Investors' Judgments, Asset Pricing Factors, and Sentiment

by

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Abstract

Fama and French describe their three factor approach to asset pricing as "brute force" because finance theory provides no compelling risk-based explanation for the empirical evidence linking realized returns to size and B/M, characteristics underlying the factors (Fama and French, 1996). Using data from 1999-2014, I present evidence suggesting that most investors' judgments of risk are negatively related to size and positively related to book-to-market equity (B/M) and to market beta. This evidence supports size, B/M, and the market premium as being the basis for the Fama-French factors. I also present evidence that investors' judgments of stock returns are strongly related to Baker-Wurgler sentiment, and in addition exhibit specific biases associated with heuristics based on representativeness and affect. Collectively these results support the contention that systematic biases in investors' judgments of risk and expected return are manifest within market prices. Baker and Wurgler (2006) report that sentiment mediates the relationship between realized returns and characteristics such as size and B/M. I find that sentiment mediates the relationship between investors' judgments of risk and characteristics in a similar manner. These results are consistent with the position that sentiment is manifest within investors' judgments of risk, which in turn serve as a major driver of stock returns.

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1. Introduction

There is a gulf between what theory and practice tell us about how risk premiums reward investors for bearing risk. An elegant theory relates expected return to both mean-variance efficient portfolios and to the covariance between returns and a pricing kernel. However, this theory has not proved to be especially valuable in empirical work, where risk premiums are instead explained using simple factor models involving size and book-to-market equity (B/M) for which there is little theoretical justification.

There is also a lack of consensus about the root cause of the factor structure associated with the cross-section of stock returns. One possibility is that the factor structure reflects fully rational prices, while another possibility is that the factor structure reflects investors' behavioral biases. Fama and French (2004) argue that it is not possible to distinguish between the two possibilities empirically, and have maintained this position even with the emergence of new results about sentiment-based predictability in returns (e.g., Baker and Wurgler, 2006, 2007). Part of the reason for the lack of agreement among scholars is reliance on realized returns to discriminate among explanations (Black, 1993). In this regard, the moments of realized returns are ex post variables, which cannot be automatically equated with investors' ex ante judgments of risk and expected returns.

To shed light on whether prices are fully rational, or instead reflect behavioral bias, I introduce new data consisting of judgments by investment professionals about the risk and returns of holding different stocks. These data were collected over a fifteen year period and paint a clear, consistent picture of the cross section of investors' judgments of stock market risk and return. My findings indicate that investors' collective judgments about risk and expected return display some of the rational pricing features emphasized by Fama and French (2004) and some of the behavioral features emphasized by Baker and Wurgler (2006, 2007).

With respect to Fama and French, I find strong and consistent evidence that investors' judgments about risk are negatively correlated with size and positively correlated with B/M. This finding accords with the Fama-French view, even though Fama and French admit that they have no compelling explanation for why size and B/M should underlie systematic risk. Nevertheless, my data show that investors do indeed judge large cap stocks to be safer than small cap stocks and growth stocks to be safer than value stocks.

With respect to Baker and Wurgler, I find that investors' collective judgments about expected return are significantly related to the sentiment variable (SENT), (Baker and Wurgler, 2006). Notably, sentiment mediates the relationship between both size and realized returns, and B/M and realized returns. My findings show that sentiment mediates investors' judgments about these relationships as well.

With respect to bias, I find that investors' collective judgments about the cross-section of expected returns are consistently at odds with the cross-section of realized returns. My results indicate that the majority of investors expect higher returns from large cap stocks than from small cap stocks, and higher returns from growth stocks than from value stocks. In other words, investors act as if they attempt to implement a Fama-French factor model, but in the course of doing so reverse the signs of the coefficients.

Fama and French's concept of the cross-section of realized returns reflecting rational prices focuses on how risk affects expected returns. In contrast, Baker and Wurgler's explanation of sentiment impacting the cross-section of realized returns involves the degree to which different stocks are easy to value and easy to arbitrage. Baker and Wurgler describe sentiment as general optimism about stocks, and focus on how sentiment affects expected returns. They connect their approach to Fama-French by demonstrating how the relationship between realized returns and a series of characteristics, such as size and B/M, vary according to whether sentiment has been positive or negative.

