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Getting Paid to Hedge: Why Don't Investors Pay a Premium to Hedge Downturns?

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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 gross domestic product growth, SMR has significant positive average returns and 4-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.

I. Introduction

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, Hodrick, Xing, and Zhang (2006)), high default probability (Campbell, Hilscher, and Szilagyi (2008)), high beta (Frazzini and Pedersen (2014)), and low quality (Asness, Frazzini, and Pedersen (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

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[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 (BAB).

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 article, 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 Standard & Poor's (S&P) 500 levels at the business-cycle frequency. We construct tradable 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 of real economic activity (e.g., Fama (1981)). In fact, bear markets as measures of bad times may provide sharper insight than macroeconomic variables because they are forward looking and do a better job matching the timing of test asset returns. For example, contemporaneous correlations between market returns and gross domestic product (GDP) growth are small, but market returns are a strong predictor of GDP growth. Thus, contemporaneous covariances of returns with economic variables may miss the true covariance of returns with real activity. But how far ahead should a researcher look? There is no clear answer because the lead–lag relation 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 Sossounov (2003) for equity indices. Our results are not sensitive to this choice (the Supplementary Material provides results for alternative algorithms). We identify 9 bear markets between 1966 and 2015, with an average duration of 14 months, which is similar to that of National Bureau of Economic Research (NBER)–dated recessions (13 months). The bear markets, listed later 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 June 1970. A similar pattern repeats for several other bear markets, including the Jan. 1973 to Sept. 1974 "oil crisis" and the Sept. 2000 to Oct. 2002 "post-dot-com crash,"

[2] As Kozak, Nagel, and Santosh (2018) 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 and travel, and postponing retirement because of losses in their financial assets during 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.

both with market returns of approximately −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 that these variables predict performance in bad times. For example, Graham (1973) writes 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 (FFC) (Carhart (1997)) model predict bear market performance.

Overall, we find evidence consistent with Graham's (1973) 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 tradable 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 (1973) 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 decile. Both portfolios are value weighted and exclude financials and microcap stocks. We impose a waiting period of 8 months so an investor using our dating algorithm in real time would classify exactly the same periods as bear markets.

Later, Figure 3 presents the key results of our article. First, it is possible to identify stocks ex ante with differing sensitivities to bear markets. Graph A plots a value-weighted index of all stocks in our sample, along with returns to safe and risky portfolios. Graph 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 U.S. treasuries. Consider investing \$1 in 3 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 approximately 0.77%, the capital asset pricing model (CAPM) alpha is 1.13%, and the FFC 4-factor alpha is 0.85% per month. Graph B also displays the levels of ZBSMR, 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. ZBSMR 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 equal weighted, or financials and microcaps are included. Our results cannot be explained by the conditional CAPM, coskewness, or idiosyncratic skewness. SMR is also distinct from the BAB anomaly of Frazzini and

Pedersen (2014). A regression of ZBSMR on a long–short beta portfolio (long the bottom and short the top beta deciles) results in an unchanged alpha for ZBSMR 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 (i.e., high marginal utility states) in standard pricing models (see, e.g., Cochrane (2005)). Bear markets are not only correlated with lower consumption, GDP, and investment growth, but also predict lower growth up to 4 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 (2001) link the equity risk premium to delays in investor decision making. If market returns predict consumption growth because of slow adjustment, 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 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 because of 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

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

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 of 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) argue that short-sale constraints and high investor sentiment can lead to an overvaluation 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 is 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 article 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, whereas 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 relation 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 on 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.

The remainder of the article is organized as follows: Section II presents the sample construction and methodology used to identify bear markets. Sections III and IV show the identification of safe and risky stocks and their subsequent performance. Section V explores possible explanations for this performance, and Section VI concludes.

II. Data and Methodology

A. Data

Our data set is all stocks in the Center for Research in Security Prices (CRSP)/Compustat universe. The CRSP data set 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 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 V.C, with the exception of BAB, quality minus junk, and boring minus jackpot returns, which are obtained from the original authors.[5] We obtain the Fama and French (2015) 5 factors as well as the momentum factor (MKT, SMB, HML, CMA, RMW, and UMD) from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) and the Hou, Xue, and Zhang (HXZ) (2015) factors from Lu Zhang.[6]

For the primary analysis, we use a restricted sample that excludes all financial firms (Standard Industrial Classification (SIC) codes between 6000 and 6999) and all microcap firms. Microcaps are defined, each month, as firms with market capitalization below the New York Stock Exchange (NYSE) 20th percentile. In robustness tests, we examine the full data set as well as subsamples that retain financials and/or microcaps. 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's Web site (http://research.stlouisfed.org). We construct log-difference growth rates of real seasonally adjusted GDP (GDP), real per capita consumption of services and nondurables (CONS), and real nonresidential private fixed investment (INV). We also use Federal Reserve data on the Treasury rate (RF),

[5]BAB 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 (available upon request).

[6]We thank Lu Zhang for providing HXZ (2015) factors.

the default spread (DS), and the term spread (TS). We obtain the Baker and Wurgler (2006) sentiment index data from Jeffrey Wurgler's Web site (http://people.stern.nyu.edu/jwurgler/).

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 approximately \$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 FFC model are a little over 1.

TABLE 1

Summary Statistics: Firm Characteristics and Factor Loadings

Table 1 provides summary statistics for our sample of merged Center for Research in Security Prices (CRSP)/Compustat firms excluding financials and microcaps (below the 20th percentile of New York Stock Exchange (NYSE) market capitalizations). ER 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 (BM) is the ratio of the book value of equity to market capitalization. Gross-profits-to-assets (GPA) is gross profits (sales − cost of goods sold) divided by total assets. Investment-to-assets (IA) is investment (change in property, plant, 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 capital asset pricing model (CAPM) market return coefficient using 60-month rolling regressions. The table also reports the Fama–French–Carhart (FFC) (Carhart (1997)) factor coefficients, β^{MKT}, 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 the 1% and 99% levels. See Appendix A for detailed definitions of all variables. The sample period is Feb. 1966 to Dec. 2015. There are 757,291 firm-month observations.

