Getting paid to hedge: Why don't investors pay a premium to hedge downturns?

Abstract

Stocks that hedge sustained market downturns should have low expected returns, but they do not. We use ex-ante firm characteristics and covariances to construct a tradable Safe Minus Risky (*SMR*) portfolio that hedges market downturns out-of-sample. Although downturns (peaks to troughs in market index levels at the business cycle frequency) predict significant declines in GDP growth, *SMR* has significant *positive* average returns and four factor alphas (both around 0.8% per month). Risk-based models do not explain *SMR's* returns, but mispricing does. Risky stocks are overpriced when sentiment is high, resulting in subsequent returns of -0.9% per month.

Stocks that seem intuitively risky do not appear to earn a premium in the cross-section of returns. For example, stocks with high volatility (Ang et al, 2006), high default probability (Campbell et al., 2008), high beta (Frazzini and Pederson, 2014), and low quality or 'junk' (Asness, Frazzini, and Pederson, 2013) have low returns. However, subsequent research argues that some of these patterns are anomalous with respect to specific factor models, but are consistent with other rational frameworks.[1] More generally, recent studies propose rational explanations for a wider set of anomalies (e.g. size, book-to-market, and asset growth) and even incorporate some as factors in asset pricing models (e.g. Fama and French, 2015).[2] Thus, it is not clear whether the returns associated with a host of characteristics represent true anomalies or the misspecification of factor models.

In this paper, r we take a different approach. Rather than testing a specific characteristic using a specific asset pricing model, we test the central intuition that underlies a broad class of asset pricing models. At the heart of most rational asset pricing models is a concept of "bad times," when the marginal utility of consumption is high. Stocks that do well in bad times should have low expected returns because of the insurance they provide. We test this hypothesis using an intuitive measure of bad times: bear markets or periods from peak to trough in S&P 500 levels at the business cycle frequency. We construct tradeable portfolios that hedge bear market risk and test whether they earn low average returns.

Bear markets are bad times for investors for two related reasons. First, on average, 30% of stock market wealth is lost in bear markets. A period with such a significant loss of wealth must be a bad time, almost by definition: such a loss of wealth has severe real consequences for investors.[3] Second, bear markets should be associated with economy-wide downturns because stock markets reflect expectations

[1] For example, see Babenko, Boguth, and Tserlukevich (2016) for idiosyncratic volatility, Garlappi, Shu, and Yan (2008) for default probability, and Cederburg and O'Doherty (2016) for betting against beta.
[2] As Kozak, Nagel, and Santosh (2017) point out, the existence of a factor structure does not distinguish between rational and behavioral explanations for the cross-section of expected returns.
[3] Investors are forced to change their lifestyle following the loss of wealth in market downturns. For example, Americans report cutting back on expenses, travel, and postponing retirement due to losses in their financial asset in the recent financial crisis (Brown, 2009). In the extreme, Chang, Stuckler, Yip, and Gunnell (2013) and Engelberg and Parsons (2016) find that suicides and hospitalizations spike around market downturns.

of real economic activity (e.g. Fama, 1981). In fact, bear markets as measures of bad times may provide sharper insight than macroeconomic variables since they are forward-looking and better match the timing of test asset returns. For example, contemporaneous correlations between market returns and GDP growth are small, but market returns are a strong predictor of GDP growth. Thus, contemporaneous covariances of returns with economic activity may miss the true covarianceof returns with real activity. But how far ahead should a researcher look? There is no clear answer because the lead-lag relationship varies over time. Rather than impose a fixed lead-lag structure, we use periods of sustained market declines to detect times when the market expects adverse real outcomes.

We identify bear markets based on the popular Bry and Boschan (1971) business-cycle dating algorithm parameterized by Pagan and Soussanov (2003) for equity indices. Our results are not sensitive to this choice (the Internet Appendix provides results for alternative algorithms). We identify nine bear markets between 1966 and 2015, with an average duration of 14 months which is similar to that of NBER-dated recessions (13 months). The bear markets, listed in Table 2, overlap with significant economic events. For example, the first recession in our sample from Dec. 1969 to Nov. 1970 is predated by a bear market from Dec. 1968 to Jun. 1970. A similar pattern repeats for several other bear markets, including the Jan. 1973-Sep. 1974 'oil crisis' and the 'post-dot com crash' from Sep. 2000 to Oct. 2002, both with market returns of around -45% and subsequent NBER-dated recessions.

We test whether a broad set of commonly analyzed variables predicts relative stock performance in bear markets. These variables include size, leverage, dividend yield, market-to-book ratio, investment, and past returns. Early investment advice suggests these variables predict performance in bad times. For example, Benjamin Graham writes in 1971 that a defensive investor, who wants little risk without much selection effort, should hold large, prominent, conservatively financed, and continuous dividend payer firms that are modestly priced relative to earnings. We also consider recent, research-driven variables and test whether factor loadings in the Fama-French-Carhart model predict bear market performance.

Overall, we find evidence consistent with Graham's early intuition: small, growth stocks, with high short-term debt, high capital expenditures, and low dividend yields suffer the most during downturns. To estimate the ex-ante bear market risk premium we form a tradeable bear market hedge portfolio, Safe minus Risky (*SMR*). To ensure that *SMR* is constructed using only real-time information, we use expanding-window Fama-MacBeth cross-sectional regressions of individual stock returns in all prior bear markets on variables known at the start of each bear market. Based on real-time parameter estimates, we predict a stock's return conditional on the realization of a bear market. Safe stocks are in the highest decile of predicted bear market returns and risky stocks are in the lowest. Both portfolios are value-weighted and exclude financials and microcap stocks. We impose a waiting period of eight months so an investor using our dating algorithm in real time would classify exactly the same periods as bear markets.

Figure 2 presents the key results of our paper. First, it is possible to identify stocks ex-ante with differing sensitivities to bear markets. Panel A plots a value-weighted index of all stocks in our sample, along with returns to safe and risky portfolios. Panel B shows that *SMR* succeeds in hedging against bear markets out-of-sample: *SMR* has out-of-sample average monthly returns of 3.6% in bear markets. Second, the unconditional average returns of safe stocks are much greater than those of risky stocks. In fact, the safe portfolio outperforms the index, and the risky portfolio underperforms US treasuries. Consider investing one dollar in three portfolios from May 1967 through Dec. 2015. A dollar yields $99 if invested in the index, $256 in the safe portfolio, and only 92 cents in the risky portfolio. The average returns for the *SMR* portfolio are about 0.77%, the CAPM alpha is 1.13%, and the Fama-French-Carhart four factor alpha is 0.85% per month. Panel B also displays the levels of zb*SMR*, a version of *SMR* constructed to have zero beta ex-ante. A dollar invested in this portfolio results in $136 at the end of 2015. zb*SMR* outperforms a value-weighted index of all stocks in our sample (less the risk-free rate) despite having a zero beta. There appears to be no costs and only benefits to the bear-market hedge that *SMR* provides.

The high returns for *SMR* are robust to a battery of tests. Results are similar if historical market beta is included as an additional bear market performance predictor, portfolios are equally-weighted, or financials and microcaps are included. Our results cannot be explained by the conditional CAPM, co-skewness, or idiosyncratic skewness. *SMR* is also distinct from the Betting Against Beta anomaly of

Frazzini and Pedersen (2014). A regression of zb*SMR* on a long-short beta portfolio (long the bottom and short the top beta deciles) results in an unchanged alpha for zb*SMR* and an R^2 of only 15%. Furthermore, returns for *SMR* in bull markets are essentially zero. Hence, an “inverse peso problem,” with too many bear markets relative to investor expectations, cannot explain the high average returns of *SMR*.

Our results are puzzling because they suggest that insuring against bad times is not valuable to investors. It could be that bear markets are not bad times, but this is unlikely as bear markets are associated with economy-wide downturns, which are bad times—high marginal utility states—in standard pricing models (see for example Cochrane, 2005). Bear markets are not only correlated with lower consumption, GDP, and investment growth, but also predict lower growth up to four quarters ahead. One could argue that a period of falling stock prices in expectation of a future recession is not really a “bad time” if current consumption is still high, but this cannot explain why consumption lags market returns. Given their low contemporaneous correlation with consumption growth, equity markets should not carry a high risk premium. In fact, Grossman and Laroque (1990) and Marshall and Parekh (1999) use the slow adjustment of consumption to help explain the equity risk premium. In a similar spirit, Lynch (1996) and Gabaix and Laibson (2002) link the equity risk premium to delays in investor decision-making. If market returns predict consumption growth due to slow adjustment, then bear markets that reflect both current and anticipated consumption should be bad times. For example, in Grossman and Laroque (1990) low market returns, not current consumption, reflect bad times.[4] More generally, 30% of stock market wealth is destroyed during bear markets. It seems unlikely that bear markets are good times for investors, which is what a risk-based explanation would require to justify the abnormally high returns of *SMR*.

It is possible that bear markets are not special in the sense that our predictor variables are always associated with good performance in both bear and bull markets. To test this hypothesis, we bootstrap 1,000 bear market hedge portfolios where we randomize bear market start dates (preserving frequency

[4] In the Grossman and Laroque (1990) model, the slow adjustment of consumption implies that the CAPM holds but the consumption CAPM does not.

and duration). Our estimated bear market premium is unlikely to be observed by chance (not a single simulated alpha is as high as our estimate). Thus, our results are not driven by unconditional premia to our predictors, but are specific to the ability of these variables to predict bear market performance.

Many of the variables (e.g. low asset growth, high profitability, high book-to-market) we use to predict bear market performance have been shown to predict high average returns. A key contribution of our study is to show that these variables predict relatively good performance in bear markets, making their high average returns all the more puzzling. If hedging bear market risk is valuable to investors, these variables should be associated with low average returns due to the premium for bear market protection.

Given this puzzling lack of a premium for hedging bear market risk for many predictor variables individually, it is natural to ask whether we learn anything new by combining them into the *SMR* portfolio. We argue there are at least three reasons to examine *SMR*. The first is parsimony: *SMR* provides a single series that summarizes the price of hedging bear market risk. The second is magnitude: Few of the predictor variables are associated with positive mean returns in our ex-microcap sample so the fact that *SMR* has large average mean returns is not obvious by just looking at the average loadings in the prediction regression. The third is cross-sectional interactions. We find that the alpha of *SMR* remains significant after controlling for all the individual predictor long-short portfolio returns. *SMR* is not a linear combination of the returns of the anomaly portfolios, rather it is based on sorts on linear combinations of the predictors. *SMR* is long large, profitable, dividend-paying, value stocks that make smaller investments with limited debt. This combination of characteristics appears important in both predicting bear market performance and achieving high mean returns.

The time-series behavior of *SMR* suggests an explanation for the low returns of risky stocks. The risky leg of the *SMR* portfolio does particularly well in the internet boom in the late 1990s and declines sharply in the subsequent crash. This suggests that stocks that are the most overvalued before a bear market perform the worst during the bear market, when their prices correct sharply as investor sentiment falls. Stambaugh, Yu, and Yuan (2012; henceforth SYY) argue that short sale constraints and high investor sentiment can lead to an over-valuation of the short leg of anomalous portfolios. This hypothesis predicts low returns for risky stocks following high sentiment periods. The hypothesis also predicts no difference in returns for safe stocks following high and low sentiment periods, or for risky stocks following low sentiment periods.

We find exactly this pattern for our safe and risky portfolios using the Baker and Wurgler (2006) sentiment index. Risky portfolios constructed using our characteristics-based model, earn average excess returns of -0.87% (0.33%) per month if the prior month's sentiment was above (below) the median. Investor sentiment does not predict differences in the next month's average returns for our safe stock portfolio. Overall, the difference in average returns between high and low sentiment periods is 1.21% per month for *SMR*. Because *SMR* excludes microcaps, the effect of sentiment appears to affect stocks of economically meaningful market capitalization.

Our paper is related to research that tests whether exposure to business-cycle risks earns a premium in the cross-section of returns. Some studies (e.g. Vassalou, 2003; Goetzmann, Watanabe and Watanabe, 2012; and Chen, Roll, and Ross, 1986) find a premium for covariance with macroeconomic variables, while others find none (e.g. Hansen and Singleton, 1982). Our setup differs from these papers in three important respects. First, we use bear markets rather than a contemporaneous relationship or a fixed lead-lag structure between stock returns and macroeconomic variables. Second, we use individual stocks rather than factor-sorted portfolios as basis assets (e.g. Vassalou, 2003). This is important because Lewellen, Nagel, and Shanken (2010) find that the strong factor structure of size and book-to-market sorted portfolios can yield misleading results. Finally, we focus only on downturns rather than symmetric realizations of macroeconomic variables.

Overall, our results support behavioral explanations for differences in the cross-section of stock returns and raise the bar for rational explanations. Rational asset pricing models should explain why bear market risk earns a negative risk premium.

I. Data and methodology

A. *Data*

Our dataset is all stocks in the CRSP/Compustat universe. The CRSP dataset includes all monthly stock returns adjusted for delisting, the prior month's market capitalization and the stock price. Stock return volatility is calculated as the standard deviation of daily returns over the past year. Momentum is defined as the cumulative returns over months t-12 to t-2. Firm-level factor loadings are calculated using the CRSP monthly return file and the Fama-French-Carhart (FFC) factor data. Compustat data are used to calculate firm-level characteristics (for a complete list of Compustat variables used see Appendix A). Appendix B provides the specifications used to estimate the rolling factor loadings (betas) for each stock. Each specification uses 60-month rolling estimation windows. We construct anomaly portfolios as described in Section IV.C, with the exception of betting against beta, quality minus junk, and boring minus jackpot returns which are obtained from the original authors.[5] We obtain the Fama and French (2015) five factors from Prof. French's website and the Hou, Xue and Zhang (2014) factors from Prof. Zhang.

For the primary analysis we use a restricted sample that excludes all financial firms (SIC codes between 6000 and 6999) and all micro-cap firms. Micro-caps are defined, each month, as firms with market capitalization below the NYSE 20th percentile. In robustness tests we examine the full dataset as well as subsamples that retain financials and/or micro-caps. To restrict the impact of outliers, we winsorize all variables at the 1% and 99% levels.

We obtain macroeconomic variables from the Federal Reserve Bank of St. Louis' website. We construct log-difference growth rates of real seasonally adjusted gross domestic product (*GDP*), real per capita consumption of services and non-durables (*CONS*), and real non-residential private fixed investment (*INV*). We also use Federal Reserve data on the Treasury rate (*rf*), the default spread (*DS*), and the term spread (*TS*). We obtain the Baker and Wurgler (2006) sentiment index data from Jeffrey Wurgler's website.

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[5] Betting against beta and quality minus junk portfolio returns are obtained from https://www.aqr.com/library/data-sets/betting-against-beta-equity-factors-monthly and, boring minus jackpot returns are obtained from Nishad Kapadia.