Because my data involve investors' judgments about both risk and expected returns, I am able to provide an integrated approach to the risk-based approach emphasized by Fama-French and to the sentiment-based approach emphasized by Baker-Wurgler. In particular, I am able to identify key biases in investors' judgments and to analyze how these biases are impacted by changes in sentiment over time.

Central to my analysis are biases in judgments about the relationship between risk and expected return. Ganzach (2000) reports evidence that investors perceive risk and expected return to be negatively related. In Shefrin (2001) I pointed out that the negative correlation between perceived risk and expected return stems is in line with two behavioral heuristics, one based on representativeness and the other on affect. Representativeness is about reliance on stereotypes for making judgments. Investors who judge that the stocks of good companies are representative of good stocks rely on the representativeness heuristic "good stocks are stocks of good companies" (Solt and Statman, 1989). To that I would add the representativeness counterpart for risk that "stocks of financially sound companies are safe stocks."

Affect can be viewed as synonymous with the experience of emotion, and in the context of the affect heuristic relates to how people associate degree of positivity or negativity to objects in their memories. Finucane (2002) discusses why judgments based on affect generally induce people to believe that risk and benefits are negatively related: in this regard, stocks are just one example. My data indicate that the majority of investors form judgments of risk and expected return as if they believe that the capital market line is negatively sloped and the security market line is negatively sloped. Therefore, even if they form appropriate judgments about a security's risk, most form biased judgments about the associated expected return.

My data make clear that not all investors are alike. There is substantial heterogeneity in investors' judgments of risk and return. Roughly ten percent of the investors in my sample make judgments in line with the Fama-French view. I became aware of this heterogeneity in 1999 when I ran an in-company workshop for a U.S. hedge fund specializing in value investing. My analysis showed that along almost every dimension, the judgments of the fund's director of research and chief investment officer (CIO) were in line with the Fama-French view. However, my analysis also showed that less than fifteen percent of the portfolio managers and analysts reporting to the CIO formed like-minded judgments. Instead, most expected higher returns from larger cap stocks than from smaller cap stocks, expected higher returns from growth stocks than from value stocks, and judged the relationship between risk and return to be negative.

I suggest that taken together, four elements combine to make the case that prices are not fully rational, and instead reflect behavioral bias. First, Baker and Wurgler (2006, 2007) document return predictability based on sentiment. Second, the relationship between investors' judgments of expected return and Baker-Wurgler sentiment is positive and statistically significant. Third, investors' judgments of risk display sentiment-conditioning patterns that are consistent with Baker and Wurgler's cross-sectional findings for realized returns. Fourth, the judgments about risk and expected return in my data feature biases that are strong and consistent over the fifteen years of my sample.

There is a long tradition in finance about the difficulty of using realized returns alone to identify the degree to which prices are fully rational. Black (1993) suggests that the connection of realized returns to size and B/M most likely stems from data mining. It was with this in mind that Shefrin and Statman (1995, 2003) suggest analyzing whether size and B/M drive investors' judgments, instead of focusing exclusively on realized returns. Doing so avoids the data mining quandary. To this end, they use data involving judgments about stocks' value as a long-term investment (VLTI) from *Fortune* magazine's annual corporate reputation survey. Notably, they find that judgments about VLTI strongly and consistently reflect size and B/M over time.[2]

Shefrin and Statman report that VLTI is positively related to size and negatively related to B/M, which are opposite in sign to those for realized returns. They argue that this pattern is suggestive that prices reflect bias, and therefore are not fully rational. This line of argument appears to have had a limited impact among those debating whether or not prices are "rational," or instead "behavioral" (Fama and French, 2004). There are at least two possible reasons why. First VLTI, unlike expected return, has no clear or precise definition. Second, demonstrating irrationality on the part of some investors, even many investors, does not necessarily imply that these irrational elements are manifest in market prices.