Variable	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
ER	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
BM	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
β	1.16	0.61	−0.54	0.76	1.10	1.48	4.64
β^{MKT}	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

C. Identifying Bear Markets

We identify bull and bear markets based on the level of the S&P 500 index from Feb. 1966 through Dec. 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 8-month windows and then ensures the alternation of peaks and troughs and imposes a minimum length of 4 months on each leg of the cycle. The 4-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 Supplementary Material provides results for Lunde and Timmerman's (2004) bear market identification, which identifies the same bear markets as Pagan and Sossounov, and a few additional shorter episodes. Our results are robust to the use of either algorithm.

Table 2 lists the characteristics of each bear market. We identify 9 bear markets ranging in duration from 3 to 25 months. Each episode reflects a significant decline in stock prices, with an average cumulative return of approximately −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

Bear Markets

Table 2 provides the start and end dates, duration, and cumulative return on the value-weighted (VW) and equal-weighted (EW) market portfolios for each bear market. The last set of columns provides measures of gross domestic product (GDP) growth for 3 windows around the beginning of the bear market. Real GDP growth is the annualized change in seasonally adjusted quarterly real GDP. The 3 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 Standard & Poor's (S&P) 500 index series. The sample period is Feb. 1966 to Dec. 2015.

			Cumulative Returns (%)		Real GDP Growth (%)		
Start Date	End Date	Duration (Months)	VW	EW	[−4, −1]	[0, +1]	[+2, +5]
Feb. 1, 1966	Sept. 30, 1966	8	−15.5	−15.7	8.5	5.9	2.6
Dec. 1, 1968	June 30, 1970	19	−33.3	−48.3	5.4	4.1	0.4
Jan. 1, 1973	Sept. 30, 1974	21	−46.2	−49.9	4.1	−1.1	−1.8
Dec. 1, 1980	July 31, 1982	20	−17.8	−12.8	−1.6	8.1	−2.3
Dec. 1, 1983	May 31, 1984	6	−9.6	−12.4	5.8	8.4	4.6
Sept. 1, 1987	Nov. 30, 1987	3	−29.6	−32	3.4	5.3	3.9
June 1, 1990	Oct. 31, 1990	5	−16.3	−24.3	2.9	0.9	−0.1
Sept. 1, 2000	Sept. 30, 2002	25	−44.9	−23.8	5.3	1.4	0.2
Nov. 1, 2007	Feb. 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 2 also presents changes in real GDP around each bear market. Before the start of a bear market, average U.S. 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 1 quarter), GDP growth is similarly strong. However, over the following 4 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.

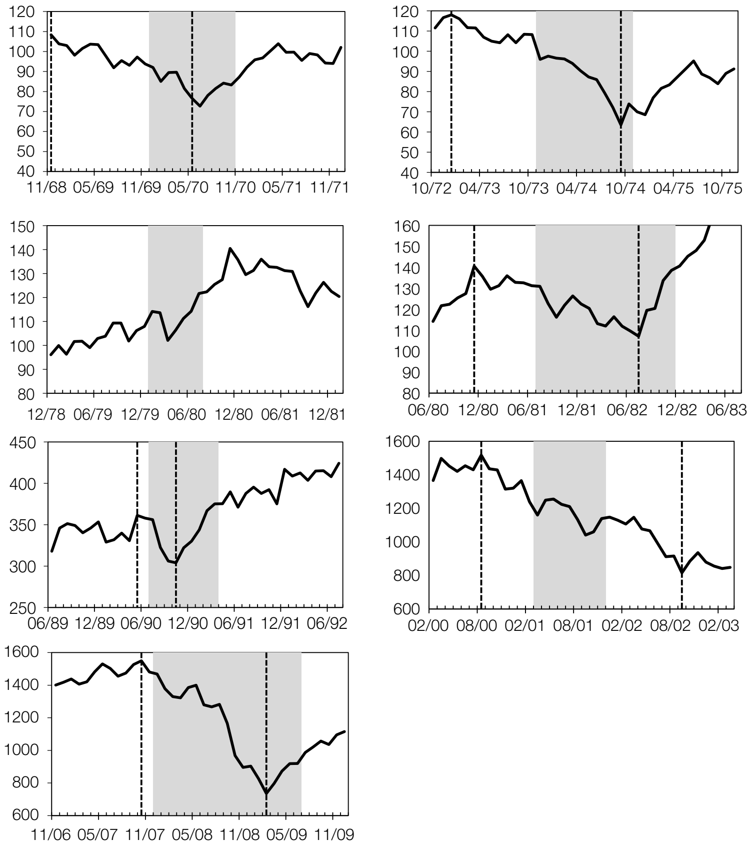
Figure 1 depicts the relation between bear markets and recessions. For each recession in the 1963–2015 sample, we present the closest bear market and the market index level. Although we identify bear markets without using any information on the state of the economy other than the S&P 500 level, the bear market periods correspond closely to NBER recessions. Six of the 7 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. Graph B shows averages across all recessions in the sample. The market peak is 8 months before the recession starts, and the market begins to recover on average 5 months before the recession ends. Thus, on average, bear markets anticipate recessions. In Section V.A we present more formal tests of the relation between bear markets and the state of the economy that confirm this intuition.

FIGURE 1

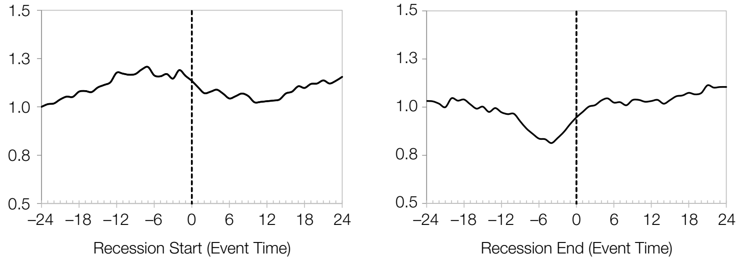
NBER Recessions and the Stock Market

Figure 1 shows the behavior of the Standard & Poor's (S&P) 500 index around National Bureau of Economic Research (NBER) recessions. Graph A plots individual NBER recessions (shaded in gray) 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. Graph 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 Feb. 1966 and Dec. 2015.