B. *Summary statistics*

Our sample consists of 757,291 firm-month observations. Table 1 provides summary statistics. The average (median) firm in the sample has a market capitalization of about $3.5 billion ($709 million) and a book-to-market ratio of 0.63 (0.50). Average daily volatility is 2% and average market betas from the CAPM and the Fama-French-Carhart model are a little over 1.

C. *Identifying bear markets*

We identify bull and bear markets based on the level of the S&P 500 index from February 1966 through December 2015. In particular, we implement the Pagan and Sossounov (2003) parameterization of the Bry and Boschan (1971) algorithm to identify peaks and troughs of the index over the monthly time series. The algorithm first identifies local maxima and minima over rolling eight-month windows and then ensures the alternation of peaks and troughs and imposes a minimum length of four months on each leg of the cycle. The four-month restriction is omitted if the price change is greater than 10% (this happens only during the crash of 1987). Bull markets are from trough to peak and bear markets are from peak to trough. Appendix C details the algorithm. The Internet Appendix provides results for Lunde and Timmerman's (2004) bear market identification, which identifies the same bear markets as Pagan and Sossounov (2003), and a few additional shorter episodes. Our results are robust to the use of either algorithm.

Table 2 lists the characteristics of each bear markets. We identify nine bear markets ranging in duration from three to 25 months. Each episode reflects a significant decline in stock prices with an average cumulative return of about -30%. Bear markets generally correspond to significant economic events such as the oil crisis of the early 1970s, the Volcker recession in the early 1980s, the collapse of internet stock prices in 2000, and the financial crisis of 2008.

Table 2 also presents changes in real GDP around each bear market. Prior to the start of a bear market, average US economic growth is 4.0%, roughly equal to its long run average of 3.3%. During the start of the bear market (current quarter, plus one quarter) GDP growth is similarly strong. However, over the following four quarters, real GDP growth declines to 0.5%, which is below the 15th percentile of quarterly GDP growth over the sample period. The algorithm appears to perform qualitatively well at identifying periods of sustained market declines and these declines anticipate changes in real economic output.

Figure 1 depicts the relation between bear markets and recessions. For each recession in the 1963-2015 sample, we present the closest bear market, and the market index level. . Although we identify bear markets without using any information on the state of the economy other than the S&P 500 level, the bear market periods correspond closely to NBER recessions. Six of the seven recessions in our sample intersect with bear markets. The exception is the short recession in 1980. The onset of a bear market typically precedes the start of the recession and the market begins to recover before the recession ends. Figure 1, Panel B shows averages across all recessions in the sample. The market peak is eight months before the recession starts and the market begins to recover on average five months before the recession ends. Thus, on average, bear markets anticipate recessions. In section IV.A we present more formal tests of the relation between bear markets and the state of the economy that confirm this intuition.

D. Variables that predict bear market performance

Our objective is to identify stocks that perform particularly poorly in bear markets. To do so, we forecast individual stock returns during bear markets using information on stock characteristics and factor covariances known prior to the onset of the bear market. We test whether we can predict bear market performance both in-sample and out-of-sample using different sets of forecasting variables.

We first consider measures of systematic risk, like CAPM beta, because stocks with higher historical betas should do worse during bear markets. Our next set of predictor variables are factor loadings from the Fama-French-Carhart four factor model. Liew and Vassalou (2000) find that small stocks and value stocks are more sensitive to macroeconomic declines and Chordia and Shivakumar (2002) find that momentum payoffs are sensitive to macroeconomic conditions. Thus, the size, value, and momentum loadings may provide incremental information on bear market performance beyond CAPM betas. We estimate all factor loadings ($\beta^{Market}, \beta^{SMB}, \beta^{HML}, \beta^{UMD}$) using regressions over the 60 months prior to the beginning of the bear market. Appendix B details our methods.

In addition to the traditional covariance-based measures of risk, we also use characteristics-based measures. We use both financial statement data and capital markets data such as past stock returns and market capitalization. Prior research suggests that stock characteristics might provide information on discount rates because true factors are not known or factor loadings are measured with error (e.g., Lin and Zhang, 2013). Characteristics, therefore, could be useful for predicting bear market stock returns. We use a number of variables that might be related to firm risk: firm size (*Size*), stock price momentum (*Mom*), book-to-market (*B/M*), gross profits to assets (*GPA*), investment intensity (*IA*), long-term debt ratio (*DLT*), short-term debt ratio (*DST*) and the dividend yield (*DY*). These characteristics generally reflect screening variables used by investment professionals for portfolio selection and variables used in prior research in a risk-based context.[6] Our final set of characteristics reflects a balance between spanning multidimensional risk and parsimony. We construct these variables using standard approaches described in Appendix A.

II. The setup: is bear market performance predictable?

A. Predicting bear market stock performance in-sample

To understand the determinants of bear market performance in the cross-section of stocks, we estimate Fama-MacBeth regressions of average monthly returns of individual stocks during bear market periods on factor loadings and stock characteristics known at the beginning of the bear market. We first run cross-sectional regressions for each bear market, $b=1,2,\ldots 9$:

$$\overline{r}_{i,b} = X'_{i,b}\gamma_b + \varepsilon_{i,b}$$

where $\overline{r}_{i,b}$ is the monthly average continuous compounded (log) return of stock i in bear market b, and X is a vector of firm-specific forecasting variables that include both characteristics and factor loadings known

[6] For example, Gertler and Gilchrist (1994) shows that small firms are more sensitive to monetary policy shocks than large firms. Also see Daniel and Titman (1997) and Hou, Xue, and Zhang (2014) for discussion of these characteristics in an asset pricing context. We include both long- and short-term debt as short-term debt may reflect financial constraints beyond those captured by total indebtedness (Almeida, Campello, Laranjeira and Weisbenner, 2012).

at the beginning of bear market *b*. The predictor variables are winsorized at the 1% and 99% levels and standardized to have mean zero and unit standard deviation in each cross-section. Table 3 presents the average coefficients, $\overline{\gamma}$, across the nine bear markets. Standard errors are computed as in Fama and MacBeth (1973). The first specification includes only market beta (Table 3, Column 1). As expected, we find that high beta stocks have significantly lower returns during bear markets. A one-standard-deviation increase in beta is associated with 1.75% lower returns per month in bear markets. In the second specification we measure risk as downside beta (computed using only months in the last 5 years with below-average market returns). Table 3, Column 2 shows that a one-standard-deviation increase in downside beta is associated with a bear market return of -1.19% per month. The R^2 for the model with CAPM beta is 14.3% but declines to 7.5% when using downside beta. Although downside beta is designed to capture downside risk, the measure does not perform well. Evidently, any benefits from the measure are offset by additional error resulting from a smaller estimation sample.

In the third specification, we test the forecast performance of loadings on each factor in the FFC four factor model (Table 3, Column 3). We find that market beta is smaller, but still significant (-1). The SMB loading has the largest magnitude of the FFC factors (-1.3) while HML has a positive point estimate of 1.03. This suggests that, during bear markets, value stocks are safer than growth stocks.[7] The momentum coefficient (UMD) is modest (-0.49) and insignificant at the 5% confidence level. The R^2 for the FFC factor loadings is 22.1%. The addition of covariance-based measures of risk improves the forecasts of stock performance during bad times, relative to the single factor CAPM model.

Factor models specify not only that factor loadings measure risk, but also that the set of loadings can be combined to get a single expected return. To form a multifactor estimate of risk exposure, the fourth specification combines the risk factor loadings into one measure for each stock:

[7] This result contrasts with Zhang (2005) who argues that value stocks are riskier in recessions because assets in place are less flexible. While Zhang focuses on NBER dated recessions, our results suggest these effects do not extend to the bear markets in stock prices that anticipate those recessions.

$$E_t(r_{(i,t+1)} - rf_t) = \beta_t^{Market}\overline{MKT_t} + \beta_t^{SMB}\overline{SMB_t} + \beta_t^{HML}\overline{HML_t} + \beta_t^{UMD}\overline{UMD_t}$$

where each factor risk premium ($\overline{MKT_t}$, $\overline{SMB_t}$, $\overline{HML_t}$, $\overline{UMD_t}$) is estimated as the historical average of factor returns using all available data up to month *t*, the month before the prior to the start of the bear market for which returns are being predicted. Although this specification imposes the factor model, it performs the worst empirically (Table 3, Column 4). The R^2 for this risk measure is 4%, suggesting that the factor model does not help to describe the cross-section of returns during bear markets. The underperformance is likely explained by the observation that β^{HML} predicts bear market returns with the opposite sign of other factor loadings.

In the remaining specifications, we use firm-level characteristics to explain bear market performance. We first consider a specification that includes all nine proposed firm characteristics and no market factors. This characteristics-only specification (Table 3, Column 5) reveals that bear market stock returns are significant and positively related to firm size (*Size*), momentum (*Mom*), book-to-market (*B/M*), profitability (*GPA*), and dividend yield (*DY*) and significant and negatively related to investments (*IA*) and short-term debt (*DST*). Together these characteristics explain 19.2% of the cross-sectional variation in bear market returns. It appears, therefore, that large, high-yielding, profitable value stocks with positive momentum that haven't recently made large increases in investment and have not taken on short-term debt provide the best shelter from bad outcomes in the worst market environments.

In the next specification, we combine CAPM beta with firm characteristics (Table 3, Column 6). This model yields an R^2 of 23.5% for the bear market Fama-MacBeth regressions. Market beta is strongly significant but the magnitude of the coefficient (-1.17) is lower than when risk is measured by market beta alone (-1.75). Including characteristics erodes market beta's predictive ability because the characteristics contain some of the same information as market beta. Table 3, Column 7 considers a variation that uses downside beta along with the characteristics. This specification does not improve performance. We also replace market beta with the expected return from the FFC four-factor model (Table 3, Column 8). The

FFC expected return contributes little to the predictive regression compared to the firm level characteristics.

In the final specification we include both covariance-based and characteristic-based risk measures (Table 3, Column 9). In this regression, the magnitude of the covariance measures drops by about a third but they all remain significant. The story is more complex for the characteristics. In this specification, firm size, book-to-market, and dividend yield remain significant despite large reductions in the coefficient estimates. Stock price momentum (*Mom*) is now significant, the point estimate for profitability is nearly halved and remains insignificant, and short-term debt (DST) is now marginally significant. The magnitudes of the contributions of investment intensity and the short-term debt ratio are stable and strongly significant across the specifications. The adjusted-R^2 increases to 26.45% for this regression.

On the whole, the results presented in Table 3 suggest there is predictability regarding which stocks provide the best protection in bear markets based on both characteristics and factor loadings. An investor hoping to avoid the worst outcomes during bear markets should shun small, growth firms that have just made big investments using short-term debt.

B. Out-of-sample estimates of expected bear market stock returns

Could an investor have known in real time which stocks to avoid during bear markets? To answer this question, we test whether our models succeed in predicting a stock's bear market performance out-of-sample. In our analysis, we focus on the characteristics model (Characteristics) and the CAPM plus characteristics model (CAPM + Characteristics). The Characteristics model is specification 5 in Table 3 with *ln(Size)*, *ln(Mom)*, *ln(B/M)*, *GPA*, *IA*, *DLT*, *DST* and *DY* as predictor variables. The CAPM + Characteristics model is specification 6 in Table 3 and includes market β as an additional predictor variable. To mitigate data-mining concerns, we retain all characteristics in the model regardless of statistical significance

1. Constructing out-of-sample predicted bear market returns

We construct out-of-sample forecasts of a firm's expected return in a bear market using expanding window versions of the Fama-MacBeth regressions in Table 3. In particular, to construct bear market predicted returns for month *t*, we first estimate the parameters in Fama-MacBeth regressions of bear market returns on characteristics (Table 3, Column 5) or characteristics and beta (Table 3, Column 6) using only bear markets that end at least eight months prior to month *t*. Because the Pagan and Sossounov (2003) algorithm requires an eight-month window to classify a bear market, our approach ensures that the end of the bear market is known by investors. Therefore, there is no look-ahead bias in identifying bear markets.[8] We then use the estimated parameters from the Fama-MacBeth regression and current stock characteristics (and also market beta for the CAPM + Characteristics model) to construct expected bear market returns for each stock. To form the expected value, we use average coefficient estimates over bear markets *b = 1, 2…, B* with *B* ending prior to month *t-8*, and firm-specific attributes known as of the end of month *t*-1. We roll this procedure forward each month to generate a time-series of each stock's predicted bear market return. Note that the γ parameters change relatively infrequently, only after the end of a bear market is known by investors and then, as the average of an expanding window.

Figure 3 presents the time series of coefficient estimates ($\bar{\gamma}_t$) that we use to generate out-of-sample predicted bear market returns. The solid lines report coefficient estimates for each bear market and the dashed lines presents an expanding time series moving average of the coefficients. That is, the initial coefficient is estimated from the first bear market, the second is based on the first two bear markets$(\gamma_1 + \gamma_2)/2$, and so on. The parameter estimates are fairly stable, particularly after including the first three bear markets. The book-to-market (*B/M*) parameter flips from negative in the first bear market to a stable positive estimate by the fourth bear market. Similarly, the short-term and long-term debt (*DST* and *DLT*) parameters flip from positive estimates in the first bear market to consistently negative estimates as the estimation window expands.

2. Evaluating the accuracy of predicted bear market returns

[8] We confirm that the same periods would have been identified as bear markets by investors applying the algorithm in real-time. In fact, waiting for eight months after the end of the bear market (as we do) is conservative; all bear markets in our sample are identified at most 6 months after their end.

We employ two tests to evaluate the accuracy of the predicted bear market returns. Our first test measures whether portfolios formed from sorts on predicted bear market returns perform as predicted during subsequent bear markets. We rank stocks into deciles based on their out-of-sample predicted bear market returns with the riskiest stocks in decile 1 (most negative predicted returns) and the safest in decile 10 (least negative predicted returns). We form value-weighted portfolio returns for each decile. We then regress these portfolio returns on an intercept and a dummy variable that takes a value of 1 in subsequent bear markets.

Table 4 provides the results of our tests for the Characteristics and CAPM + Characteristics models. The results for the Characteristics model are provided in Panel A. Adding the intercept to the coefficient on the bear market dummy yields an expected return during bear markets. The model works well in out-of-sample tests. Stocks predicted to have the lowest returns during bear markets have returns of -5.5% per month while the safest stocks yield -1.9% per month leading to a bear market spread of 3.6% in a safe minus risky (*SMR*) hedge portfolio. Also, there is no difference in returns between safe and risky stocks in non-bear (bull) markets.

In the second specification we augment the Characteristics model with the market factor. The CAPM + Characteristics model also succeeds in predicting bear market performance. The riskiest stocks have average returns of -6.4% per month in bear markets and the safest have average returns of -1.6%, yielding a safe minus risky spread of nearly 4.7% per month. Overall, both characteristics and the market beta provide useful information for classifying stocks by their out-of-sample performance in bear markets.