In Shefrin (2001), I reported the results from data based on workshops given in 1999 and 2000. My new data strongly reinforce the original findings from Shefrin (2001), and provide additional insight into the arguments advanced in Shefrin and Statman (1995, 2003). In my sample, VLTI is almost always positively related to size and negatively related to B/M. Moreover, with few exceptions, the size and B/M sign patterns for my data coincide with those from the *Fortune* data, for the years in which I have access to data from both. These findings provide further indications that the associations involving VLTI, size, and B/M are robust.

At the same time, my data suggest that VLTI is not a perfect proxy for judgments of expected return. I find that although VLTI is positively correlated with judgments of expected return, at times it is also negatively correlated with perceived risk. Moreover, the strengths of the correlations vary over time. From 2005 on, perceived risk impacts VLTI as strongly as expected return. Indeed, in both 2009 and 2012, perceived risk is statistically significant, but expected return is not. These results make clear that treating VLTI as a perfect proxy for expected return can be problematic.[3] The results also make clear why having data directly measuring expected returns is important.

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[2] Henceforth, I omit mentioning that VLTI refers to investors' judgments, and leave it as understood.

[3] In the early phase of my sample, VLTI was effectively a proxy for expected return, with the perceived risk component being small. After 2004, VLTI behaved more like a risk-adjusted return. In this respect, asset pricing factor equations explain raw returns rather than risk-adjusted returns.

The remainder of this paper is organized as follows. Section 2 reviews current thinking about the nature of risk and expected return in the asset pricing literature. Section 3 describes my new data. Section 4 discusses the cross-sectional properties of perceived risk, and Section 5 discusses the cross-sectional properties of expected returns. Section 6 analyzes the behavioral features underlying the relationship between perceived risk and expected return. Section 7 describes the relationship between investors' judgments and the Baker-Wurgler sentiment index. Section 8 discusses the cross-sectional properties of the expected return series derived from analysts' target prices. Section 9 relates the findings in this paper to earlier work based on the annual *Fortune* magazine reputation survey. This discussion serves as a robustness test. Section 10 recapitulates the main issues and concludes. An appendix contains additional supporting details and a Bayesian perspective on interpreting results.

2. Current Thinking about the Nature of Risk and Return

Fama and French (2004) survey the theory and evidence associated with the capital asset pricing model (CAPM). They point out that the CAPM provides a theoretical definition for total risk, and a decomposition of total risk into the sum of systematic and non-systematic components. In this section, I summarize key features of the Fama-French survey, and quote extensively from it in order to capture the nuance and flavor of Fama and French's language.

One of the strengths of the CAPM is in identifying systematic risk as the sole basis for risk premiums. At the same time, the CAPM is plagued by a variety of weaknesses, both theoretically in how to define the "market portfolio," and empirically in whether beta explains realized returns. In addressing these weaknesses, Fama and French state: "In the end, we argue that whether the model's problems reflect weaknesses in the theory or in its empirical implementation, the failure of the CAPM in empirical tests implies that most applications of the model are invalid" (p. 26).

Fama and French discuss the intertemporal capital asset pricing model (ICAPM) developed by Merton (1973), which extends the CAPM by drawing attention to the importance of state variables associated with future consumption and investment. Examples of state variables are labor income and prices of consumption goods. The state variable approach is central to modern asset pricing theory that has the notion of a pricing kernel at its core

(Cochrane, 2005; Hansen and Renault, 2009), and features both the CAPM and ICAPM as special cases.

The pricing kernel approach provides a theoretical definition for systematic risk, based upon the covariance of a security's return with the pricing kernel. Despite the elegance of the pricing kernel framework as a basis for empirical asset pricing, in practice expected returns turn out to be much better explained by simpler, linear factor models which have no clear basis in theory. The factors which Fama and French emphasize in their own work (Fama and French, 1993, 1996) relate to size (market capitalization) and the ratio of book-to-market equity (B/M). In this regard, Fama and French state: "… though size and book-to-market equity are not themselves state variables, the higher average returns on small stocks and high book-to-market stocks reflect unidentified state variables that produce undiversifiable risks (covariances) in returns that are not captured by the market return and are priced separately from market betas… Based on this evidence, Fama and French (1993, 1996) propose a three-factor model for expected returns…" (p. 38)

The factors in the Fama-French three-factor model are the excess return on the market portfolio (meaning the return in excess of the risk-free rate), a size factor (SMB) and a value factor (HML) which Fama and French (2004) describe as follows: "SMB_t (small minus big) is the difference between the returns on diversified portfolios of small and big stocks, HML_t (high minus low) is the difference between the returns on diversified portfolios of high and low B/M stocks …" (p. 38).