Graph A. Individual Recession S&P 500 Returns



Graph B. Average Recession S&P 500 Returns



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 before 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, such as CAPM beta, because stocks with higher historical betas should do worse during bear markets. Our next set of predictor variables is factor loadings from the FFC 4-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 (β^{MKT}, β^{SMB}, β^{HML}, β^{UMD}) using regressions over the 60 months before the beginning of the bear market. Appendix B details our methods.

In addition to the traditional covariance-based measures of risk, we 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 variables that might be related to firm risk: firm size (SIZE), stock price momentum (MOM), book-to-market (BM), gross profits to assets (GPA), investment-to-assets (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.[7] 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.

III. 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 (1973) 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, $b = 1, 2, \ldots, 9$:

$$\bar{r}_{i,b} \quad = \quad \boldsymbol{X}'_{i,b}\gamma_b + \varepsilon_{i,b},$$

[7] For example, Gertler and Gilchrist (1994) show that small firms are more sensitive than large firms to monetary policy shocks. Also see Daniel and Titman (1997) and Hou, Xue, and Zhang (2015) for a 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)).

where $\bar{r}_{i,b}$ is the monthly average continuous compounded (log) return of stock i in bear market b, and $\boldsymbol{X}$ is a vector of firm-specific forecasting variables that include both characteristics and factor loadings known 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 9 bear markets. Standard errors are computed as in Fama and MacBeth (1973). The first specification includes only market beta (column 1). As expected, we find that high-beta stocks have significantly lower returns during bear markets. A 1-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). Column 2

TABLE 3

Fama–MacBeth Bear Market Regressions

Table 3 provides estimates from Fama–MacBeth (1973) 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 definitions of all variables. Coefficients are averaged across the 9 bear markets identified following Pagan and Sossounov (2003) based on Standard & Poor's (S&P) 500 returns. The stock sample is merged Center for Research in Security Prices (CRSP)/Compustat firms excluding financials and microcaps (below the 20th percentile of New York Stock Exchange (NYSE) market capitalizations). The sample period is Feb. 1966 to Dec. 2015. There are 10,490 firm-episode observations for each specification. The t-statistics (in parentheses) are computed using White (1980) standard errors.

Variable	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^{MKT}			−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(BM)					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

shows that a 1-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 4-factor model (column 3 of Table 3). We find that market beta is smaller but still significant (−1.0). The SMB loading has the largest magnitude of the FFC factors (−1.3) and HML has a positive point estimate of 1.03. This suggests that during bear markets, value stocks are safer than growth stocks.[8] 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.

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:

$$\mathrm{E}_t\left(r_{i,t+1} - r_{ft}\right) \quad = \quad \beta_t^{\mathrm{MKT}}\overline{\mathrm{MKT}}_t + \beta_t^{\mathrm{SMB}}\overline{\mathrm{SMB}}_t + \beta_t^{\mathrm{HML}}\overline{\mathrm{HML}}_t + \beta_t^{\mathrm{MKT}}\overline{\mathrm{UMD}}_t$$

where each factor risk premium ($\overline{\mathrm{MKT}}_t, \overline{\mathrm{SMB}}_t, \overline{\mathrm{HML}}_t, \overline{\mathrm{UMD}}_t$) is estimated as the historical average of factor returns using all available data up to month t, the month before the start of the bear market for which returns are being predicted. Although this specification imposes the factor model, it performs the worst empirically (column 4 of Table 3). The R^2 for this risk measure is 4%, suggesting that the factor model does not help 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 9 proposed firm characteristics and no market factors. This characteristics-only specification (column 5 of Table 3) reveals that bear market stock returns are significant and positively related to firm size (SIZE), momentum (MOM), book-to-market (BM), profitability (GPA), and dividend yield (DY), and significant and negatively related to investment-to-assets (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 have not 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.

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

In the next specification, we combine CAPM beta with firm characteristics (column 6 of Table 3). This model yields an R^2 of 23.5% for the bear market Fama–MacBeth (1973) 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 the predictive ability of the market beta because the characteristics contain some of the same information as market beta. 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 4-factor model (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 (column 9 of Table 3). 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 is now significant, the point estimate for profitability is nearly halved and remains insignificant, and short-term debt is now marginally significant. The magnitudes of the contributions of investment-to-assets 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 that characteristics and factor loadings can predict which stocks provide the best protection in bear markets. 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(BM), GPA, IA, DLT, DST, and DY as predictor variables. The CAPM + Characteristics model is specification 6 in Table 3 and includes market beta 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 (1973) 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 (column 5) or characteristics and beta (column 6) using only bear markets that end at least 8 months before month t. Because the

Pagan and Sossounov (2003) algorithm requires an 8-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.[9] We then use the estimated parameters from the Fama–MacBeth regression and current stock characteristics (and 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 $b=1,2,\ldots,B$ with B ending before 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 2 shows the time series of coefficient estimates ($\overline{\gamma}_t$) that we use to generate out-of-sample predicted bear market returns. The solid lines show coefficient estimates for each bear market and the dashed lines show an expanding time-series moving average of the coefficients. For the moving average, the initial coefficient is estimated from the first bear market, the second is based on the first 2 bear markets $(\gamma_1+\gamma_2)/2$, and so on. The parameter estimates are fairly stable, particularly after including the first 3 bear markets. The book-to-market (BM) parameter flips from negative in the first bear market to a stable positive estimate by the fourth bear market. Similarly, the short- 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

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 equals 1 in subsequent bear markets.

Table 4 presents 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 and the safest stocks yield −1.9% per month, leading to a bear market spread of 3.6% in an SMR hedge portfolio. Also, there is no difference in returns between safe and risky stocks in nonbear (bull) markets.