In the Internet Appendix we provide results for a second set of tests based on out-of-sample mean squared prediction errors for bear market returns of individual stocks. These tests provide similar inferences as the portfolio-based tests described above. Both models are more accurate than a naïve model that uses the average bear market return (over prior bear markets) as the predicted bear market return. The most accurate model is the CAPM + Characteristics model, followed by the Characteristics model. Overall, our tests show that a stock's bear market performance is predictable using information known prior to the start of the bear market.

III. Primary results: The performance of safe and risky stocks

A. The unconditional average returns of safe and risky stocks

The previous section shows that the safe minus risky (*SMR*) portfolio earns an out-of-sample return of roughly 4% per month in the worst times. This portfolio provides insurance against "bad times" and should earn low average unconditional returns. We find, however, that the *SMR* portfolio earns high, not low, average unconditional returns.

The first panel in figure 2 provides our basic result. We plot the time series of the riskiest (decile portfolio 1) and safest (decile portfolio 10) cumulative compounded price index along with the value-weighted index of all stocks in our sample for comparison. NBER dated recessions and bear market periods are shaded. A number of interesting features emerge. First, the portfolio of safest stocks performs remarkably well during market crashes and recessions. Safe stocks hedge bad times, but this insurance has no cost as there is no difference between the returns of Safe and Risky stocks in bull markets. Risky stocks on other hand, do badly. The average return of the Risky portfolio is less than the average return to a one-month US treasury bill. To trade at a premium to the risk-free asset, these stocks must provide a significant hedge to some bad outcome or simply be mispriced. They do not hedge against bad times as measured by bear markets; in fact, they do exceptionally poorly during such times, making their low unconditional returns puzzling.

Table 5 presents more detailed versions of these results for all value-weighted decile portfolios formed from sorts on out-of-sample predicted bear market returns from the Characteristics model (Panel A) and the CAPM + Characteristics model (Panel B). Unconditional average excess returns increase from the riskiest decile (1) to the safest decile (10) in both panels. The safe portfolio from both prediction models earns excess returns over the one-month risk-free rate of 0.7% per month. As a reference, the average excess return for a value-weighted portfolio of all stocks in our sample is 0.5%. The riskiest portfolio from the Characteristics model, on the other hand, earns average excess returns of -0.1% per month, while the riskiest portfolio from the CAPM + Characteristics model earns average excess returns of 0.1% per month. This is a stark result: stocks that are predicted to do the worst in bear markets do not outperform the risk-free asset unconditionally.

The *SMR* portfolio from the Characteristics model earns returns of 0.8% per month or 9.2% per year, while the *SMR* portfolio from the CAPM + Characteristics model earns a return of 0.5% per month or 6.5% per year. The magnitude of the average *SMR* portfolio returns is large, particularly recognizing that we exclude microcap stocks (market capitalization less than the NYSE 20th size percentile). Fama and French (2008) argue that many anomalies are concentrated in illiquid microcap stocks that represent a small fraction of aggregate investor wealth. Our results are not due to small, illiquid stocks, but rather represent pervasive patterns across the market. (In robustness tests, we show that the sample with microcaps included yields similar results.)

The next set of results in each panel is from CAPM regressions on the decile portfolios. Not surprisingly, the riskiest stocks have the highest betas. Betas decline as we go from risky portfolios to safe portfolios. The *SMR* portfolio has a beta of about -0.7 from the Characteristics model and -1.1 from the CAPM+Characteristics model. This makes its positive mean return even more anomalous with respect to the CAPM. CAPM alphas are 1.1% per month or 13.6% per year for both models. It is also interesting that the CAPM explains a relatively small fraction of the variation in *SMR* returns; the CAPM R^2 is about 40% for both models. Thus the bear market prediction models are different from simply sorting on ex-post CAPM betas.

The next set of results in each panel is from FFC four factor regressions. The alphas are 0.85% per month (Characteristics model) and 0.52% per month (CAPM + Characteristics model).

Finally, we test whether the Fama and French (2015) and the Hou, Xue, and Zhang (2014) factor models can explain *SMR*'s alphas. We find that the alphas remain about the same for the Characteristics model at 0.7% for both factor models. The alpha for the CAPM +Characteristics model is lower at 0.4% for the Fama-French five factor model and an insignificant 0.2% for the Hou-Xue-Zhang model. Note that all SMR alphas are not negative, which is what a premium for hedging bear markets would predict.

To better understand the *SMR* portfolio, we strip out its strong negative market exposure. To do so, we construct a zero beta *SMR*; i.e., a bear market hedge portfolio that has zero exposure to the market in expectation. We first estimate the CAPM betas of the safe and risky portfolios out of sample using a 60-month rolling window (minimum window of 12 months). We use these estimates to construct the zero beta *SMR* portfolio in the following month. Letting $\hat{\beta}_{St}$ and $\hat{\beta}_{Rt}$ be estimates of the safe and risky portfolio CAPM betas over the period [t-60, t-1], the return on the zero beta *SMR* portfolio during month *t* is defined as:

$$zbSMR_t = \frac{R_t^S}{\hat{\beta}_{St}} - \frac{R_t^R}{\hat{\beta}_{Rt}}$$

where R_t^S and R_t^R are the returns on the safe and risky portfolios during month *t*.

The final column in each panel of Table 5 provides the unconditional and risk-adjusted return results for zb*SMR*. The portfolio has a mean excess return of about 1% per month, or 12% annually, under both the Characteristics and the CAPM + Characteristics models. The CAPM regressions, with insignificant market coefficients, reveal that zbSMR has no ex post market exposure. The CAPM and FFC alphas, however, are large, significant, and similar to the alphas of the original *SMR* portfolios. The Fama-French 5 factor alphas for the Characteristics model are 0.5% and are 0.6% for the Hou-Xue-Zhang model. For the CAPM+Characteristics alphas are 0.3% in both models with t-stats of 1.81 and 1.6 respectively. The second panel of Figure 2 illustrates the performance of *SMR* and *zbSMR*. Both the *SMR* and zb*SMR* portfolios outperform the excess returns of the value-weighted index of all stocks in our sample.

Overall, these results provide evidence against the joint hypothesis that bear markets represent adverse realizations of systematic risk and that stocks that hedge systematic risk earn higher expected returns. The prices of stocks that hedge bad times do not appear to include an insurance premium. Instead, investors appear to get paid to hedge bad times.

B. Robustness Tests

We test if our results are robust to alternative bear market dating algorithms, alternative sample selection criteria, and the conditional CAPM. First, we use the Lunde and Timmerman (2004) business cycle dating algorithm instead of the Pagan and Sossounov (2003) algorithm to identify bear markets. The two algorithms identify the same start and end dates for all of the bear markets we report. The Lunde and Timmerman (2004) algorithm identifies a few additional, shorter, episodes as bear markets. In the internet appendix we show that changing the algorithm does not change our conclusions.

We also confirm that the *SMR* alpha is robust to two alternative samples. The first retains financials but not microcaps and the second includes all stocks. We also consider equal-weighted rather than value-weighted portfolios. Table 6 presents the FFC risk-adjusted return analysis for both the Characteristics and CAPM + Characteristics *SMR* portfolios. Our results are not qualitatively sensitive to these choices: the FFC alphas are little changed for any of the alternative Characteristics *SMR* portfolios and are stronger for the alternative CAPM + Characteristics *SMR* portfolios. For example, when we include all stocks, the FFC alpha for the CAPM + Characteristics portfolio is 0.8% per month and significant. In unreported results we find that *SMR* four factor alphas are robust to excluding momentum from the bear market performance prediction model.

Cederburg and O'Doherty (2015) show that a conditional CAPM explains the Betting Against Beta anomaly. Because *BAB* can be thought of as a safe minus risky portfolio where only beta is used to measure risk, it is possible that the conditional CAPM may explain the *SMR* alpha. In Panel C, we test whether the conditional CAPM can explain the alphas of *SMR*. We employ the test suggested by Boguth et al (2011), and implemented in Cederburg and O'Doherty (2015). We first use daily data over the prior 3 and 36 months to estimate 3-month and 36-month lagged component betas every quarter for safe, risky, and *SMR* portfolios as weighted averages of the betas of the individual stocks in each portfolio. We then estimate conditional CAPM regressions:

$$r_{i,t} = \alpha + (\gamma_{0,i} + \gamma_{i,1}' Z_{i,t-1}) r_{m,t}$$

where $r_{i,t}$ are quarterly safe, risky, or *SMR* portfolio returns, $r_{m,t}$ is the market excess return, Z is a vector of instruments containing the 3-month and the 36-month lagged component-betas (Beta LC3 and Beta-LC36). Panel C shows that the alphas are similar for the Characteristics (2.8% a quarter for conditional, 2.9% for unconditional CAPM) and CAPM+Characteristics model (2.6% a quarter for conditional, 2.9% for unconditional CAPM). Thus, although the conditional CAPM explains the returns for the *BAB* strategy in Cederburg and O'Doherty (2015), it has no effect on the *SMR* strategy. This further underscores the differences between *BAB* and *SMR.*

In the Internet Appendix, we test whether the bear market portfolio betas depend on the state of the market. We regress returns of the predicted bear market return decile portfolios on the market and an interaction of the market return with a dummy variable that takes on the value of 1 in bear markets. We find a small, statistically insignificant, increase in the betas of the riskiest stocks during bad times, while the betas of safe stocks stay the same. Thus, state-dependent betas cannot explain the low average returns of risky stocks.

C. Does SMR repackage anomalies?

Another possible interpretation of our results is that *SMR*'s alpha is not due to bear markets at all. Perhaps *SMR* merely repackages existing anomalies. If SMR's high returns are driven by unconditional risk premia that the predictor variables have in both bull and bear markets, then the coefficients in regressions of returns on these characteristics would always be negative and bear market prediction regressions would simply reflect this pattern.

To ensure that bear market performance drives our results, we randomly assign bear/bull episodes to our sample period and construct safe and risky portfolios on the basis of these placebo bear markets. We randomize the incidence of bear and bull markets, while preserving the empirical duration and relative frequency of each. We randomly assign the first episode as a bull or a bear and draw a random duration from the relevant empirical distribution. We then alternate bull and bear markets, each time drawing a random duration until the end of the sample period. For this 'bootstrapped' sample, we re-estimate coefficients for our Characteristics model using average returns during the prior placebo bear markets as the dependent variable. These coefficients are then used to construct safe and risky portfolios. We repeat this procedure 1,000 times and store the FFC alpha of the *SMR* portfolio each time. Figure 4 plots a histogram of the simulated *SMR* alphas. The 0.85% SMR alpha reported in Table 5 is unlikely to occur by chance. None of 1,000 placebo *SMR*s have an alpha greater than 0.85%, which implies an empirical p-value in the bootstrap sample of 0.00. Thus, it is unlikely that the alpha of *SMR* is due to unconditional premia of the predictor variables. We obtain additional evidence that bear market are important by predicting performance in bull markets as a placebo test. In the Internet Appendix we show that a bull market hedge portfolio formed using the same variables has zero average returns.

Thus, it is clear that *SMR*'s high average returns are not because the predictor variables always predict good performance but because bear markets are special. However, some of our predictor variables have been shown by prior research to be associated with high average returns. For example, firms with low investments, high profitability, and high momentum predict better bear market performance in our tests and are associated with high average returns. A key result from our tests is that stocks with such characteristics do well in bad times making rational explanations for their high returns less plausible. Given the loadings in the bear market prediction regression, *SMR* is a combination of variables that (mostly) predict high average returns. Do we learn anything from *SMR*, beyond what we learn from the bear market prediction regression? Is *SMR* bigger than the sum of its parts?

To examine this question, we form long-short portfolios by sorting stocks into deciles on each of the nine predictors in the CAPM+Characteristics model for the same sample of stocks used to construct *SMR*. Table 7 shows that of these nine long-short portfolios, only momentum, profitability and asset growth have mean returns different from zero in this sample. The lack of significance of the mean returns for a majority of the variables is consistent with results in Zhang (2017) that many anomalies do not survive in the ex-microcap sample. The ex-ante probability that combining these variables randomly will generate positive mean returns is small.

The alphas to *SMR* remain positive after controlling for the predictor variables either by themselves or when combined with each other. Table 7 Panel B shows regressions of *SMR* returns on long-short portfolios formed from decile sorts on each of the predictor variables. *SMR*'s alpha remains significant across specifications. In particular, *SMR*'s alpha, although smaller than before, remains significant even in a regression with all the predictor long-short portfolios as explanatory variables. This may appear surprising, because *SMR* is constructed from the same variables that underlie the predictor decile portfolios. However, *SMR* is not a linear combination of the returns of the portfolios formed from the predictor variables, rather it is based on sorts of linear combinations of the predictors themselves. This combination of characteristics appears important in both predicting bear market performance and in achieving high mean returns.

IV. Why do safe stocks earn high average returns and risky stocks low average returns?

In this section, we test a number of explanations for the low returns of the risky portfolio and the high returns of the safe portfolio.

A. Bear markets and economic growth

One explanation of our results is that bear markets do not correspond to bad economic times. This seems unlikely given prior research that shows that stock markets predict real economic activity (e.g., Fama, 1981) and the results in Figure 1 that show that bear markets are typically associated with NBER recessions. Nevertheless, to test this hypothesis, we regress the quarterly growth (log differences) of three macroeconomic variables – real GDP (*GDP*), real per-capita consumption of non-durables and services (*CONS*), and real non-residential fixed private investment (*INV*) – on our bear market dummy variable:

$$y_{t+k} = \alpha + \beta Bear\ Dummy + \varepsilon_{t+k}$$

where $Bear\ Dummy_t = 1$ if the last month in quarter t is a bear market month, 0 otherwise, and y_{t+k} is either *GDP*, *CONS*, or *INV* and k = 0,1,..,4. Note that the predictive regressions for up to three quarters ahead are not feasible in real-time given the waiting time involved in identifying bear markets. However, this set of specifications allows us to test how far ahead the market forecasts macroeconomic aggregates. Our results are presented in the left panel of Table 8. The bear market dummy is significant in predicting all three macroeconomic variables at all five horizons. Moreover, the market is forward looking and the degree of predictability is large. The R^2 typically peaks at quarter t+2 and a simple bear dummy variable for quarter t predicts 25% of the quarter t+2 variation in both real GDP growth and investment growth and 12% in consumption growth. In bear markets, quarterly GDP growth two quarters ahead is -0.09% per quarter, the 13th percentile of quarterly GDP growth. Results for consumption and investment show similar economic magnitudes.