Fama and French (2004) are quite explicit about the absence of a theoretical basis for their model, stating: "From a theoretical perspective, the main shortcoming of the three-factor model is its empirical motivation. The small-minus-big (SMB) and high-minus-low (HML) explanatory returns are not motivated by predictions about state variables of concern to investors. Instead they are brute force constructs meant to capture the patterns uncovered by previous work on how average stock returns vary with size and the book-to-market equity ratio …" (p. 39).[4]

When contrasting a rational risk-based explanation with a behavioral explanation for why the three-factor model works, Fama and French (2004) describe the behavioral view as long-term overreaction. In doing so, they state that the behavioral "view is based on evidence that stocks

[4] This brute force approach is by the fact that the size effect is manifest in January, but in no other months of the year. A similar statement holds in connection with the overreaction effect (De Bondt and Thaler, 1985, 1987) which Fama and French present as the behavioral view.

with high ratios of book value to market price are typically firms that have fallen on bad times, while low B/M is associated with growth firms (Lakonishok, Shleifer and Vishny, 1994; Fama and French, 1995). The behavioralists argue that sorting firms on book-to-market ratios exposes investor overreaction to good and bad times. Investors overextrapolate past performance, resulting in stock prices that are too high for growth (low B/M) firms and too low for distressed (high B/M, so-called value) firms. When the overreaction is eventually corrected, the result is high returns for value stocks and low returns for growth stocks. Proponents of this view include DeBondt and Thaler (1987), Lakonishok, Shleifer and Vishny (1994) and Haugen (1995)" (p. 37).

As for distinguishing the rational and behavioral perspectives, Fama and French (2004) write: "Intuitively, to test whether prices are rational, one must take a stand on what the market is trying to do in setting prices—that is, what is risk and what is the relation between expected return and risk? When tests reject the CAPM, one cannot say whether the problem is its assumption that prices are rational (the behavioral view) or violations of other assumptions that are also necessary to produce the CAPM (our position)… In truth, however, one can't tell whether the problem is bad pricing or a bad asset pricing model. A stock's price can always be expressed as the present value of expected future cash flows discounted at the expected return on the stock (Campbell and Shiller, 1989; Vuolteenaho, 2002). It follows that if two stocks have the same price, the one with higher expected cash flows must have a higher expected return. This holds true whether pricing is rational or irrational. Thus, when one observes a positive relation between expected cash flows and expected returns that is left unexplained by the CAPM or the three-factor model, one can't tell whether it is the result of irrational pricing or a mis-specified asset pricing model." (p. 40).

In 2013, Fama, Hansen, and Shiller shared the Nobel Prize in Economics for their work on asset pricing. Their comments and reflections around the award make clear that little has changed since 2004 in respect to the general understanding about the nature and impact of risk on stock returns. That is not to say that nothing has changed. There is now increased attention on the findings about momentum (Jegadeesh and Titman, 1993, 2001), the notion of momentum as a fourth factor (Carhart, 1997), an operational notion of sentiment (Baker and Wurgler, 2006, 2007), and profitability as an additional driver of returns (Novy-Marx, 2012).

The issues identified by Fama and French set the stage for the discussion about insights to be gained by considering over a decade of data pertaining to investors' perceptions. In doing so, I begin with risk perceptions and investigate whether perceived risk about stock returns is related to the variables emphasized by Fama and French, namely the market premium, size, and B/M. I then extend the discussion to investigate whether perceived risk is related to momentum and the overreaction effect, by including prior returns in the analysis. To round out the discussion, I discuss how judgments of risk reflect profitability.