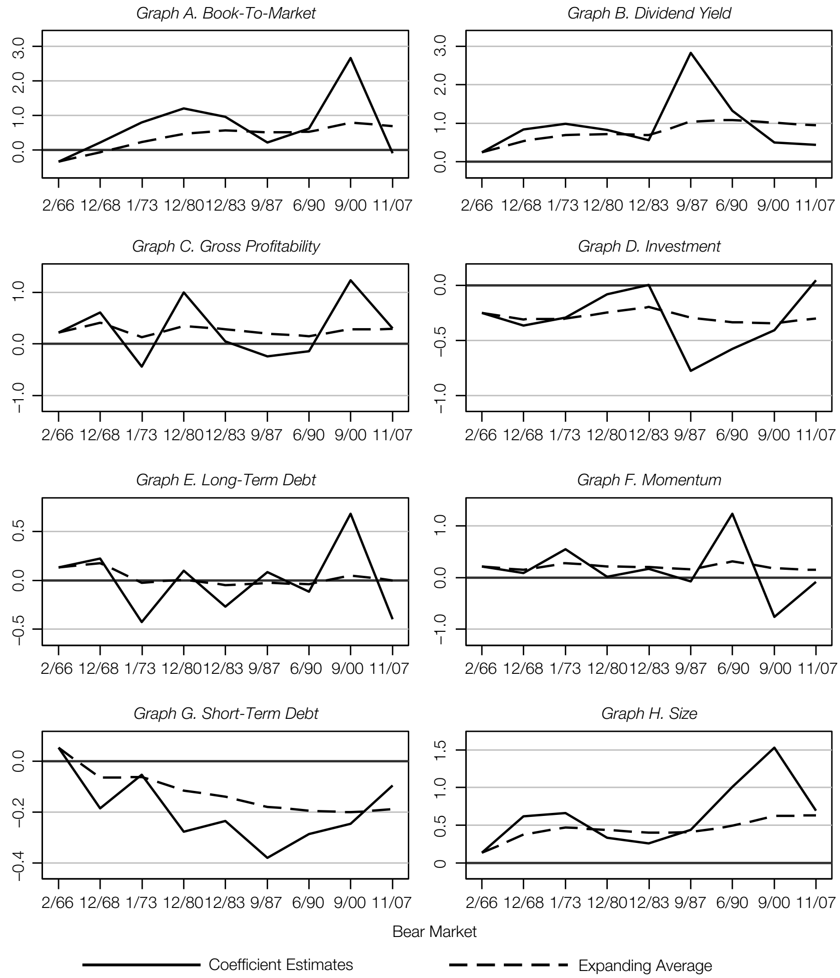
In the second specification (Panel B of Table 4), we augment the Characteristics model with market betas. The CAPM + Characteristics model also succeeds in predicting bear market performance. The riskiest stocks have average returns of

[9]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 8 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.

FIGURE 2

Time Series of Coefficient Estimates

Figure 2 presents Fama–MacBeth (1973) regression coefficient estimates (solid line) and their expanding average (dashed line) across 9 bear markets. We regress the average firm return in each bear market over various firm characteristics known at the beginning of the bear market. The sample includes Center for Research in Security Prices (CRSP)/Compustat firms excluding financials and microcaps (below the 20th New York Stock Exchange (NYSE) percentile). Bear markets are identified following Pagan and Sossounov (2003) based on Standard & Poor's (S&P) 500 returns. The sample period is Feb. 1966 to Dec. 2015.



−6.4% per month in bear markets and the safest have average returns of −1.6%, yielding an SMR 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 Supplementary Material, 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 previously. Both models are more accurate than a naïve model that

TABLE 4

Bear Market Predicted Return Decile Portfolios

Table 4 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 capital asset pricing model (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(BM), GPA, IA, DLT, DST, and DY. See Appendix A for definitions of all variables. The stock sample is merged Center for Research in Security Prices (CRSP)/Compustat firms excluding financials and microcaps (below the 20th percentile of New York Stock Exchange (NYSE) market capitalizations). The sample period is Feb. 1966 to Dec. 2015. There are 583 monthly observations in each regression. The t-statistics (in parentheses) are computed using Newey–West (1987) standard errors with a 1-month lag.

	Portfolio										
	Low	2	3	4	5	6	7	8	9	High	High–Low
Panel A. Characteristics Model											
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 Model											
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

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 before the start of the bear market.

IV. Primary Results: Performance of Safe and Risky Stocks

A. Unconditional Average Returns of Safe and Risky Stocks

Section III.B.2 shows that the 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.

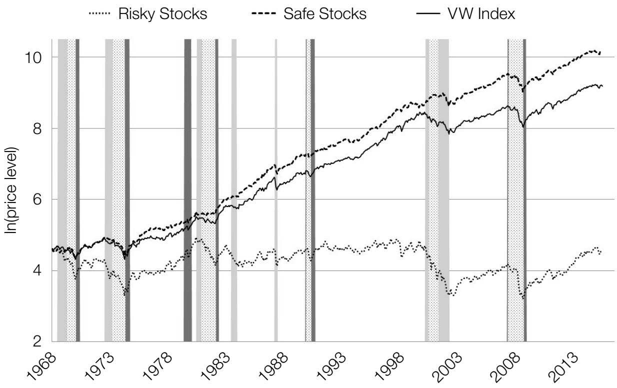
Graph A of Figure 3 illustrates our basic result. We plot the time series of the riskiest (decile portfolio 1) and safest (decile portfolio 10) cumulative compounded price index along with the value-weighted index of all stocks in our sample for comparison. NBER-dated recessions and bear market periods are shaded. Several 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, in contrast, do badly. The average return of the risky portfolio is less than the average return to a 1-month U.S. Treasury bill. To trade at a premium to the risk-free asset, these stocks must