In the first set of columns in Table 8, we test whether the bear market predictability derives from information distinct from past realizations of the macroeconomic variable itself. We estimate

$$y_{t+k} = \alpha + \beta Bear\ Dummy + \gamma_1 y_t + \gamma_2 y_{t-1} + \varepsilon_{t+k}$$

where, as before, $k=0,1,..,4$.[9] These results show that market returns contain significant information not in the contemporaneous realizations of the macroeconomic series. Thus, examining contemporaneous covariances between measures of "bad times" as classified by macroeconomic variable realizations and stock or portfolio returns is likely to be misleading, because stock market returns respond to expectations of future macroeconomic realizations.

B. Sentiment-driven mispricing

SMR does badly during the internet boom period of the late 1990s, suggesting that its returns may be related to investor sentiment. The stocks we identify as risky may be the ones that are most overvalued in periods of high sentiment, and are thus most likely to perform the worst when sentiment falls in bear markets. Stambaugh, Yu, and Yuan (2012; hereafter SYY) hypothesize that if short-sale constraints are binding and sentiment is high, some stocks may become overpriced. In our context, this hypothesis predicts that the risky short leg of the *SMR* portfolio will have low average returns following high sentiment periods. Sentiment should not affect the long leg (safe stocks), nor should the short leg be underpriced in low sentiment periods. Following SYY, we classify each month as low or high sentiment

[9] The contemporaneous term is dropped for $k=0$.

based on the median of the Baker and Wurgler (2006) sentiment index. We then examine average returns (in excess of the risk-free rate) of safe and risky stocks, and of *SMR* and *zbSMR,* in the next month.

Table 9 presents our results. Using portfolios constructed with our Characteristics model, we present average returns separately for the safe, risky, and *SMR* portfolios during high and low sentiment periods. Our results show strong support for the sentiment hypothesis. Excess returns of safe stocks are no different in high or low sentiment periods. However, risky stocks have excess returns of -0.87% per month in high sentiment periods and 0.33 % per month in times of low sentiment. The differential of 1.2% per month is economically and statistically significant. Thus, both *SMR* and *zbSMR* have different returns following periods of high or low sentiment. The differential between high and low sentiment periods for each of these portfolios, 1.21% (*SMR*) and 0.98% (*zbSMR*), is large and economically significant. Results are qualitatively similar for portfolios constructed using the CAPM + Characteristics model.[10]

Our results suggest that sentiment-induced mispricing can explain the time-series variation in the returns of safe and risky stocks. Importantly, these portfolios are explicitly designed to reflect situations in which rational asset pricing models have sharp predictions. We find that sentiment-driven mispricing appears to prevail over hedging bad times.

C. Relationship to other anomalies

In this section, we test whether other known anomalies and "risk factors" are related to *SMR*. Our purpose is not an "explanation" of the anomalies but is rather a "data reduction" exercise in the spirit of Cochrane (2011). If the payoffs of anomalies are correlated with *SMR*, and controlling for *SMR* attenuates their alphas, then there may be a common explanation for SMR and an entire set of anomalies.

[10] These results are not driven by the "dot com" period, a period often associated with high investor sentiment (see SYY). Specifically, in unreported results we find that if we exclude observations from 1996-2004 from our sample the difference between times of high and low sentiment is 1.7% for *SMR* and 1.4% for *zbSMR*.

We examine the set of anomalies from SYY, augmented with three new anomalies published subsequent to their research that may be related to *SMR*, and the four FFC factors. The anomalies in SYY are

1. [AG] Asset Growth: growth rate of total assets, motivated by Cooper, Gulen, Schill (2008).
2. [CEI] Composite Equity Issues: Equity issuance from Daniel and Titman (2006).
3. [CHS] Default Probability: probability of failure using model of Campbell et al (2008).
4. [GP] Gross Profit-to-Assets: Novy-Marx (2013) argues high GP earns high returns.
5. [IA] Investment-to-Assets: Annual change in scaled gross PP&E+Inventories. Xing (2008) finds firms with greater IA earn lower returns.
6. [IVOL] Idiosyncratic Volatility: Ang, Hodrick, Xing and Zhang (2006). Stocks are sorted on squared residuals from FF-3 regressions for daily returns over the prior month.
7. [NOA] Net Operating Assets: Cumulative difference between accounting and cash value added [Hirshleifer, Hou, Teoh, and Zhang (2004)].
8. [NSI] Net Share Issuance: Growth rate of shares outstanding. Ritter (1991) argues equity issuers underperform non-issuers.
9. [O] Ohlson Score: the probability of firm failure based on Ohlson (1980).
10. [ROA] Return on Assets: Fama and French (2006) show profitability earns higher returns.
11. [TAC] Total Accruals: Sloan (1996) finds firms with high accruals earn low returns.

We augment this set with three new anomalies:

12. [BAB] Betting against Beta: Long low beta stocks and short high beta stocks rescaled to have a zero beta. Frazzini and Pedersen (2014) show this earns high average returns.
13. [QMJ] Quality Minus Junk: Long quality and short junk. Quality is assessed on measures of profitability, growth, safety, and payout. Asness, Frazzini, and Pedersen (2013) argue this portfolio earns high returns.
14. [BMJ] Boring minus Jackpot: Long low probability of jackpot returns, short high probability of jackpot returns. Conrad, Kapadia, and Xing (2014) show that this portfolio earns high returns.

We also consider the FFC factors for size (SMB), value (HML), and momentum (UMD), bringing our test portfolios to 17. Note that these anomalies are constructed using the entire sample of stocks, while *SMR* and *zbSMR* are constructed using only the ex-microcap sample.

Table 10, Panel A provides, as benchmarks, the CAPM and FFC alphas of each of the anomalies. As is well known, all of these portfolios except for SMB have significant CAPM alphas over our sample period. We then provide the results of regressing each anomaly long-short portfolio on the market and the Characteristics *SMR* (Table 10, Panel B) and on the market and the Characteristics zb*SMR* (Table 10, Panel C). This allows us to test how the CAPM alphas change when we control for *SMR.* In Panel B, we show that the Characteristics *SMR* is significantly correlated with 15 of the 17 anomalies. Only Asset growth and UMD are insignificant. Only SMB is negatively correlated with *SMR*. This is consistent with our prior results because *SMR* is long large safe stocks and short small, risky stocks. *SMR* is positively correlated with 14 of the anomalies and thus reduces their alpha. By itself, the overwhelming number of positive correlations between *SMR* and the anomalies is noteworthy. Almost all anomalies have returns that covary with the differential between safe and risky stocks. This common variation is beyond any common dependence on the market, since we also control for market returns in the regression. In terms of alphas, controlling for *SMR* reduces the absolute CAPM alpha for the median (mean) test portfolio reduces by 38% (44%) to 0.46 (0.49). The test assets whose CAPM alphas become insignificant after controlling for *SMR* are those related to profitability (ROA), distress (O Score), idiosyncratic skewness (BMJ) and value (HML). In addition, alphas of test assets that are variations on these themes also diminish substantially, but some are still statistically significant. This includes gross profitability (GP), with alpha reduced by 34%, the Campbell et al measure of distress (CHS), with alpha reduced by 30%. The alphas for composite equity issuance (CEI) and idiosyncratic volatility (IVOL) also reduce by about half.

In the next specification, we regress each anomaly's return on the zero beta version of *SMR* (*zbSMR*). This specification tests the strength of the relation between each anomaly and *SMR*, while removing any common dependence on the market. The R^2s for these regressions range from 1% to 31% and the alphas are generally lower. In particular, the median (mean) absolute alpha reduces to 0.42 (0.44), corresponding to a 48% (46%) reduction from the CAPM alpha.

Importantly, the betting against beta anomaly has an R^2 of only 2.69% with *zbSMR* and its CAPM alpha does not substantially attenuate when we control for *zbSMR*. Thus, our bear market based measure of risk appears to identify a source of variation in returns that is independent of the betting against beta anomaly.

Figure 5 summarizes the results from the Characteristics model. For each anomaly, confidence intervals for alpha estimates using the CAPM and FFC four factor model are compared to similar estimated intervals obtained after controlling for *SMR* returns and zero-beta *SMR* returns. These results establish that a subset of anomalies (or risk factors) is related to *SMR.* A large number of anomalies are positively correlated with *SMR* and *SMR* reduces the median anomaly alpha by a factor of 30%-40%. These anomalies are related to profitability, distress, idiosyncratic volatility, skewness, and value. These results suggest that a factor with positive mean returns and countercyclical variation in returns (high returns in market downturns) can explain a significant fraction of the alphas of a set of anomalies.

How efficient is *SMR* in extracting pricing information from the 9 bear market performance predictor variables? To understand this question, we consider two other methods of combining the long-short decline portfolios formed from the predictor variables as in Table 7. These include the ex-post mean-variance efficient portfolio and the Tu and Zhou (2011) ex-ante optimal portfolio. The results of using these portfolios' returns to explain anomaly returns are presented in Panel D. These two portfolios reduce the median absolute anomaly CAPM alpha by about 20%, or about half the reduction from *SMR* and *zbSMR*.

VI. Conclusion

Simple intuitive measures of risk like firm size, leverage, book-to-market ratio, investment and indebtedness are good predictors of bad performance during severe market downturns. We use out-of-sample predictions of bear market returns based on these variables to form a bear market hedge portfolio, *SMR*. This portfolio is long safe stocks – those forecasted to suffer the least in a bear market – and short risky stocks – those forecasted to perform the worst in a bear market. This portfolio succeeds in providing insurance against bear markets out of sample.

Standard asset pricing models argue that a stock or portfolio that hedges against bad times is valuable to investors and should earn a premium or, equivalently, have a low expected return. Bad times in these models are typically cyclical downturns, when consumption growth declines. For example, Cochrane (2005) (page 451) characterizes bad times as times "… *when stock prices are low after a long and depressing bear market; in the bottom of a recession or financial panic; a time when long-term bond prices and corporate bond prices are unusually low. This is a time when few people have the guts (the risk tolerance) or the wallet to buy risky stocks or risky long-term bonds.*"

We show that *SMR* earns high average returns and factor model alphas and that bear markets predict large declines in GDP, consumption, and investment growth. The high returns are robust and pervasive – they exist with and without microcaps or financial firms in the sample, for equal- and value-weighted returns, and when adjusting for risk with the conditional CAPM. Overall, these results provide evidence against the hypothesis that hedging against periods when the stock market expects large cyclical declines in GDP, consumption, and investment growth is valuable to investors.

To be consistent with these results, a risk-based theory must argue that economic downturns are not high marginal utility of consumption states. We also find that the Baker and Wurgler (2006) sentiment measure predicts the returns of *SMR*, with low returns for risky stocks following high sentiment periods. Importantly, returns for the risky portfolio are significantly negative (1.17% per month) following high sentiment periods. A risk-based story must argue that small, volatile stocks with high investment funded with short-term debt (the characteristics of stocks in the risky portfolio) are safer than the risk-free asset in periods of high sentiment. This is unlikely. In a setting designed to test rational asset pricing theory, we find that the best explanation for our results is a behavioral one.

Appendix A. Variable definitions

Size	Market capitalization of the firm is obtained from CRSP as the product of shares outstanding and stock price.
β	Beta is the market coefficient in a 60-month rolling CAPM regression.
Down β	Downside beta is calculated in the same way as beta but using only days when the market return is below the unconditional mean market return.
β^{Market} β^{SMB} β^{HML} β^{UMD}	The FFC factor loadings are the coefficients of the Fama-French market, SMB, HML, and UMD factors estimated using a 60-month rolling regression of each stock return time series on the FFC factor-model (Mkt, SMB, HML, and UMD).
ER	Expected return is calculated by applying the coefficients of the FFC four-factor model estimated over an expanding window of prior bear markets to the historical means of the four factors.
DST	Short-term debt to assets is obtained from Compustat as current liabilities scaled by total assets.
GPA	Gross profits is obtained from Compustat as Sales minus COGS divided by total assets.
Mom	Momentum is the cumulative return on the stock between months t-12 and t-2.
B/M	Book-to-market is obtained from Compustat and CRSP as the ratio of the book value of equity to market capitalization.
DY	Dividend yield is obtained from Compustat and CRSP as dividends per share divided by stock price.
IA	Investment to assets is obtained from Compustat as investment (change in property, plant, and equipment plus change in inventory) divided by total assets.
Vol	Volatility is calculated as the standard deviation of daily returns over the past year.
DLT	Long-term debt to assets is obtained from Compustat as long-term debt divided by total assets.
Rf	The 3-month Treasury rate is obtained from the Federal Reserve Bank of St. Louis's website (http://research.stlouisfed.org).
DS	The default spread is the difference between the Moody's seasoned Baa corporate bond yield and the Aaa corporate bond yield obtained from the Federal Reserve Bank of St. Louis' website.
TS	The term spread is the difference between the yields on 10-year and 3-month U.S. Treasury securities obtained from the Federal Reserve Bank of St. Louis' website.

All firm-level characteristics and factor loadings are winsorized at the 1% and 99% levels.

Appendix B. Factor models

In our analysis we use estimates of the exposure of each stock to various risk factors. Below are the models we estimate.

CAPM	$r_{it} - rf_t = \alpha + \beta_{mkt} * (r_{mt} - rf_t)$
Fama-French	$r_{it} - rf_t = \alpha + \beta_{mkt}\left(r_{mt} - rf_t\right) + \beta_{SMB}SMB_t + \beta_{HML}HML_t$
Fama-French-Carhart	$r_{it} - rf_t = \alpha + \beta_{mkt}\left(r_{mt} - rf_t\right) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD$
Down Beta	$r_{it} - rf_t = \alpha + \beta_{mkt}\left(r_{mt} - rf_t\right) I_{r_{mt} < \bar{r}_m}$
Fama-French-Carhart + BAB	$r_{it} - rf_t = \alpha + \beta_{mkt}\left(r_{mt} - rf_t\right) + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{UMD}UMD + \beta_{BAB}BAB_t$

r_{it} is the return on stock i, r_{ft} is the risk-free rate, and r_{mt} is the market return, all during month t. The factors $SMB, HML,$ and UMD are obtained from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) and the BAB factor is obtained from Frazzini's website (https://www.aqr.com/library/data-sets/betting-against-beta-equity-factors-monthly). The indicator function $I_{r_{mt}<\bar{r}_m}$ equals one in months when the market return is below its time-series mean and zero otherwise. Each model is estimated using a rolling 60-month window of monthly returns for each individual stock. The time series of parameter estimates are winsorized at the 1% and 99% level.

Appendix C. The bear market identification algorithm

We identify bear markets using the algorithm in Pagan and Sossounov (2003). We reproduce the algorithm from Appendix B in Pagan and Sossounov (2003) below:

1. Determination of initial turning points in raw data.

   (a) Determination of initial turning points in raw data by choosing local peaks (troughs) as occurring when they are the highest (lowest) values in a window eight months on either side of the date.

   (b) Enforcement of alternation of turns by selecting highest of multiple peaks (or lowest of multiple troughs).