I repeat the analysis for judgments of expected return, defined as the return which investors state they would expect to earn by holding the stock for twelve months. Because my data pertains both to the cross-section and to the time series of investors' judgments, I investigate the relationship between investors' return/risk judgments and Baker-Wurgler sentiment. For sake of comparison, I repeat my analysis for expected returns derived from analysts' target prices.

After analyzing the structure of investors' perceptions of risk and return, I return to the issues that were the focal points of Shefrin (2001). Using responses from the other questions in my investor surveys, I investigate the behavioral basis for investors' perceptions of risk and return. I suggest that doing so provides an indication of how to assess whether asset prices are fully rational, or instead whether prices feature a behavioral component.

3. Data

The data for Shefrin (2001) came from surveys I administered in workshops for hedge fund portfolio managers and analysts. As explained in Shefrin (2001), the surveys elicited judgments about one-year return expectations, perceived risk, and all the questions from *Fortune* magazine's annual survey on corporate reputation. At the time, my survey used a group of eight technology companies: Dell, Novell, Hewlett–Packard, Unisys, Microsoft, Oracle, Intel, and Sun Microsystems.[5]

The instructions in the survey ask respondents to specify the return they expect for each of the eight stocks over the following twelve months, expressed as a percentage. The survey also

[5] I chose technology stocks because I ran the initial survey in the Santa Clara University (SCU) MBA program: SCU is located in the heart of Silicon Valley where most students were already familiar with these particular firms.

asks respondents to rate their perception of the riskiness of each stock on a scale of 0-to-10, with 0 being risk-free and 10 being extremely speculative.[6]

The *Fortune* magazine survey consists of seven questions that pertain to a company and one question that pertains to the company's stock. All answers to the *Fortune* questions are on a scale from 0 to 10. The seven questions ask about the quality of the company's management, the quality of its products, its financial soundness (FS), the degree to which it makes wise use of corporate assets, its innovativeness, its ability to attract, develop, and keep talented people, and its responsibility to the community and the environment. The eighth question in the *Fortune* magazine survey relates to the company's stock, and asks for a rating from 0 to 10 on long-term investment value (VLTI).

Shefrin and Statman (1995, 2003) used VLTI as a proxy for expected return, and studied the connection between VLTI and the other seven questions. In order to provide an independent test of the degree to which VLTI serves as a proxy for expected return, I initially included all the *Fortune* magazine reputation survey questions in my study. Before 2001, I provided survey respondents with copies of data downloaded from Bridge Information Systems (later Reuters), and asked them to use whatever other data sources they normally would in making judgments about stocks.

After 2001, I continued to run my survey, albeit with some changes. I increased the number of stocks from eight to ten, by adding eBay and Walmart. When companies were delisted from exchanges, as happened with Novell and Sun Microsystems, I replaced them with firms having similar financial characteristics. For example, I replaced Novell with BlackBerry and Sun Microsystems with Cisco Systems. In administering the questionnaire, I also provided specific web links to Yahoo Finance for all ten companies. In 2013, I replaced Dell with Facebook after Dell's management announced that it wished to take the company private. In 2014, I began to modify the composition of companies, replacing Oracle with JP Morgan and Cisco with Twitter.

The data I discussed in Shefrin (2001) were collected in 1999 and 2000. Between 2001 and 2014, I collected additional data in every calendar year. Much of the data comes from workshops for executive education and in-company programs conducted in the U.S., Europe and

[6] There is no major time pressure associated with this task. Workshop participants are given at least two weeks to provide responses.

Asia. I also collected data are from faculty and graduate students in finance at European universities: these data were collected in 2005, 2007, 2009, and 2014.

In order to describe the experience of those who provided judgments of perceived risk and expected return, I provide a selection of job titles in the appendix. In the list, I avoid duplicate titles, so that the list provides an indication of the diversity of titles. The majority of participants are portfolio managers and financial analysts from both large and small financial institutions. In this regard, large financial institutions are well represented. Some participants work in treasury departments of large, global industrial firms.