FIGURE 3

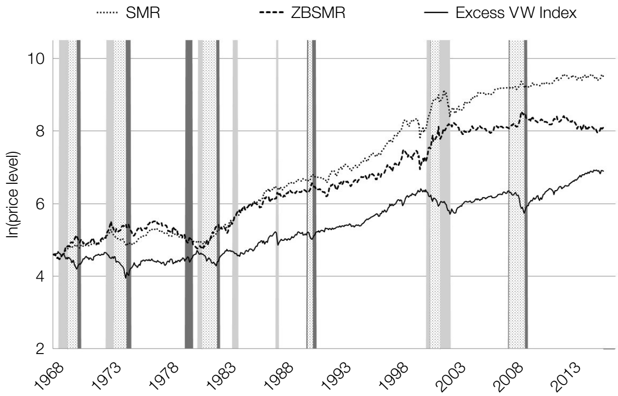
Safe and Risky Portfolio Performance

Figure 3 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. Graph A plots the safe and risky portfolios and the VW index. Graph B plots indexes of cumulative returns of safe minus risky (SMR), zero-beta safe minus risky (ZBSMR), and value-weighted excess returns over the risk-free rate of all stocks in our sample (excess VW index). All series are normalized to 100 in the first month. National Bureau of Economic Research (NBER) recessions are shaded in dark gray, bear markets are in light gray, and overlapping periods are dotted. Bear markets are identified following Pagan and Sossounov (2003) based on Standard & Poor's (S&P) 500 returns. The stock sample is merged Center for Research in Security Prices (CRSP)/Compustat firms excluding financials and microcaps (below the 20th percentile of New York Stock Exchange (NYSE) market capitalizations). The sample period is May 1967 to Dec. 2015.

Graph A. Safe and Risky Portfolios



Graph B. SMR and ZBSMR Portfolios



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 1-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, conversely, earns average excess returns of −0.1% per month and 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, and the SMR portfolio from the CAPM + Characteristics

TABLE 5

Risk-Adjusted Performance of Bear-Market-Predicted Return Portfolios

Table 5 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 (ZBSMR) hedge portfolios. Model parameters are estimated over an expanding window of prior bear markets and are applied to firm characteristics (and capital asset pricing model (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). 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 12 portfolios are evaluated using the CAPM, the Fama–French–Carhart (FFC) (Carhart (1997)) 4-factor model, the Fama–French (2015) 5-factor (FF5) model, and the Hou–Xue–Zhang (HXZ) (2015) factor model. Expected bear market returns are estimated using the Characteristics model in Panel A and the CAPM + Characteristics model in Panel B. The characteristics are ln(SIZE), ln(MOM), ln(BM), GPA, IA, DLT, DST, and DY. See Appendix A for definitions of all variables. The stock sample is merged Center for Research in Security Prices (CRSP)/Compustat firms excluding financials and microcaps (below the 20th percentile of New York Stock Exchange (NYSE) market capitalizations). The sample period is Feb. 1966 to Dec. 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 and West (1987) standard errors with a 1-month lag.

	Portfolio											
	Risky	2	3	4	5	6	7	8	9	Safe	SMR	ZBSMR
Panel A. Characteristics Model												
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)
$MKT - R_f$	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)
$MKT - R_f$	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)
$MKT - R_f$	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

(continued on next page)

TABLE 5 (continued)
Risk-Adjusted Performance of Bear-Market-Predicted Return Portfolios

	Portfolio											
	Risky	2	3	4	5	6	7	8	9	Safe	SMR	ZBSMR
Panel B. CAPM + Characteristics Model												
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)
MKT − R_f	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)
MKT − R_f	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 − R_f	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

model earns returns 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 that includes microcaps yields similar results.)

The next set of results in each panel of Table 5 is from CAPM regressions on the decile portfolios. It is not surprising that 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 approximately −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 approximately 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 of Table 5 is from FFC 4-factor regressions. The alphas are 0.85% per month (Characteristics model) and 0.52% per month (CAPM + Characteristics model).

Finally, we test whether the FF5 and HXZ factor models can explain the SMR 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 FF5 model and an insignificant 0.2% for the HXZ 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 ZBSMR, which is 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 ZBSMR 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 ZBSMR portfolio during month t is defined as:

$$\text{ZBSMR}_t = \frac{R_t^S}{\hat{\beta}_{St}} - \frac{R_t^R}{\hat{\beta}_{Rt}},$$

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 ZBSMR. 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. For the Characteristics model, the alphas for the FF5 model are 0.5% and for the HXZ model are 0.6%. For the CAPM + Characteristics model, alphas are 0.3% in both the FF5 and HXZ models, with t-statistics of 1.81 and 1.6, respectively. Graph B of Figure 3 illustrates the performance of SMR and ZBSMR. Both the SMR and ZBSMR 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 whether our results are robust to alternative bear market dating algorithms, alternative sample selection criteria, and the conditional CAPM. First, we use the Lunde and Timmermann (2004) business-cycle dating algorithm instead of the Pagan and Sossounov (2003) algorithm to identify bear markets. The 2 algorithms identify the same start and end dates for all of the bear markets we report. The Lunde and Timmerman algorithm identifies a few additional, shorter, episodes as bear markets. In the Supplementary Material, we show that changing the algorithm does not change our conclusions.

We also confirm that the SMR alpha is robust to 2 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

TABLE 6

SMR Portfolio Risk-Adjusted Returns: Robustness

Table 6 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 model and capital asset pricing model (CAPM) + Characteristics model 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 Center for Research in Security Prices (CRSP)/Compustat firms and does not exclude financial firms and microcaps (below the 20th percentile of New York Stock Exchange (NYSE) market capitalizations). The second specification uses all firms including financials but excludes microcaps. 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 Fama–French–Carhart (FFC) (Carhart (1997)) factor model. The characteristics are ln(SIZE), ln(MOM), ln(BM), GPA, IA, DLT, DST, and DY. See Appendix A for definitions of all variables. The sample period is Feb. 1966 to Dec. 2015. There are 583 monthly observations in each regression. The t-statistics (in parentheses) are computed using Newey–West (1987) standard errors with a 1-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- 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				Including Financials			
	Including Microcaps	No Microcaps	Equal-Weighted Portfolios	Annual Rebalancing	Including Microcaps	No Microcaps	Equal-Weighted Portfolios	Annual Rebalancing
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 − R_f	−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

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)
β	0.547	0.147	−0.441	−0.177	0.022	−0.107
	(2.45)	(0.66)	(−3.52)	(−0.30)	(0.11)	(−0.48)
β_{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)
β_{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)
No. of obs.	189	189	189	189	189	189
Adj. R^2	82.05	76.49	42.27	80.98	70.81	54.46

alpha for the CAPM + Characteristics portfolio is a significant 0.8% per month. In unreported results we find that SMR 4-factor alphas are robust to excluding momentum from the bear market performance prediction model.