2. Censoring operations (ensure alternation after each).

   (a) Elimination of turns within 6 months of beginning and end of series.

   (b) Elimination of peaks (or troughs) at both ends of series which are lower or higher.

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Table 1. Summary Statistics: Firm Characteristics and Factor Loadings

The table provides summary statistics for our sample of merged CRSP and Compustat firms excluding financials and micro-caps (below the 20th percentile of NYSE market capitalizations). Excess Return is the excess monthly return over the risk free rate. Size is the market capitalization from CRSP. Momentum (*Mom*) is the cumulative return between months t–12 and t–2. Volatility (*Vol*) is the standard deviation of daily returns over the past year. Book-to-market (B/M) is the ratio of the book value of equity to market capitalization. Gross profits to assets (*GPA*) is gross profits (sales - COGS) divided by total assets. Investment to assets (*IA*) is investment (change in plant property and equipment + change in inventory) divided by total assets. *DLT* is long-term debt divided by assets, and *DST* is debt in current liabilities scaled by total assets. The dividend yield (*DY*) is dividends per share divided by stock price. β is calculated as the CAPM market return coefficient using 60-month rolling regressions. The table also reports the FFC factor coefficients, β^{Market}, β^{SMB}, β^{HML} and β^{UMD}. Downside beta (*Down β*) is calculated in the same way as β but using months when the market return is below the unconditional mean. All firm-level characteristics and factor loadings are winsorized at 1% and 99% levels. See Appendix A for a detailed definition of all variables. The sample period is February 1966 to December 2015. There are 757,291 firm-month observations.

	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Excess Ret.	0.69%	11.30%	-63.79%	-5.40%	0.39%	6.40%	150.53%
Size ($mil)	3,520	11,789	18	245	709	2,102	190,600
Mom	0.20	0.53	-0.91	-0.08	0.12	0.37	15.97
Vol	0.02	0.01	0.01	0.02	0.02	0.03	0.11
B/M	0.63	0.50	0.00	0.28	0.50	0.84	6.99
GPA	0.37	0.24	-0.55	0.19	0.33	0.50	1.24
IA	0.10	0.15	-0.43	0.02	0.07	0.14	2.34
DLT	0.20	0.16	0.00	0.06	0.19	0.31	0.71
DST	0.04	0.05	0.00	0.00	0.02	0.05	0.35
DY	0.02	0.03	0.00	0.00	0.01	0.03	0.30
B	1.16	0.61	-0.54	0.76	1.10	1.48	4.64
β^{Market}	1.06	0.51	-0.82	0.72	1.02	1.35	3.58
β^{SMB}	0.58	0.80	-1.47	0.02	0.49	1.04	4.92
β^{HML}	0.06	0.86	-4.48	-0.41	0.13	0.60	3.59
β^{UMD}	-0.08	0.54	-2.99	-0.37	-0.06	0.22	2.43
Down β	1.14	0.83	-2.46	0.62	1.08	1.58	6.55

Table 2. Bear Markets

This table provides the start/end dates, duration, and the cumulative return on the value-weighted (VW) and the equal-weighted (EW) market portfolios for each bear market. The last set of columns provides measures of GDP growth for three windows around the beginning of the bear market. Real GDP growth is the annualized change in seasonally adjusted quarterly real gross domestic product. The three windows are constructed such that the quarter containing the first month of the bear market corresponds to t = 0. Bear markets are identified by applying the algorithm in Pagan and Sossounov (2003) to the S&P 500 index series. The sample period is February, 1966 to December, 2015.

		Duration	Cumulative Returns (%)		Real GDP Growth (%)		
Start Date	End Date	(Months)	VW	EW	[-4,-1]	[0,+1]	[+2,+5]
2/1/1966	9/30/1966	8	-15.5	-15.7	8.5	5.9	2.6
12/1/1968	6/30/1970	19	-33.3	-48.3	5.4	4.1	0.4
1/1/1973	9/30/1974	21	-46.2	-49.9	4.1	-1.1	-1.8
12/1/1980	7/31/1982	20	-17.8	-12.8	-1.6	8.1	-2.3
12/1/1983	5/31/1984	6	-9.6	-12.4	5.8	8.4	4.6
9/1/1987	11/30/1987	3	-29.6	-32	3.4	5.3	3.9
6/1/1990	10/31/1990	5	-16.3	-24.3	2.9	0.9	-0.1
9/1/2000	9/30/2002	25	-44.9	-23.8	5.3	1.4	0.2
11/1/2007	2/28/2009	16	-51.4	-54.8	2.3	-0.7	-3.4
	Average	14	-29.4	-30.4	4	3.6	0.5

Table 3. Fama-MacBeth Bear Market Regressions

The table provides estimates from Fama-MacBeth regressions of bear market stock returns on factor loadings and characteristics. Bear market returns are the average monthly return for each firm over the duration of each bear market. The independent variables in each Fama-MacBeth specification are observed at the beginning of the bear market, month *t*. See Appendix A for a definition of all variables. Coefficients are averaged across the nine bear markets identified following Pagan and Sossounov (2003) based on S&P 500 returns. The stock sample is merged CRSP and Compustat firms excluding financials and micro-caps (below the 20th percentile of NYSE market capitalizations). The sample period is February, 1966 to December, 2015. There are 10,490 firm-episode observations for each specification. The t-statistics (in parentheses) are computed using White's standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-4.64	-4.64	-4.64	-4.64	-4.64	-4.64	-4.64	-4.64	-4.64
	(-3.93)	(-3.93)	(-3.93)	(-3.93)	(-3.93)	(-3.93)	(-3.93)	(-3.93)	(-3.93)
β	-1.75					-1.17			
	(-4.48)					(-4.09)			
Down β		-1.19					-0.66		
		(-4.89)					(-3.95)		
ER				-0.46				-0.22	
				(-2.40)				(-1.60)	
β^{Market}			-1.00						-0.85
			(-4.16)						(-4.28)
β^{SMB}			-1.28						-0.99
			(-4.96)						(-5.37)
β^{HML}			1.03						0.78
			(2.25)						(1.93)
β^{UMD}			-0.49						-0.33
			(-1.87)						(-1.53)
Ln(Size)					0.63	0.53	0.54	0.60	0.28
					(4.42)	(3.96)	(4.08)	(3.79)	(3.06)
Ln(Mom)					0.15	0.09	0.11	0.18	0.17
					(0.83)	(0.63)	(0.61)	(0.94)	(1.83)
Ln(B/M)					0.70	0.53	0.61	0.70	0.35
					(2.35)	(2.20)	(2.13)	(2.44)	(2.15)
GPA					0.29	0.24	0.26	0.25	0.16
					(1.53)	(1.45)	(1.42)	(1.42)	(1.27)
IA					-0.30	-0.28	-0.29	-0.28	-0.27
					(-3.31)	(-3.71)	(-3.60)	(-3.12)	(-3.77)
DLT					0.00	-0.07	0.00	-0.01	-0.14
					(0.01)	(-0.81)	(-0.00)	(-0.12)	(-1.74)
DST					-0.19	-0.18	-0.18	-0.19	-0.19
					(-4.21)	(-3.72)	(-3.91)	(-4.23)	(-3.47)
DY					0.95	0.47	0.72	0.87	0.33
					(3.67)	(2.36)	(2.86)	(3.24)	(1.98)
Adj. R^2	14.26	7.47	22.06	3.98	19.22	23.50	21.08	20.39	26.45

Table 4. Bear Market Predicted Return Decile Portfolios

The table provides estimates of regressions of value-weighted average returns for decile portfolios formed based on our bear-market risk model. Model parameters are estimated over an expanding window of prior bear markets and are applied to firm characteristics (and CAPM betas) known at the beginning of the month to predict the return for each stock. Based on these out-of-sample predicted returns each stock is assigned to a decile and all stocks in a decile are used to form a value-weighted portfolio. The time-series of portfolio returns for each decile is regressed on a bear market dummy variable. In Panel A expected bear-market returns are estimated using the Characteristics model and in Panel B using the CAPM + Characteristics model. The characteristics are ln(*Size*), ln(*Mom*), ln(*B/M*), *GPA*, *IA*, *DLT*, *DST* and *DY*. See Appendix A for a definition of all variables. The stock sample is merged CRSP and Compustat firms excluding financials and micro-caps (below the 20th percentile of NYSE market capitalizations). The sample period is February, 1966 to December, 2015. There are 583 monthly observations in each regression. The t-statistics (in parentheses) are computed using Newey-West standard errors with a one-month lag.

	Low	2	3	4	5	6	7	8	9	High	Hi-Lo
Panel A: Characteristics											
Intercept	1.22	1.67	1.57	1.56	1.52	1.41	1.53	1.35	1.21	1.31	0.09
	(3.98)	(5.91)	(6.05)	(6.38)	(6.75)	(6.62)	(7.65)	(7.10)	(7.12)	(8.51)	(0.35)
Bear Market	-6.72	-6.20	-5.69	-5.39	-4.78	-4.94	-4.67	-4.41	-3.70	-3.24	3.49
	(-7.58)	(-7.29)	(-7.16)	(-7.35)	(-6.57)	(-7.87)	(-7.80)	(-8.04)	(-7.65)	(-6.90)	(4.89)
Adj. R^2	12.70	12.51	12.13	12.07	10.65	13.42	13.24	13.05	11.93	10.90	5.72
Panel B: CAPM + Characteristics											
Intercept	1.71	1.78	1.71	1.54	1.53	1.46	1.43	1.32	1.23	1.24	-0.48
	(4.63)	(5.57)	(6.17)	(6.16)	(6.69)	(6.96)	(7.11)	(7.29)	(7.11)	(8.49)	(-1.48)
Bear Market	-8.09	-6.59	-6.05	-5.49	-5.20	-4.81	-4.38	-4.03	-3.73	-2.95	5.14
	(-7.39)	(-7.17)	(-7.06)	(-6.71)	(-7.47)	(-7.17)	(-7.99)	(-7.63)	(-7.48)	(-6.69)	(5.25)
Adj. R^2	0.12	0.11	0.12	0.12	0.12	0.13	0.12	0.12	0.12	0.10	0.07

Table 5. Risk-Adjusted Performance of Bear Market Predicted Return Portfolios

The table reports the out-of-sample risk-adjusted performance of the bear-market-predicted-return decile portfolios formed based on our bear-market risk model and the corresponding safe minus risky (*SMR*) and zero-beta safe minus risky hedge portfolios. Model parameters are estimated over an expanding window of prior bear markets and are applied to firm characteristics (and CAPM betas) known at the beginning of the month to predict the return for each stock. Based on these out-of-sample predicted returns each stock is assigned to a decile and all stocks in a decile are used to form a value-weighted portfolio. *SMR* is a portfolio that is long the highest decile portfolio (safe) and short the lowest decile portfolio (risky). Zero-beta *SMR* (*zbSMR*) is formed in the same manner as *SMR* but using the CAPM betas for the safe and risky portfolios (estimated out of sample as described in the text) to construct a portfolio that has no ex ante market exposure. The returns to these twelve portfolios are evaluated using the CAPM, the FFC 4-factor model, the Fama-French 5-factor Model (FF5), and the Hou-Xue-Zhang Factor model (HXZ). Expected bear-market returns are estimated using the Characteristics model in Panel A and using the CAPM + Characteristics model in Panel B. The characteristics are ln(*Size*), ln(*Mom*), ln(*B/M*), *GPA*, *IA*, *DLT*, *DST* and *DY*. See Appendix A for a definition of all variables. The stock sample is merged CRSP and Compustat firms excluding financials and micro-caps (below the 20th percentile of NYSE market capitalizations). The sample period is February, 1966 to December, 2015. There are 583 monthly observations in each regression except the *zbSMR* regressions which use 570 monthly observations. The t-statistics (in parentheses) are computed using Newey-West standard errors with a one-month lag.

Table 5, cont'd. Risk-Adjusted Performance of Bear Market Predicted Return Portfolios

Panel A: Characteristics Model

	Risky	2	3	4	5	6	7	8	9	Safe	*SMR*	*zbSMR*
Mean Excess return	-0.11	0.44	0.45	0.49	0.58	0.43	0.61	0.48	0.48	0.67	0.77	1.00
	(-0.33)	(1.46)	(1.60)	(1.88)	(2.35)	(1.88)	(2.80)	(2.36)	(2.69)	(4.15)	(3.10)	(4.67)
CAPM alpha	-0.82	-0.23	-0.18	-0.12	0.00	-0.11	0.09	-0.02	0.05	0.31	1.13	0.99
	(-5.59)	(-1.77)	(-1.53)	(-1.17)	(0.02)	(-1.45)	(1.19)	(-0.36)	(0.78)	(3.50)	(5.66)	(4.43)
CAPM Beta	1.46	1.37	1.28	1.24	1.18	1.10	1.05	1.01	0.87	0.72	-0.73	0.03
Adj. R^2	0.79	0.80	0.81	0.85	0.85	0.89	0.89	0.91	0.86	0.72	0.34	0.00
FFC alpha	-0.62	-0.06	-0.04	-0.01	0.09	-0.04	0.15	0.04	-0.03	0.23	0.85	0.78
	(-5.10)	(-0.59)	(-0.38)	(-0.10)	(1.08)	(-0.47)	(1.97)	(0.67)	(-0.51)	(2.94)	(5.48)	(4.18)
Mktrf	1.24	1.17	1.10	1.12	1.07	1.05	1.03	1.01	0.94	0.83	-0.41	0.33
SMB	0.61	0.57	0.49	0.31	0.26	0.09	-0.01	-0.10	-0.19	-0.26	-0.87	-0.91
HML	-0.36	-0.34	-0.37	-0.29	-0.23	-0.21	-0.15	-0.13	0.14	0.26	0.62	0.62
UMD	-0.13	-0.10	-0.04	-0.01	-0.01	0.01	0.01	0.00	0.05	-0.01	0.12	-0.03
Adj. R^2	0.87	0.89	0.90	0.89	0.89	0.90	0.89	0.91	0.89	0.81	0.67	0.46
FF5 alpha	-0.63	-0.05	0.01	0.05	0.17	0.01	0.16	0.01	-0.16	0.10	0.73	0.50
	(-4.93)	(-0.53)	(0.15)	(0.50)	(2.04)	(0.16)	(2.03)	(0.15)	(-2.88)	(1.33)	(4.83)	(2.90)
Mktrf	1.23	1.16	1.09	1.10	1.06	1.04	1.03	1.02	0.98	0.86	-0.37	0.41
SMB	0.56	0.55	0.44	0.28	0.19	0.05	-0.02	-0.10	-0.11	-0.19	-0.76	-0.83
HML	-0.22	-0.19	-0.31	-0.23	-0.21	-0.21	-0.17	-0.18	-0.03	0.17	0.39	0.36
CMA	-0.20	-0.25	-0.09	-0.11	-0.04	0.01	0.05	0.11	0.32	0.19	0.39	0.58
RMW	-0.21	-0.13	-0.18	-0.14	-0.25	-0.12	-0.04	0.03	0.30	0.24	0.45	0.36
Adj. R^2	0.87	0.89	0.90	0.89	0.89	0.90	0.90	0.92	0.91	0.82	0.69	0.50
HXZ alpha	-0.56	0.05	0.07	0.13	0.18	0.01	0.16	0.02	-0.18	0.14	0.71	0.59
	(-4.17)	(0.48)	(0.70)	(1.13)	(1.97)	(0.11)	(1.97)	(0.25)	(-2.85)	(1.65)	(4.08)	(3.11)
MKT	1.26	1.17	1.11	1.12	1.08	1.06	1.04	1.02	0.96	0.83	-0.43	0.33
ME	0.55	0.51	0.43	0.25	0.22	0.07	-0.02	-0.10	-0.13	-0.23	-0.79	-0.86
IA	-0.57	-0.63	-0.57	-0.47	-0.34	-0.26	-0.15	-0.07	0.32	0.38	0.95	1.08
ROE	-0.11	-0.09	-0.06	-0.07	-0.06	0.02	0.04	0.05	0.19	0.06	0.17	-0.02
Adj. R^2	0.87	0.89	0.88	0.89	0.88	0.90	0.89	0.91	0.90	0.79	0.63	0.40

