173	0.988	0.41	0.577
	(5.92)	(12.51)	(0.78)	(6.71)	(6.48)	(3.81)
Momentum	-0.212	1.211	-1.423	0.161	1.552	-1.391
	(-0.32)	(16.29)	(-2.17)	(0.27)	(17.58)	(-2.36)
Reversal	2.927	1.79	1.137	0.586	0.318	0.267
	(8.79)	(14.25)	(3.54)	(2.59)	(4.64)	(1.21)
Asset Growth	1.799	1.202	0.597	1.718	0.557	1.161
	(5.44)	(25.04)	(1.84)	(3.33)	(11.52)	(2.28)
Capital Investment	1.412	0.9	0.511	0.846	0.547	0.298
	(7.56)	(10.86)	(2.62)	(15.71)	(17.93)	(4.82)
Equity Issuance	0.837	1.069	-0.233	1.177	0.63	0.546
	(3.74)	(19.88)	(-1.06)	(3.84)	(11.83)	(1.8)
Accruals	0.616	0.477	0.138	0.897	0.427	0.47
	(5.24)	(16.93)	(1.16)	(5.53)	(5.99)	(2.74)
NOA	1.706	0.5	1.206	1.481	0.418	1.063
	(4.93)	(9.03)	(3.54)	(5.65)	(8.97)	(4.01)
Gross Profitability	0.59	0.59	-0.001	1.639	0.389	1.25
	(1.5)	(8.28)	(-0.01)	(1.99)	(9.24)	(1.52)
ROA	-0.322	1.071	-1.393	0.164	0.497	-0.333
	(-0.72)	(9.55)	(-3.31)	(0.29)	(4.18)	(-0.62)
O-Score	-0.699	0.544	-1.244	0.157	0.588	-0.432
	(-1.06)	(4.12)	(-1.96)	(0.25)	(2.91)	(-0.71)

Table 6. Joint Estimation of Markov Switching Model Using Four Anomalies

I jointly estimate the Markov switching model in Section 5 using four anomaly spread portfolios: size, book-to-market, asset growth and gross profitability. The top part of the table contains estimates of the parameters in the conditional mean equation (constant and dividend yield) as well as the conditional volatility parameters, for each anomaly, in each state. The bottom part of the table contains estimates of the parameters governing the transition probabilities in the model (constant and LEI). All anomalies are value-weighted. p-values are in parentheses.

	Parameters in mean equations				**Variance Parameters**	
	Constant		**Dividend Yield**			
	State1	*State2*	*State1*	*State2*	*State1*	*State2*
Size	0.0104	-0.0124	6.5048	3.5651	0.0063	0.0014
	(0.655)	(0.05)	(0.491)	(0.064)	(0.000)	(0.000)
BM	0.0023	-0.0089	8.0048	3.233	0.0055	0.0014
	(0.922)	(0.137)	(0.339)	(0.081)	(0.000)	(0.000)
Asset Growth	0.0566	-0.0092	-9.6735	3.5546	0.0044	0.0011
	(0.004)	(0.07)	(0.198)	(0.034)	(0.000)	(0.000)
Gross Profitability	0.0566	0.0052	-21.592	0.2934	0.0086	0.001
	(0.053)	(0.304)	(0.126)	(0.853)	(0.000)	(0.000)

Transition probability parameters (common to all four equations)

	Constant		**LEI**	
	State1	*State2*	*State1*	*State2*
	0.4675	-1.4958	-6.7418	0.637
	(0.02)	(0.000)	(0.006)	(0.773)

Table 7. Joint Estimation of Markov Switching Model using Five Anomalies

I jointly estimate the Markov switching model in Section 5 using five anomaly spread portfolios. Four of the anomalies: size, book-to-market, asset growth and gross profitability are common to all models and for the fifth, I cycle one-by-one through the rest of the anomalies. Each row in the table indicates what was used as the fifth anomaly. The variance parameters presented in the table correspond to this fifth anomaly. All anomalies are value-weighted. p-values are in parentheses.

Name of fifth variable in the model	**LEI**		**Variance**	
	State 1	*State 2*	*State 1*	*State 2*
Momentum	-6.712	1.8865	0.0157	0.0016
	(0.007)	(0.308)	(0.000)	(0.000)
Reversal	-6.1347	2.3151	0.0091	0.0012
	(0.013)	(0.245)	(0.000)	(0.000)
Capital Investment	-6.2239	1.747	0.0018	0.0007
	(0.011)	(0.379)	(0.000)	(0.000)
Equity Issuance	-6.173	2.3507	0.0038	0.0006
	(0.009)	(0.24)	(0.000)	(0.000)
Accruals	-3.5792	2.405	0.0026	0.0007
	(0.115)	(0.213)	(0.000)	(0.000)
NOA	-4.0316	1.8744	0.0061	0.0007
	(0.084)	(0.37)	(0.000)	(0.000)
ROA	-4.9159	2.946	0.0108	0.0017
	(0.042)	(0.137)	(0.000)	(0.000)
O-Score	-8.6186	-0.9373	0.01	0.0016
	(0.000)	(0.655)	(0.000)	(0.000)

Table 8. Joint Estimation of Markov Switching Model using Five Anomalies

I jointly estimate the Markov switching model in Section 5 using five anomaly spread portfolios. Four of the anomalies: size, book-to-market, asset growth and gross profitability are common to all models and for the fifth, I cycle one-by-one through the rest of the anomalies. Each row in the table indicates what was used as the fifth anomaly. After estimating each model, I split the sample into periods (months) in which the smoothed probability of being in the high volatility state is over 50% ("HI") and periods in which it is below 50% ("LO"). I then calculate averages of expected spread portfolio returns, separately for "HI" and "LO" periods. The table reports the differences between these averages ("HI" - "LO") for each anomaly used in each model. All anomalies are value-weighted. All point estimates are in percentage points. t-statistics are in parentheses.

Name of fifth variable	**5th Var.**	**Size**	**BM**	**AG**	**G. Prof.**
Momentum	-1.558	1.352	1.084	1.297	-0.3
	(-3.09)	(8.72)	(6.00)	(5.34)	(-0.65)
Reversal	0.183	1.032	0.709	1.307	-0.008
	(0.65)	(7.79)	(5.47)	(5.66)	(-0.02)
Capital Investment	0.833	1.392	1.196	1.602	-0.306
	(6.31)	(8.47)	(8.32)	(7.70)	(-0.93)
Equity Issuance	0.337	1.075	0.916	1.647	-0.048
	(1.06)	(5.59)	(4.70)	(8.35)	(-0.11)
Accruals	0.441	1.133	0.864	1.3	-0.073
	(4.40)	(6.71)	(5.56)	(8.89)	(-0.26)
NOA	0.615	1.385	1.094	1.79	-0.226
	(1.78)	(5.30)	(3.71)	(16.38)	(-0.55)
ROA	-1.087	1.234	1.074	1.628	-0.237
	(-2.79)	(6.33)	(4.25)	(14.34)	(-0.53)
O-Score	-1.015	1.4	1.336	1.718	-0.305
	(-1.95)	(8.00)	(5.66)	(7.69)	(-0.61)