Cederburg and O'Doherty (2016) show that a conditional CAPM explains the BAB anomaly. Because BAB can be thought of as an SMR portfolio where only beta is used to measure risk, it is possible that the conditional CAPM may explain the SMR alpha. In Panel C of Table 6, we test whether the conditional CAPM can explain the alphas of SMR. We employ the test suggested by Boguth, Carlson, Fisher, and Simutin (2011), and implemented in Cederburg and O'Doherty. We first use daily data over the prior 3 and 36 months to estimate 3- 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:

$$r_{i,t} \quad = \quad \alpha + (\gamma_{0,i} + \gamma_{i,1}^{'} \mathbf{Z}_{i,t-1}) r_{m,t},$$

where $r_{i,t}$ are quarterly safe, risky, or SMR portfolio returns, $r_{m,t}$ is the market excess return, $\mathbf{Z}$ is a vector of instruments containing the 3- and the 36-month lagged component betas (β_{LC3} and β_{LC36}). Panel C shows that the alphas are similar for the Characteristics model (2.8% per quarter for conditional, 2.9% for unconditional CAPM) and CAPM + Characteristics model (2.6% per 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, it has no effect on the SMR strategy. This further underscores the differences between BAB and SMR.

In the Supplementary Material, 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 equals 1 in bear markets. We find a small, statistically insignificant increase in the betas of the riskiest stocks during bad times, whereas 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, 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 reestimate 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 SMRs has 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 markets are important by predicting performance in bull markets as a placebo test. In the Supplementary Material, we show that a bull market hedge portfolio formed using the same variables has zero average returns.

Thus, it is clear that the high average returns of SMR 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 these questions, we form long–short portfolios by sorting stocks into deciles on each of the 9 predictors in the CAPM + Characteristics model for

FIGURE 4

Bear Market Placebo Tests

Figure 4 presents a histogram of the distribution of Fama–French–Carhart (FFC) (Carhart (1997)) alphas for the safe minus risky (SMR) 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 in Table 5 for the Characteristics model. The vertical line is the alpha of the SMR portfolio constructed using the actual bear markets in the data.

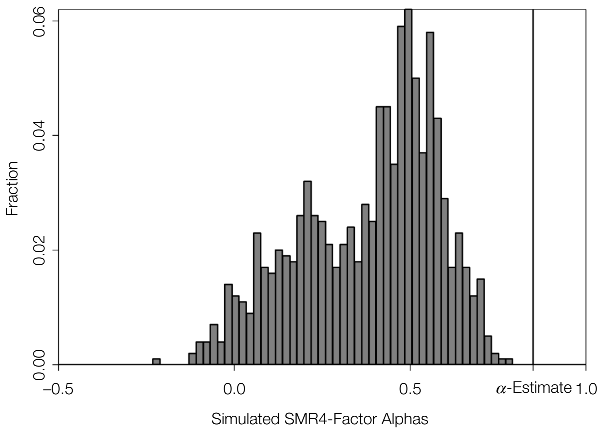


TABLE 7
Characteristics-Based Portfolios

Table 7 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 capital asset pricing model (CAPM) + Characteristics bear market prediction model are used to construct long–short decile portfolios. Panel A reports the average excess return, CAPM alpha, and Fama–French–Carhart (FFC) (Carhart (1997)) 4-factor alpha 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:

$$(\mathrm{ZB})\,\mathrm{SMR}_t \quad = \quad \alpha + \beta \times r_{i,t} + \varepsilon_t,$$

where $r_{i,t}$ 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 of the long–short portfolio returns as explanatory variables. See Appendix A for definitions of all variables. The sample period is Feb. 1966 to Dec. 2015 and the t-statistics (in parentheses) are computed using Newey–West (1987) standard errors with a 1-month lag.

Panel A. Characteristic Long–Short Portfolio Returns

	Portfolio								
	β	SIZE	MOM	BM	GPA	IA	DLT	DST	DY
Excess return	−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)
FFC 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 Characteristics Portfolio-Adjusted Returns

	Characteristics		CAPM + Characteristics	
	SMR	ZBSMR	SMR	ZBSMR
β	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)
MOM	0.79	1.15	0.48	1.09
	(3.05)	(5.38)	(1.33)	(4.25)
BM	0.72	0.93	0.48	0.88
	(2.97)	(4.58)	(1.48)	(3.81)
GPA	0.78	1.02	0.54	0.98
	(3.15)	(4.77)	(1.61)	(3.98)
IA	0.60	0.95	0.37	0.94
	(2.47)	(4.44)	(1.12)	(3.73)
DLT	0.82	1.03	0.63	1.01
	(3.39)	(5.02)	(1.99)	(4.42)
DST	0.88	1.09	0.71	1.09
	(4.06)	(5.73)	(2.70)	(5.24)
DY	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)

the same sample of stocks used to construct SMR. Table 7 reports that of these 9 long–short portfolios, only momentum, profitability, and asset growth have mean returns different from 0 in this sample. The lack of significance of the mean returns for most of the variables is consistent with the results in Hou, Xue, and 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 of SMR remain positive after controlling for the predictor variables either by themselves or when combined with each other. Panel B of Table 7 presents 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, as 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 achieving high mean returns.