Table 5, cont'd. Risk-Adjusted Performance of Bear Market Predicted Return Portfolios

Panel B: CAPM + Characteristics Model

	Risky	2	3	4	5	6	7	8	9	Safe	*SMR*	*zbSMR*
Mean Excess return	0.12	0.48	0.51	0.46	0.50	0.51	0.57	0.52	0.49	0.66	0.54	0.96
	(0.30)	(1.42)	(1.71)	(1.66)	(2.04)	(2.20)	(2.72)	(2.75)	(2.73)	(4.33)	(1.61)	(3.91)
CAPM alpha	-0.74	-0.26	-0.17	-0.18	-0.08	-0.04	0.07	0.06	0.07	0.33	1.07	0.97
	(-3.96)	(-1.74)	(-1.38)	(-1.56)	(-0.99)	(-0.47)	(0.93)	(0.88)	(0.96)	(3.59)	(4.25)	(3.83)
CAPM Beta	1.75	1.50	1.39	1.29	1.19	1.11	1.02	0.94	0.86	0.66	-1.09	-0.03
Adj. R^2	0.76	0.79	0.82	0.84	0.86	0.88	0.87	0.86	0.82	0.66	0.41	0.00
FFC alpha	-0.31	-0.01	0.04	-0.01	0.03	0.04	0.10	0.02	-0.02	0.21	0.52	0.60
	(-1.87)	(-0.10)	(0.32)	(-0.13)	(0.36)	(0.40)	(1.25)	(0.23)	(-0.21)	(2.63)	(2.55)	(2.92)
Mktrf	1.45	1.27	1.22	1.17	1.09	1.07	1.02	0.98	0.94	0.77	-0.67	0.34
SMB	0.65	0.60	0.40	0.29	0.27	0.03	-0.07	-0.14	-0.20	-0.29	-0.94	-0.99
HML	-0.64	-0.47	-0.35	-0.24	-0.21	-0.14	-0.06	0.04	0.22	0.24	0.87	0.79
UMD	-0.28	-0.13	-0.12	-0.11	-0.07	-0.02	0.01	0.05	0.01	0.05	0.34	0.10
Adj. R^2	0.86	0.89	0.88	0.87	0.89	0.88	0.88	0.87	0.86	0.76	0.68	0.44
FF5 alpha	-0.28	0.08	0.04	0.02	0.04	0.02	0.03	-0.05	-0.18	0.11	0.40	0.33
	(-1.81)	(0.69)	(0.35)	(0.15)	(0.39)	(0.20)	(0.35)	(-0.72)	(-2.71)	(1.52)	(2.13)	(1.81)
Mktrf	1.44	1.24	1.22	1.15	1.09	1.08	1.04	1.00	0.99	0.80	-0.64	0.42
SMB	0.48	0.49	0.34	0.24	0.22	0.02	-0.03	-0.09	-0.12	-0.20	-0.69	-0.85
HML	-0.39	-0.27	-0.23	-0.07	-0.19	-0.15	-0.11	-0.08	0.07	0.12	0.52	0.40
CMA	-0.30	-0.31	-0.15	-0.28	0.01	0.05	0.10	0.23	0.31	0.20	0.49	0.75
RMW	-0.65	-0.43	-0.22	-0.20	-0.20	-0.04	0.16	0.19	0.31	0.32	0.97	0.57
Adj. R^2	0.87	0.89	0.88	0.87	0.89	0.88	0.88	0.88	0.89	0.79	0.71	0.49
HXZ alpha	-0.12	0.21	0.20	0.09	0.14	0.06	0.03	-0.09	-0.20	0.11	0.23	0.33
	(-0.63)	(1.55)	(1.54)	(0.85)	(1.13)	(0.70)	(0.39)	(-1.22)	(-2.52)	(1.33)	(1.01)	(1.60)
MKT	1.49	1.27	1.24	1.18	1.10	1.09	1.04	1.00	0.96	0.77	-0.72	0.33
ME	0.45	0.47	0.27	0.20	0.19	0.00	-0.06	-0.08	-0.13	-0.24	-0.69	-0.84
IA	-0.80	-0.76	-0.51	-0.42	-0.31	-0.15	0.01	0.15	0.41	0.36	1.16	1.29
ROE	-0.48	-0.27	-0.24	-0.14	-0.15	-0.02	0.10	0.18	0.18	0.16	0.64	0.21
Adj. R^2	0.84	0.88	0.87	0.87	0.88	0.88	0.88	0.88	0.86	0.75	0.63	0.37

Table 6. Safe Minus Risky Portfolio Risk-Adjusted Returns: Robustness

The table reports the out-of-sample risk-adjusted performance of the safe minus risky (*SMR*) hedge portfolio created using out-of-sample return predictions from the Characteristics and CAPM + Characteristics models using alternative samples and portfolio construction methods. Model parameters are estimated over an expanding window of prior bear markets and are applied to firm characteristics (and CAPM betas) known at the beginning of the month to predict the return for each stock. Based on these out-of-sample predicted returns each stock is assigned to a decile and all stocks in a decile are used to form a portfolio. *SMR* is a portfolio that is long the highest decile portfolio (Safe) and short the lowest decile portfolio (Risky). In Panel A, the first specification uses the full sample of stocks of merged CRSP and Compustat firms and does not exclude financial firms and micro-caps (below the 20th percentile of NYSE market capitalizations). The second specification uses all firms including financials but excludes micro-caps. The third specification forms equal-weighted instead of value-weighted decile portfolios. The final specification in Panel A forms the portfolios annually in July of each year. Each portfolio's performance is evaluated using the FFC factor model. The characteristics are ln(*Size*), ln(*Mom*), ln(*B/M*), *GPA*, *IA*, *DLT*, *DST* and *DY*. See Appendix A for a definition of all variables. The sample period is February, 1966 to December, 2015. There are 583 monthly observations in each regression. The t-statistics (in parentheses) are computed using Newey-West standard errors with a one-month lag. . In Panel B we report quarterly conditional CAPM regressions: $r_{i,t} = \alpha \, + (\gamma_{0,i} + \gamma_{i,1}' Z_{i,t-1}) r_{m,t}$, where $r_{i,t}$ are quarterly *SMR* returns, $r_{m,t}$ is the quarterly market excess return, and $Z_{i,t}$ is a set of instruments containing 3 month and 36 month lagged component betas measured as weighted average betas of the individual stocks that comprise each portfolio estimated from daily returns over the prior 3 and 36 months respectively. Newey-West t-statistics with a 5-quarter lag are reported.

Panel A: Alternate Specifications

	Characteristics Model				CAPM + Characteristics Model			
	Including Financials		Equal Weighted Portfolios	Annual Rebalancing	Including Financials		Equal Weighted Portfolios	Annual Rebalancing
	Including Microcaps	No Microcaps			Including Microcaps	No Microcaps		
Intercept	0.93	0.63	0.89	0.53	0.68	0.49	0.63	0.39
	(5.60)	(4.03)	(6.70)	(3.46)	(3.56)	(2.61)	(3.54)	(2.07)
Mkt - Rf	-0.32	-0.36	-0.36	-0.40	-0.65	-0.66	-0.62	-0.63
	(-6.04)	(-8.51)	(-10.44)	(-10.01)	(-12.39)	(-13.63)	(-13.42)	(-12.17)
SMB	-0.52	-0.82	-0.91	-0.85	-0.88	-0.90	-1.14	-0.98
	(-5.21)	(-13.66)	(-17.19)	(-14.72)	(-10.55)	(-13.67)	(-13.43)	(-14.11)
HML	0.83	0.64	0.80	0.54	0.83	0.83	0.94	0.76
	(9.58)	(8.89)	(14.22)	(7.93)	(9.38)	(8.97)	(10.69)	(8.54)
UMD	0.06	0.14	-0.01	0.09	0.33	0.32	0.28	0.30
	(1.21)	(2.89)	(-0.19)	(2.00)	(4.79)	(5.30)	(4.07)	(5.26)
Adj. R^2	0.58	0.65	0.75	0.65	0.70	0.70	0.76	0.68

Table 6, cont'd. Safe Minus Risky Portfolio Risk-Adjusted Returns: Robustness

Panel B: Conditional CAPM

	Characteristics			CAPM + Characteristics		
	Risky	Safe	*SMR*	Risky	Safe	*SMR*
Intercept	-1.984	0.783	2.756	-1.771	0.865	2.588
	(-3.60)	(3.28)	(4.09)	(-2.70)	(3.36)	(3.08)
Beta	0.547	0.147	-0.441	-0.177	0.022	-0.107
	(2.45)	(0.66)	(-3.52)	(-0.30)	(0.11)	(-0.48)
Beta - LC3	0.004	1.248	1.366	0.155	1.085	2.194
	(0.02)	(4.58)	(2.68)	(0.51)	(4.84)	(4.13)
Beta - LC36	0.686	-0.624	-0.643	1.037	-0.335	-0.939
	(2.74)	(-1.77)	(-1.53)	(1.69)	(-1.18)	(-2.03)
Obs.	189	189	189	189	189	189
Adj. R^2	82.05	76.49	42.27	80.98	70.81	54.46

Table 7. Characteristic-based Portfolios

The table reports monthly time series regression results the returns of long-short strategies built on the basis of the characteristics used in predicting bear market performance. The variables in the CAPM + Characteristics bear market prediction model are used to construct long-short decile portfolios. Panel A reports the average excess return, CAPM α, and Fama-French-Carhart α for each portfolio. Panel B uses the returns for these long-short strategies as explanatory variables in regressions of *SMR* and *zbSMR*. The panel reports the intercept of regressions of the form:

$$(zb)SMR_t = \alpha + \beta \times r_{it} + \varepsilon_t$$

where r_{it} stands for the return of the long-short portfolio associated with characteristic i. The last row of the panel reports the intercept in a regression using all the long-short portfolio returns as explanatory variables. The sample period is February, 1966 to December, 2015 and the t-statistics (in parentheses) are computed using Newey-West standard errors with a one-month lag.

Panel A: Characteristic Long-Short Portfolio Returns

	β	Size	Momentum	B/M	GP	IA	DLT	DST	DY
Excess Ret.	-0.02	0.31	1.12	0.16	0.31	0.41	0.14	0.11	0.05
	(-0.07)	(1.62)	(3.82)	(0.72)	(2.08)	(3.15)	(0.87)	(0.88)	(0.20)
CAPM alpha	0.53	0.13	1.18	0.22	0.28	0.49	0.07	0.03	0.38
	(2.14)	(0.80)	(4.08)	(0.97)	(1.90)	(3.69)	(0.40)	(0.23)	(1.94)
FF4 alpha	0.03	-0.05	0.10	0.12	0.42	0.33	0.41	0.19	0.17
	(0.15)	(-0.67)	(0.67)	(0.84)	(2.89)	(2.45)	(2.83)	(1.62)	(1.38)

Panel B: *SMR/zbSMR* Characteristic Portfolio-Adjusted Returns				
	Characteristics		**CAPM + Chars**	
	SMR	*zbSMR*	*SMR*	*zbSMR*
Beta	0.75	0.98	0.50	0.93
	(4.61)	(5.04)	(3.75)	(4.66)
Size	0.99	1.10	0.81	1.08
	(5.08)	(5.50)	(2.93)	(4.64)
Momentum	0.79	1.15	0.48	1.09
	(3.05)	(5.38)	(1.33)	(4.25)
B/M	0.72	0.93	0.48	0.88
	(2.97)	(4.58)	(1.48)	(3.81)
Profitability	0.78	1.02	0.54	0.98
	(3.15)	(4.77)	(1.61)	(3.98)
Investment	0.60	0.95	0.37	0.94
	(2.47)	(4.44)	(1.12)	(3.73)
Long-Term Debt	0.82	1.03	0.63	1.01
	(3.39)	(5.02)	(1.99)	(4.42)
Short-Term Debt	0.88	1.09	0.71	1.09
	(4.06)	(5.73)	(2.70)	(5.24)
Dividend Yield	0.69	0.93	0.42	0.87
	(4.37)	(5.35)	(2.09)	(4.65)
All	0.53	0.96	0.34	1.01
	(4.18)	(5.26)	(2.82)	(4.94)

Table 8. Bear Markets and the Macro Economy

The table provides forecasting regressions of real seasonally adjusted GDP growth (*GDP*), real non-residential private fixed investment growth *(INV)*, and real per capita consumption (*CONS*) growth. Each time series is forecasted using *Bear Dummy*, an indicator equal to one if the quarter contains a bear market month. Bear markets are identified following Pagan and Sossounov (2003) based on S&P 500 returns. Forecasts are formed up to four quarters ahead and include contemporaneous and lagged values of the dependent variable:

$$y_{t+k} = \alpha + \beta_0 BearDummy_t + \beta_1 y_t + \beta_2 y_{t-1} + \epsilon_{t+k}$$

where y_{t+k} is *GDP*, *CONS*, or *INV*. The sample period is 1963 Q1 to 2015 Q4. There are 195 quarterly observations. The t-statistics (in parentheses) are computed using Newey-West standard errors with a one-quarter lag.

	Quarters Ahead				Quarters Ahead			
	0	1	2	4	0	1	2	4
Panel A: GDP Growth								
Intercept	0.78	0.83	0.88	0.79	0.56	0.56	0.77	0.81
	(12.28)	(13.51)	(15.43)	(12.71)	(7.19)	(6.57)	(9.31)	(8.94)
Bear Dummy	-0.47	-0.70	-0.97	-0.56	-0.40	-0.57	-0.91	-0.56
	(-3.33)	(-5.13)	(-7.69)	(-4.09)	(-2.97)	(-4.22)	(-7.03)	(-3.92)
GDP_q						0.21	0.12	0.06
						(3.04)	(1.84)	(0.75)
GDP_{q-1}					0.30	0.14	0.02	-0.08
					(4.41)	(2.01)	(0.34)	(-1.16)
Adj. R^2	*5.40*	*12.00*	*23.50*	*8.00*	*14.10*	*19.80*	*25.10*	*8.70*
Panel B: Consumption (*CONS*) Growth								
Intercept	0.59	0.61	0.61	0.57	0.31	0.30	0.37	0.50
	(17.05)	(18.07)	(17.99)	(16.27)	(6.92)	(6.06)	(7.02)	(8.55)
Bear Dummy	-0.28	-0.37	-0.36	-0.18	-0.23	-0.25	-0.30	-0.14
	(-3.64)	(-5.02)	(-4.86)	(-2.35)	(-3.57)	(-3.71)	(-4.16)	(-1.78)
$CONS_q$						0.41	0.15	0.15
						(5.67)	(1.93)	(1.80)
$CONS_{q-1}$					0.51	0.13	0.28	-0.04
					(8.68)	(1.86)	(3.73)	(-0.45)
Adj. R^2	6.40	11.50	10.90	2.80	32.80	34.10	24.80	4.60
Panel C: Investment (*INV*) Growth								
Intercept	1.17	1.38	1.55	1.56	0.59	0.69	1.11	1.55
	(6.97)	(8.58)	(10.40)	(10.45)	(3.99)	(4.66)	(7.16)	(9.23)
Bear Dummy	-0.83	-1.79	-2.58	-2.65	-0.79	-1.41	-2.30	-2.57
	(-2.25)	(-5.09)	(-7.90)	(-8.17)	(-2.63)	(-4.84)	(-7.55)	(-7.79)
INV_q						0.43	0.33	0.11
						(6.21)	(4.51)	(1.37)
INV_{q-1}					0.58	0.18	0.05	-0.12
					(9.93)	(2.61)	(0.77)	(-1.57)
Adj. R^2	2.60	12.00	24.80	26.30	35.90	42.10	37.50	27.40

Table 9. Potential Explanations: Investor Sentiment

This table presents the returns on the safe, risky, safe minus risky (*SMR*), and zero-beta safe minus risky (*zbSMR*) portfolios conditioned on periods of high and low investor sentiment. We follow the analysis in Stambaugh, Yu and Yuan (2012) and report average returns (returns in excess of the risk free rate for the safe and risky portfolios, and returns for the *SMR* and *zbSMR* portfolios) in months following high (low) realizations of the Baker and Wurgler (2006) sentiment index where high and low sentiment months are defined relative to the sample median for the sentiment index. The "High-Low" column reports the difference between the "High" and "Low" sentiment returns. The sample period is July 1967 to December 2010. There are 523 monthly observations for *SMR* and 511 for *zbSMR*. The t-statistics (in parentheses) are computed using Newey-West standard errors with a one-month lag.

Safe Portfolio			Risky Portfolio			*SMR*			*zbSMR*		
Sentiment			Sentiment			Sentiment			Sentiment		
High	Low	High-Low	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Panel A: Characteristics Model											
0.62	0.62	0.01	-0.87	0.33	-1.20	1.49	0.28	1.21	1.55	0.57	0.98
(2.45)	(2.57)	(0.02)	(-1.58)	(0.76)	(-1.71)	(3.46)	(0.90)	(2.29)	(4.35)	(2.04)	(2.16)
Panel B: CAPM + Characteristics Model											
0.64	0.56	0.07	-0.84	0.99	-1.83	1.48	-0.42	1.90	1.46	0.33	1.13
(2.68)	(2.48)	(0.22)	(-1.29)	(1.82)	(-2.17)	(2.64)	(-0.97)	(2.72)	(3.65)	(0.99)	(2.20)

Table 10. Anomaly Returns and Bear Market Exposure

The table reports monthly time series regression results for 17 return anomalies and four specifications. In each specification, the anomaly returns are regressed on a set of control variables as in:

$$Anomaly_t = \alpha + X_t'\beta + \varepsilon_t$$

where X is a vector of different control variables for each specification. A full description of the anomalies and their construction is in section III.D of the text. Panel A reports risk-adjusted returns using market excess returns (CAPM) and the FFC 4-factors as control variables. Panels B augments the CAPM model using the returns of the safe minus risky portfolio (*SMR*) estimated using the Characteristics model (as described in the text) as an additional control. Panel C uses the zero-beta safe minus risky portfolio (*zbSMR)* estimated using the Characteristics model (as described in the text) as a control variable. Panels D and E repeat the analysis of Panels B and C using the CAPM + Characteristics model to form *SMR* and *zbSMR*. In Panel F we use the returns to decile long-short portfolios based on the characteristics in the bear market return prediction model to form factors, then we use these factors along with market excess returns as explanatory variables for anomaly return regressions. The first specification uses the first 4 principal components of the portfolio returns (PC), the second specification use an ex post "*mean-efficient*" portfolio of all the long-short portfolios (ME), the third specification use a naïve portfolio that has equal weights in all portfolios (1/N), and the last specification is the Tu and Zhou (2011) optimal portfolio (TZ). The sample period is February, 1966 to December, 2015. The number of observations for each anomaly regression matches the *SMR* (583) and *zbSMR* (570) monthly observations except for BMJ (456) and CHS (534). The t-statistics (in parentheses) are computed using Newey-West standard errors with a one-month lag.

	NSI	*CEI*	*NOA*	*GP*	*AG*	*ROA*	*IA*	*IVOL*	*BAB*	*BMJ*	*CHS*	*TAC*	*O*	*QMJ*	*SMB*	*HML*	*UMD*
Panel A: Risk-Adjusted Anomaly Returns																	
CAPM Alpha	0.96	0.85	0.75	0.52	0.87	0.75	0.72	1.80	0.93	1.39	1.21	0.57	0.89	0.54	0.09	0.44	0.76
	(6.75)	(6.11)	(5.24)	(2.93)	(4.70)	(2.76)	(4.94)	(5.90)	(6.16)	(3.81)	(4.42)	(3.10)	(3.58)	(5.81)	(0.76)	(3.40)	(4.32)
FF4 Alpha	0.72	0.62	0.64	0.57	0.41	0.81	0.42	1.41	0.54	1.09	0.66	0.50	1.01	0.58	0.17	0.56	0.91
	(5.58)	(5.14)	(4.32)	(3.49)	(2.53)	(3.27)	(3.03)	(5.28)	(3.47)	(4.81)	(2.64)	(2.52)	(4.74)	(7.02)	(1.37)	(4.36)	(5.27)
Panel B: Risk-Adjusted Anomaly Returns Controlling for *SMR* (Characteristics Model)																	
Alpha	0.68	0.45	0.58	0.34	0.73	-0.03	0.61	0.79	0.76	0.11	0.87	0.31	0.12	0.35	0.54	0.15	0.74
	(5.30)	(3.62)	(3.86)	(1.95)	(3.69)	(-0.10)	(4.00)	(2.99)	(4.98)	(0.36)	(3.03)	(1.68)	(0.57)	(3.86)	(4.87)	(1.19)	(3.66)
Mkt –Rf	-0.09	-0.19	0.00	-0.13	-0.14	-0.02	-0.06	-0.17	0.04	0.03	-0.35	0.01	0.01	-0.16	-0.08	-0.01	-0.12
	(-2.32)	(-5.20)	(0.05)	(-2.15)	(-2.16)	(-0.27)	(-1.14)	(-2.07)	(0.79)	(0.24)	(-3.92)	(0.30)	(0.20)	(-5.00)	(-2.05)	(-0.29)	(-1.59)
SMR	0.25	0.35	0.15	0.15	0.12	0.69	0.10	0.85	0.15	1.02	0.30	0.23	0.68	0.17	-0.40	0.26	0.02
	(7.52)	(10.65)	(3.36)	(3.39)	(1.64)	(7.48)	(2.37)	(12.07)	(4.19)	(9.12)	(3.87)	(5.22)	(11.19)	(6.77)	(-9.53)	(8.18)	(0.25)
Adj. R^2	25.54	46.46	5.94	10.52	8.06	35.22	4.58	42.04	5.09	50.07	17.86	8.32	38.56	38.83	43.24	26.15	1.52

Table 10, cont. Anomaly Returns and Bear Market Exposure

	NSI	*CEI*	*NOA*	*GP*	*AG*	*ROA*	*IA*	*IVOL*	*BAB*	*BMJ*	*CHS*	*TAC*	*O*	*QMJ*	*SMB*	*HML*	*UMD*
Panel C: Risk-Adjusted Anomaly Returns Controlling for *zbSMR* (Characteristics Model)																	
Alpha	0.63	0.35	0.65	0.27	0.64	0.05	0.58	0.81	0.77	0.19	0.78	0.29	0.19	0.30	0.48	0.11	0.78
	(4.36)	(2.13)	(4.24)	(1.53)	(3.32)	(0.16)	(3.94)	(2.37)	(5.03)	(0.45)	(2.45)	(1.59)	(0.73)	(2.67)	(3.80)	(0.85)	(3.80)
zbSMR	0.21	0.30	0.07	0.12	0.11	0.51	0.07	0.63	0.11	0.78	0.13	0.20	0.51	0.12	-0.34	0.23	-0.10
	(4.77)	(6.10)	(1.57)	(2.55)	(1.36)	(4.08)	(1.65)	(5.37)	(2.53)	(4.76)	(1.36)	(4.93)	(5.58)	(3.09)	(-7.20)	(5.91)	(-1.47)
Adj. R^2	10.05	15.15	0.88	2.08	1.68	14.38	0.98	14.74	2.69	23.99	0.77	5.46	17.07	5.83	30.89	16.16	1.06
Panel D: Risk-Adjusted Anomaly Returns Controlling for Combination Portfolios																	
Efficient	0.79	0.73	0.50	0.42	0.46	1.11	0.27	2.06	0.87	1.84	1.04	0.46	1.10	0.59	0.88	-0.19	0.26
(ex post)	(5.40)	(4.78)	(3.43)	(2.31)	(2.64)	(3.76)	(2.01)	(5.93)	(5.65)	(4.45)	(3.65)	(2.48)	(3.95)	(5.93)	(2.88)	(-1.46)	(1.84)
Efficient	0.81	0.75	0.55	0.43	0.49	1.04	0.41	1.95	0.80	1.67	0.97	0.45	1.14	0.56	0.80	-0.17	0.29
(ex ante)	(5.55)	(4.91)	(3.64)	(2.33)	(2.82)	(3.47)	(2.88)	(5.46)	(5.10)	(4.10)	(3.37)	(2.28)	(4.05)	(5.47)	(2.66)	(-1.28)	(2.06)

Figure 1: NBER Recessions and the Stock Market

This figure shows the behavior of the S&P 500 index around NBER recessions. Panel A plots individual NBER recessions (shaded in grey) in the 1966-2015 sample along with the S&P 500 index level (solid line), and an indicator of corresponding bear markets (dashed line) identified by the Pagan and Sossounov (2003) algorithm. Panel B plots the average cumulative returns of the S&P 500 index (solid line) around NBER-dated recessions. The cumulative returns are calculated monthly in event time, where the event is either the start or end of a recession (dashed line). The sample includes all NBER-dated recessions for the sample between February 1966 and December 2015.

Panel A. Individual Recession S&P 500 Returns

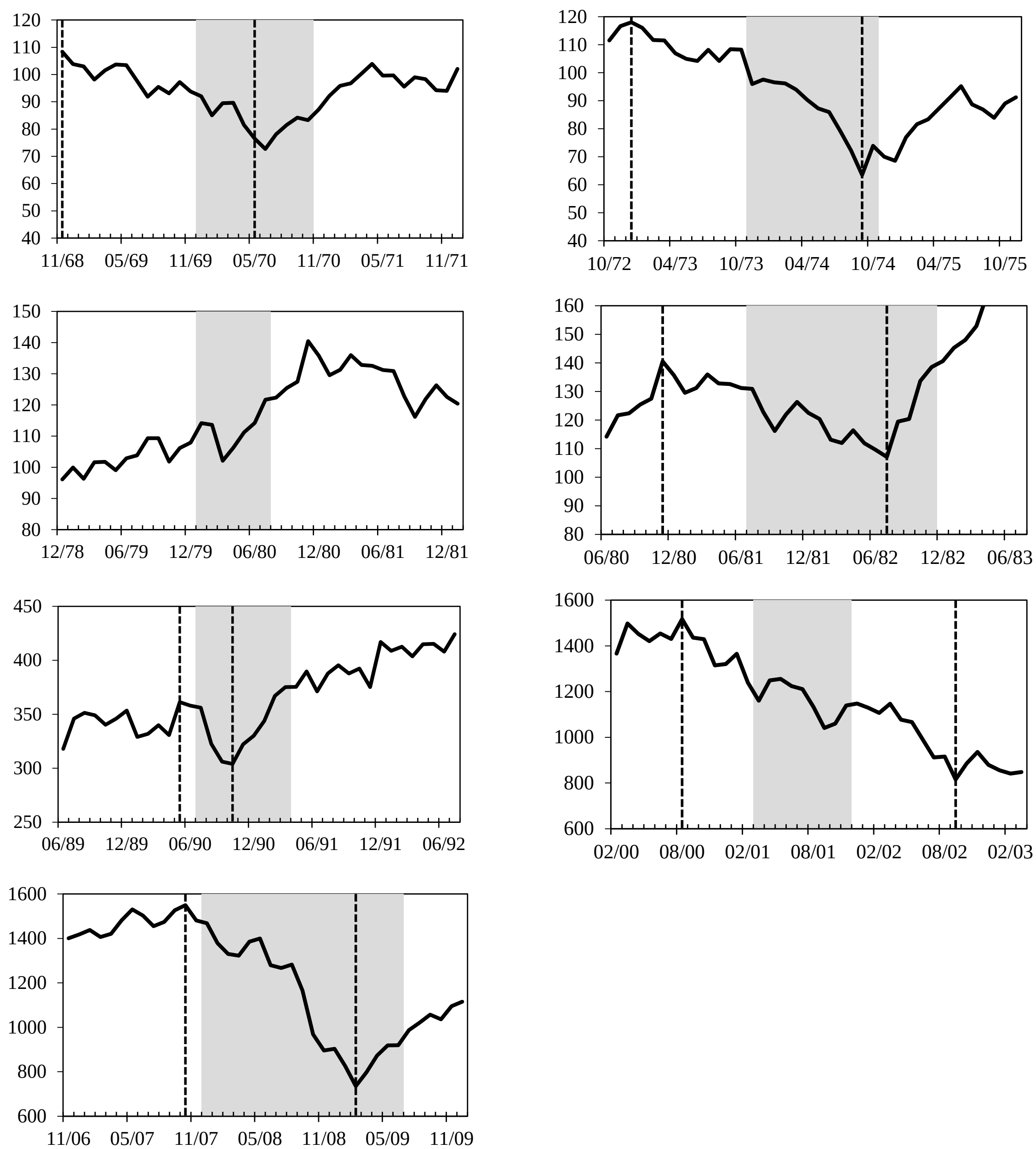
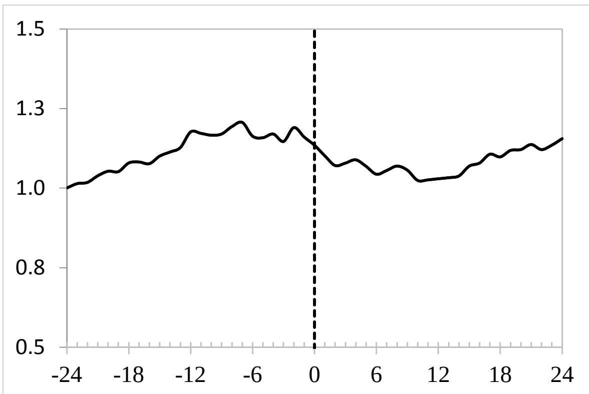
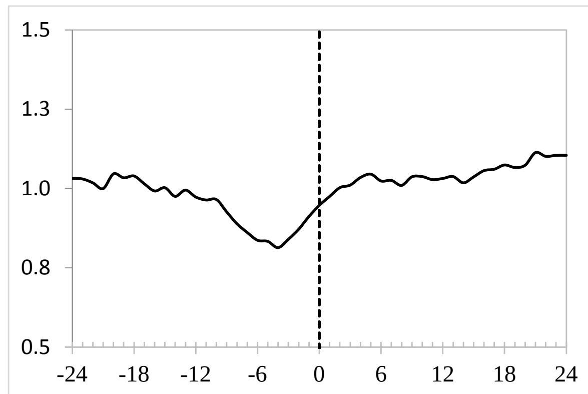