V. Why Do Safe Stocks Earn High Average Returns and Risky Stocks Low Average Returns?

In this section, we test several 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 for 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 Graph A of 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 3 macroeconomic variables, real GDP (GDP), real per capita consumption of nondurables and services (CONS), and real nonresidential fixed private investment (INV), on our bear market dummy variable:

$$y_{t+k} \quad = \quad \alpha + \beta \text{BEAR\_DUMMY}_t + \epsilon_{t+k},$$

where BEAR_DUMMY_t equals 1 if the last month in quarter t is a bear market month, and 0 otherwise, and y_{t+k} is either GDP, CONS, or INV and $k=0,1,\ldots,4$. Note that the predictive regressions for up to 3 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 first set of columns in Table 8. The bear market dummy is significant in predicting all 3 macroeconomic variables at all 5 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 2 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

$$y_{t+k} \quad = \quad \alpha + \beta \text{BEAR\_DUMMY}_t + \gamma_1 y_t + \gamma_2 y_{t-1} + \epsilon_{t+k},$$

TABLE 8
Bear Markets and the Macro Economy

Table 8 provides forecasting regressions of real seasonally adjusted gross domestic product 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 1 if the quarter contains a bear market month. Bear markets are identified following Pagan and Sossounov (2003) based on Standard & Poor's (S&P) 500 returns. Forecasts are formed up to 4 quarters ahead and include contemporaneous and lagged values of the dependent variable:

$$y_{t+k} \quad = \quad \alpha + \beta_0 \text{BEAR\_DUMMY}_t + \beta_1 y_t + \beta_2 y_{t-1} + \epsilon_{t+k},$$

where y_{t+k} is GDP, CONS, or INV. The sample period is 1963:Q1–2015:Q4. There are 195 quarterly observations. The t-statistics (in parentheses) are computed using Newey–West (1987) standard errors with a 1-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. 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. 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

where, as before, $k=0,1,\ldots,4$.[10] 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

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

risky may be those that are most overvalued in high-sentiment periods and are thus most likely to perform the worst when sentiment falls in bear markets. Stambaugh et al. (2012) 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 Stambaugh et al., we classify each month as low or high sentiment 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 using 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 low-sentiment periods. The differential of 1.2% per month is economically and statistically significant. Thus, both SMR and ZBSMR have different returns following high- or low-sentiment periods. 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.[11]

Our results suggest that sentiment-induced mispricing can explain the time-series variation in the returns of safe and risky stocks. These portfolios are

TABLE 9

Potential Explanations: Investor Sentiment

Table 9 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 Dec. 2010. There are 523 monthly observations for SMR and 511 for ZBSMR. The *t*-statistics (in parentheses) are computed using Newey–West (1987) standard errors with a 1-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)

[11]These results are not driven by the dot-com period, a period often associated with high investor sentiment (see Stambaugh et al. (2012)). Specifically, in unreported results we find that if we exclude observations from 1996 to 2004 from our sample, the difference between high- and low-sentiment periods is 1.7% for SMR and 1.4% for ZBSMR.

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. Relation 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, there may be a common explanation for SMR and an entire set of anomalies.

We examine the set of anomalies from Stambaugh et al. (2012), augmented with 3 new anomalies published after their research that may be related to SMR, and the 4 FFC factors. The anomalies in Stambaugh et al. are:

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

We augment this set with 3 new anomalies:

12. Betting against beta (BAB): Long low beta stocks and short high beta stocks rescaled to have a zero beta. Frazzini and Pedersen (2014) show that this earns high average returns.
13. Quality minus junk (QMJ): Long quality and short junk. Quality is assessed on measures of profitability, growth, safety, and payout. Asness et al. (2013) argue that this portfolio earns high returns.

14. Boring minus jackpot (BMJ): 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, whereas SMR and ZBSMR are constructed using only the ex-microcap sample.

Panel A of Table 10 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 (Panel B) and on the market and the Characteristics ZBSMR (Panel C). This allows us to test how the CAPM alphas change when

TABLE 10

Anomaly Returns and Bear Market Exposure

Table 10 reports monthly time-series regression results for 17 return anomalies and 4 specifications. For a description of the anomalies, refer to Section V.C. In each specification, the anomaly returns are regressed on a set of control variables as in:

$$\text{ANOMALY}_t \quad = \quad \alpha + \boldsymbol{X}_t' \beta + \varepsilon_t,$$

where $\boldsymbol{X}$ is a vector of different control variables for each specification. Panel A reports risk-adjusted returns using market excess returns (capital asset pricing model (CAPM)) and the Fama–French–Carhart (FFC) (Carhart (1997)) 4 factors as control variables. Panel B augments the CAPM using the returns of the safe minus risky (SMR) portfolio estimated using the characteristics model (as described in the text) as an additional control. Panel C uses the zero-beta safe minus risky (ZBSMR) portfolio estimated using the Characteristics model (as described in the text) as a control variable. In Panel D, we use the returns to decile long–short portfolios based on the characteristics in the bear market return prediction model to form factors, and 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 (PC) of the portfolio returns, the second specification uses an ex post mean-efficient (ME) portfolio of all of the long–short portfolios, the third specification uses a naïve portfolio that has equal weights in all portfolios (1/*N*), and the last specification is the Tu and Zhou (TZ) (2011) optimal portfolio. The sample period is Feb. 1966 to Dec. 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 (1987) standard errors with a 1-month lag. Variables are defined in Section V.C.

	Anomaly																
	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)
FFC 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)
MKTRF	−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
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)

we control for SMR. In Panel B, we show that the Characteristics SMR is significantly correlated with 15 of the 17 anomalies. Only AG 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 alphas. 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, as 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 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), 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 (GPA), with alpha reduced by 34%, and the Campbell et al. (2008) 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 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.

The BAB 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 BAB anomaly.

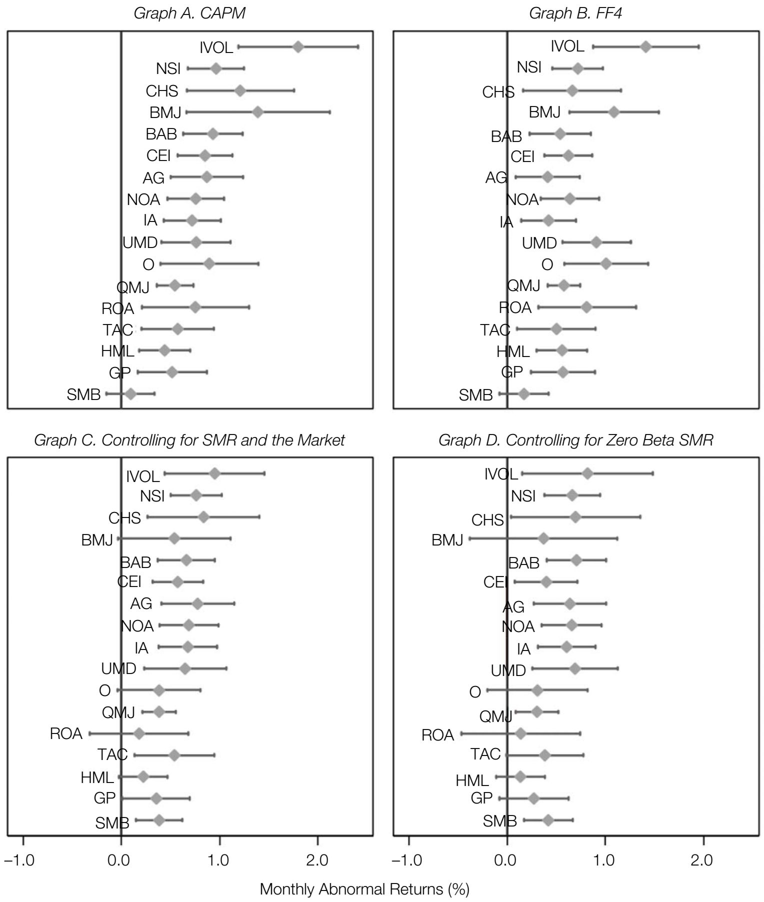
Figure 5 summarizes the results from the Characteristics model. For each anomaly, confidence intervals for alpha estimates using the CAPM and FFC 4-factor model are compared to similar estimated intervals obtained after controlling for SMR returns and ZBSMR returns. These results establish that a subset 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 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 answer this question, we consider 2 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 the returns of these portfolios to explain anomaly returns are presented in Panel D of Table 10. These 2 portfolios reduce the median absolute anomaly CAPM alpha by about 20%, or about half the reduction from SMR and ZBSMR.

FIGURE 5

Anomalies and Bear Market Hedge Portfolio Returns

Figure 5 represents risk-adjusted returns for 17 anomalies after controlling for bear market hedge portfolios. Each graph shows the point estimate and the 95% confidence interval of each anomaly's alpha. Graphs A–D present the alpha estimates for 4 sets of control variables: market excess returns (capital asset pricing model (CAPM)), the Fama–French–Carhart (FFC) (Carhart (1997)) 4 factors, CAPM augmented with the safe minus risky (SMR) portfolio, and the zero-beta safe minus risky (ZBSMR) portfolio. 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 V.C. The sample period and number of observations vary across the anomalies and are provided in the description of Table 10. Variables are defined in Section V.C.



VI. Conclusion

Simple intuitive measures of risk such as 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 (i.e., those forecasted to suffer the least in a bear market) and short risky stocks (i.e., 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) 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" (p. 451).

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. Returns for the risky portfolio are negative and significant (−0.87% 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 during high-sentiment periods. 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

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

SIZE: Market capitalization of the firm is obtained from the Center for Research in Security Prices (CRSP) as the product of shares outstanding and stock price.

β: Beta is the market coefficient in a 60-month rolling capital asset pricing model (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^{MKT}, β^{SMB}, β^{HML}, β^{UMD}: The FFC factor loadings are the coefficients of the Fama–French (1993) MKT, SMB, HML, and UMD factors estimated using a 60-month rolling regression of each stock return time series on the Fama–French–Carhart (FFC) (Carhart (1997)) factor model (MKT, SMB, HML, and UMD).

ER: Expected return is calculated by applying the coefficients of the FFC 4-factor model estimated over an expanding window of prior bear markets to the historical means of the 4 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 cost of goods sold divided by total assets.

MOM: Momentum is the cumulative return on the stock between months $t-12$ and $t-2$.

BM: 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 Web site (http://research.stlouisfed.org).

DS: The default spread is the difference between Moody's seasoned Baa corporate bond yield and the Aaa corporate bond yield obtained from the Federal Reserve Bank of St. Louis's Web site.

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's Web site.

Appendix B. Factor Models

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

CAPM
$$r_{i,t} - r_{f,t} = \alpha + \beta_{\text{MKT}} \times \left(r_{m,t} - r_{f,t}\right)$$

Fama–French (1993)
$$r_{i,t} - r_{f,t} = \alpha + \beta_{\text{MKT}} \times \left(r_{m,t} - r_{f,t}\right) + \beta_{\text{SMB}}\text{SMB}_t + \beta_{\text{HML}}\text{HML}_t$$

Fama–French–Carhart (FFC) (Carhart (1997))
$$r_{i,t} - r_{f,t} = \alpha + \beta_{\text{MKT}} \times \left(r_{m,t} - r_{f,t}\right) + \beta_{\text{SMB}}\text{SMB}_t + \beta_{\text{HML}}\text{HML}_t + \beta_{\text{UMD}}\text{UMD}_t$$

DOWN_β
$$r_{i,t} - r_{f,t} = \alpha + \beta_{\text{MKT}} \times \left(r_{m,t} - r_{f,t}\right) I_{r_{m,t} < \overline{r_m}}$$

FFC (1997) + BAB
$$r_{i,t} - r_{f,t} = \alpha + \beta_{\text{MKT}} \times \left(r_{m,t} - r_{f,t}\right) + \beta_{\text{SMB}}\text{SMB}_t + \beta_{\text{HML}}\text{HML}_t + \beta_{\text{UMD}}\text{UMD}_t + \beta_{\text{BAB}}\text{BAB}_t$$

CAPM is the capital asset pricing model. 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 small minus big (SMB), high minus low (HML), and up minus down (UMD) are obtained from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) and the betting against beta (BAB) factor is obtained from Frazzini's Web site (https://www.aqr.com/library/data-sets/betting-against-beta-equity-factors-monthly). The indicator function $I_{r_{mt} < \bar{r}_m}$ equals 1 in months when the market return is below its time-series mean, and 0 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% levels.

Appendix C. 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 as follows:

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 8 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 that are lower or higher.

Supplementary Material

Supplementary Material for this article is available at https://doi.org/10.1017/S0022109018000856.

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