Figure 1: NBER Recessions and the Stock Market (cont'd.)

Panel B. Average Recession S&P 500 Returns



Recession Start (Event Time)

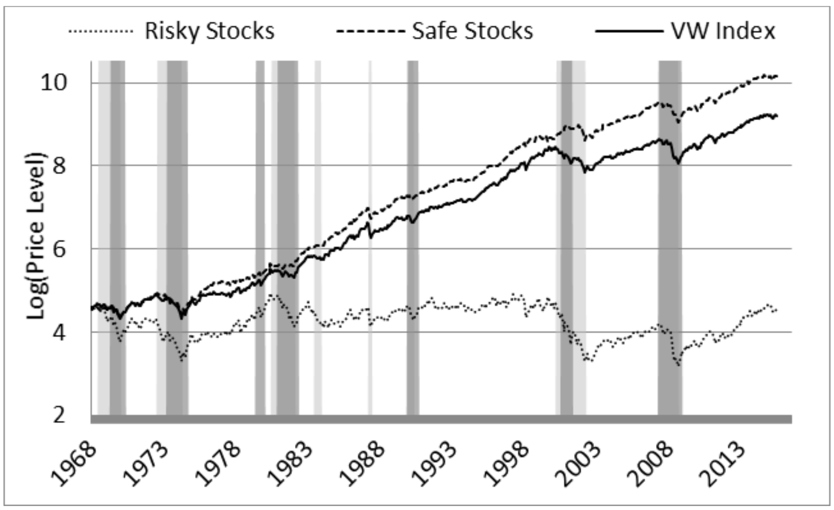


Recession End (Event Time)

Figure 2. Safe and Risky Portfolio Performance

This figure presents the time-series of portfolio log price levels for the value-weighted portfolio of all stocks in our sample (VW Index) and for portfolios formed based on our Characteristics bear-market risk model as described in the text. Panel A plots the "safe" and "risky" portfolios and the VW Index. Panel B plots indexes of cumulative returns of safe minus risky (*SMR*), zero-beta safe minus risky (*zbSMR*), and the value weighted excess returns over the riskfree rate of all stocks in our sample (Excess VW Index). All series are normalized to 100 in the first month. NBER recessions are shaded in light grey, bear markets are shaded in medium grey, and overlapping periods are in dark grey. Bear markets are identified following Pagan and Sossounov (2003) based on S&P 500 returns. The stock sample is merged CRSP and Compustat firms excluding financials and micro-caps (below the 20th percentile of NYSE market capitalizations). The sample period is May, 1967 to December, 2015.

Panel A: Safe and Risky Portfolios



Panel B: *SMR* and *zbSMR* Portfolios

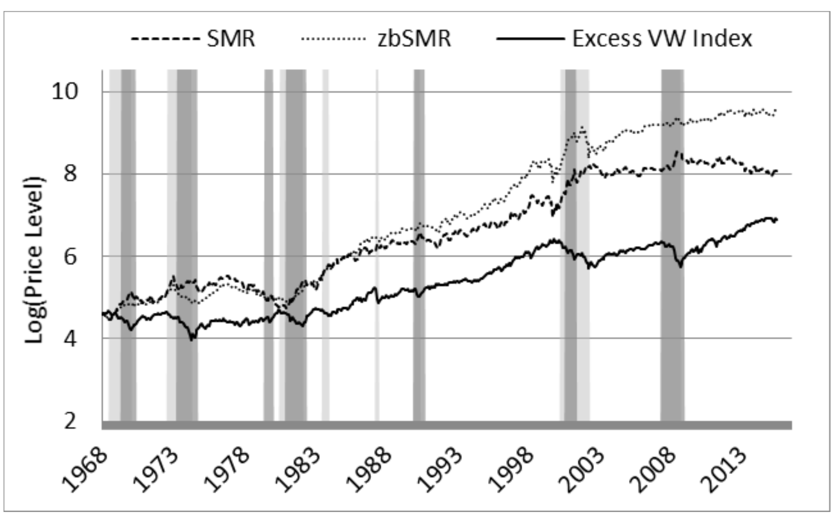


Figure 3. Time Series of Coefficient Estimates

This figure presents Fama-MacBeth regressions coefficient estimates (solid line) and their expanding average (dashed) across nine bear markets. We regress the average firm return in each bear market over various firm characteristics known at the beginning of the bear market. See Appendix A for a definition of all variables. The sample includes CRSP/Compustat firms excluding financials and micro-caps (below the 20th NYSE percentile). Bear markets are identified following Pagan and Sossounov (2003) based on S&P 500 returns. The sample period is February, 1966 to December, 2015.

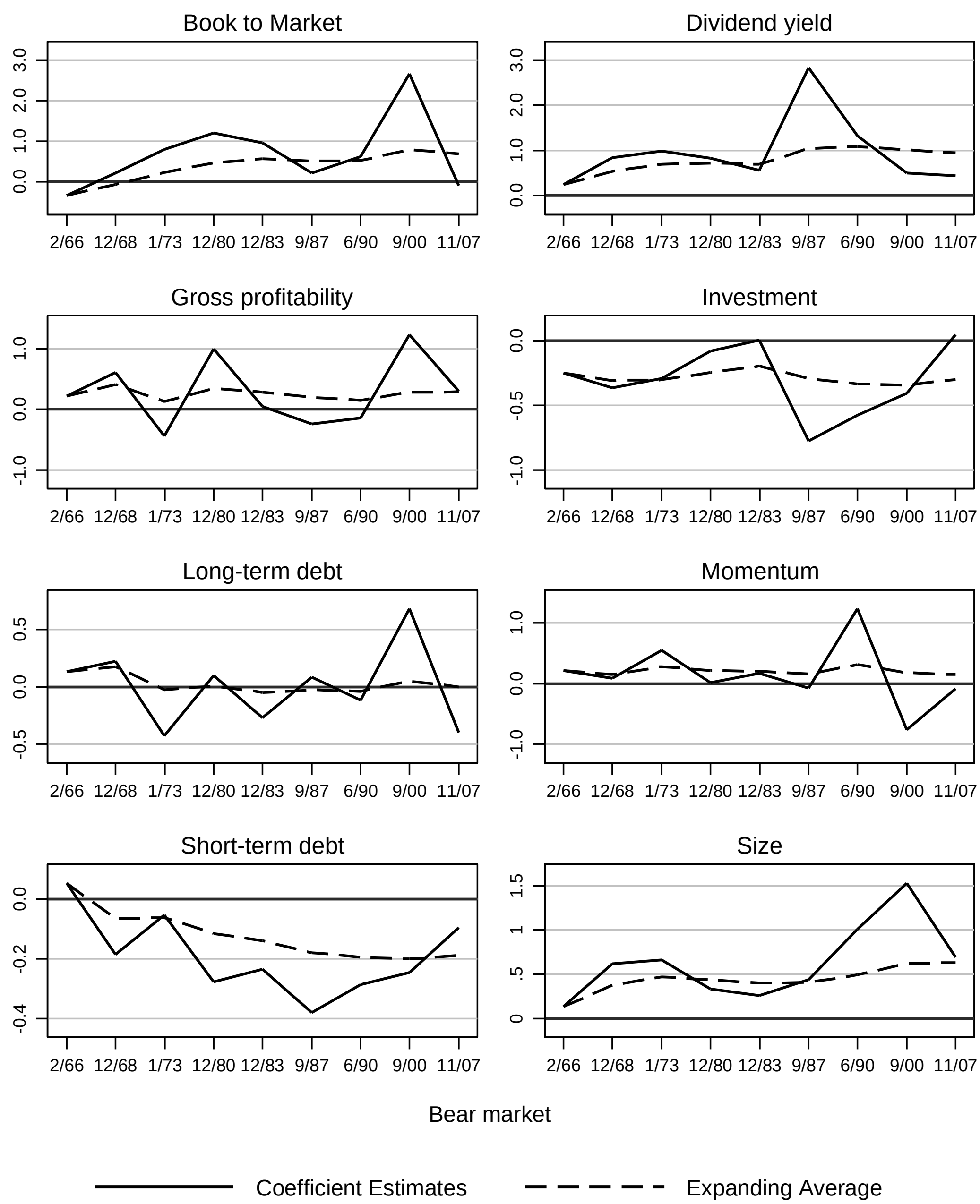


Figure 4. Bear Market Placebo Tests

This figure presents a histogram of the distribution of Fama-French-Carhart alphas for the Safe-Minus-Risky portfolios when bear markets are randomly assigned through the sample period. The histogram is constructed from 1,000 placebo tests. In each test, the sample period is randomly assigned bull/bear cycles where the duration of the bull (bear) part of the cycle is bootstrapped from the observed bull (bear) durations. Given these placebo bear market indicators, we repeat the analysis of Table 5 for the Characteristics model. The vertical line is alpha of the *SMR* portfolio constructed using the actual bear markets in the data.

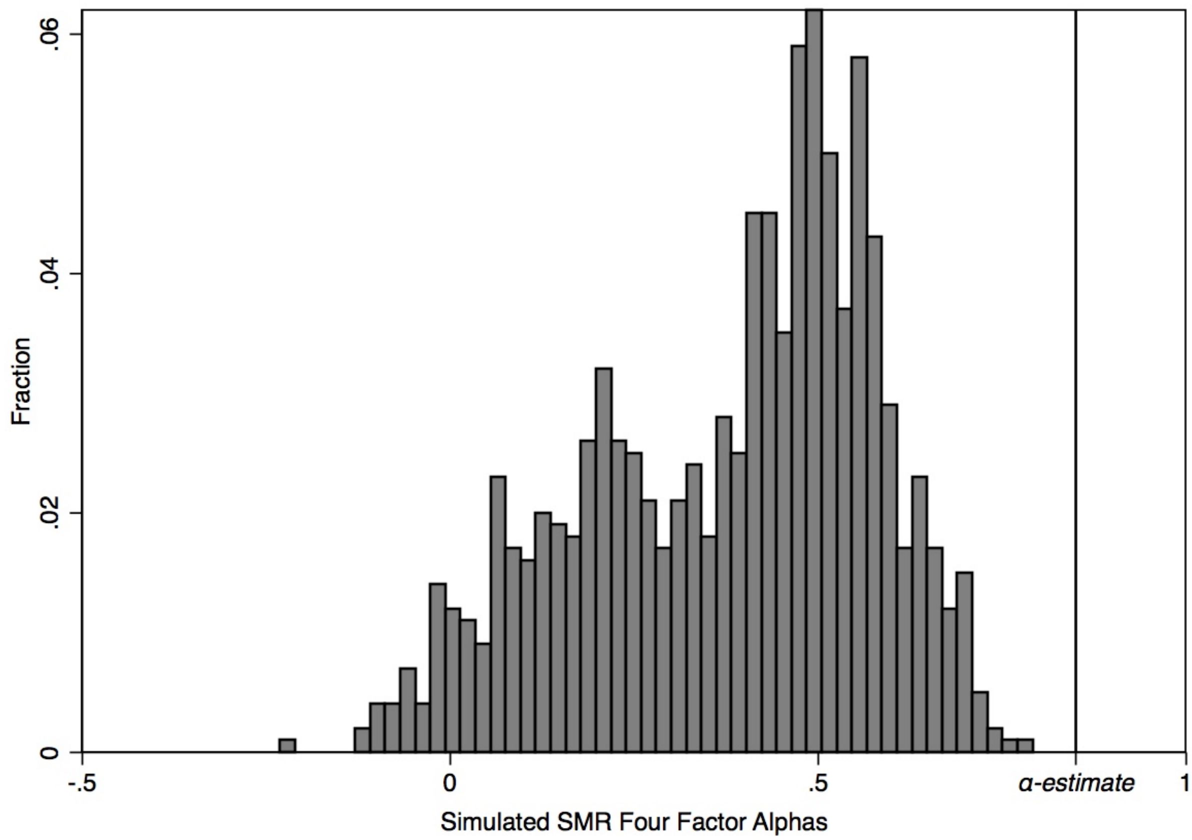


Figure 5. Anomalies and Bear Market Hedge Portfolio Returns

This figure represents risk-adjusted returns for 17 anomalies after controlling for bear market hedge portfolios. Each panel shows the point estimate and the 95% confidence interval of each anomaly's alpha. The four panels present the alpha estimates for four different sets of control variables: market excess returns (CAPM), the FFC 4-factors, CAPM augmented with the safe minus risky portfolio (*SMR*), and the zero-beta safe minus risky portfolio (*zbSMR*). *SMR* and *zbSMR* are estimated using the Characteristics model (as described in the text). A full description of the anomalies and their construction is in section III.D of the text. The sample period and number of observations vary across the anomalies and are provided in the description of Table 10.