The length and detail in the list serves is intended to emphasize that the source of the data in the body of the paper mostly comes from seasoned financial professionals, not amateurs, individual investors, or students with little practical financial experience.[7]

4. Perceived Risk and Characteristics

Consider whether investors perceive risk to be greater for stocks that have higher betas, are associated with smaller companies, and have higher B/M values than stocks that have lower betas, are associated with larger companies, and have lower B/M values. Based on the asset pricing literature described above, especially the rational view favored by Fama and French, there is good reason to hypothesize that the answer to the preceding question is yes.

In Shefrin (2001) I wrote: "I note that in my survey data, perceived risk is positively correlated with both book-to-market equity and with beta, and is negatively correlated with size." (p. 178). I also noted that these correlations are consistent with the view favored by Fama and French. In this section, I first revisit data upon which I based this statement, and then discuss the degree the statement has proved to be robust over time.

[7] I also collected data from undergraduate business students and MBA students. I set aside the student data to provide a contrast to the responses of professionals, and discuss the results in the addendum.

Risk	Mean	Median	StDev	Min	Max	GroupMeans
Beta	19.3%	26.1%	41.6%	-58.8%	80.3%	52.1%
Size	-23.0%	-19.5%	45.1%	-78.5%	68.5%	-82.4%
B/M	12.1%	17.6%	43.7%	-71.0%	74.6%	58.0%
Ret6	11.2%	21.8%	52.3%	-73.0%	96.9%	32.1%
Ret12	8.1%	4.0%	46.1%	-65.1%	81.2%	35.7%
Ret36	-9.3%	-10.2%	33.6%	-64.3%	68.7%	-2.3%

Sample size	20

Table 1

Table 1 displays summary statistics based upon responses from 20 participants who participated in an in-company workshop I conducted for a U.S. hedge fund in July 1999, and who completed this exercise. This particular hedge fund is run by seasoned professionals and has a client base featuring ultra-high net worth investors. Of the 20 workshop participants, half were portfolio managers and analysts. The remainder had different functions within the hedge fund, mostly administrative.

Table 1 displays statistics for simple correlation coefficients between perceived risk and six variables. The first three variables are beta, size measured by the logarithm of market value of equity, and B/M. The second three variables are lagged returns (annualized) for three horizons; six months, 12 months, and 36 months. For each of the 20 respondents, I computed correlation coefficients between risk responses (for the eight stocks) and respectively beta, size, B/M, and the lagged returns. The leftmost column titled Mean in Table 1 records the mean value of 20 correlation coefficients.

As illustrated by the Table 1columns for standard deviation and range, there is considerable variation across the group of respondents. However, in terms of sign, the average correlation for beta is positive, for size is negative, and for B/M is positive. The sign patterns for these variables are consistent with the rational view. In addition, the signs of the average correlation coefficients associated with perceived risk and lagged returns are in line with risk-based explanations for short-term momentum and long-term reversals.

Risk	Beta	Size	B/M	Ret6	Ret12	Ret36
1999	0.21	-0.33	0.19	0.07	0.07	0.07
2000	0.02	0.04	-0.11	0.11	0.18	0.10
2001	0.18	-0.08	0.06	-0.13	-0.07	0.09
2002	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2003	0.27	-0.25	-0.05	-0.04	0.02	-0.16
2004.1	0.38	-0.51	0.10	-0.05	0.28	0.08
2004.2	0.05	-0.44	0.23	-0.08	-0.04	0.04
2005	0.48	-0.47	0.29	-0.27	-0.28	0.01
2006	0.59	-0.55	0.41	-0.30	-0.20	-0.20
2007.1	0.24	-0.66	-0.25	0.36	-0.09	-0.13
2007.2	0.08	-0.53	0.01	-0.03	0.06	-0.06
2008	0.70	-0.64	0.45	-0.24	-0.15	-0.14
2009.1	0.61	-0.70	0.54	0.50	-0.69	-0.64
2009.2	0.50	-0.58	0.30	0.45	-0.48	-0.54
2010.1	0.48	-0.61	0.48	0.11	0.37	-0.52
2010.2	0.25	-0.43	0.27	-0.06	0.18	-0.18
2010.3	0.41	-0.57	0.33	-0.15	-0.07	-0.43
2011.1	0.26	-0.21	0.08	-0.01	0.09	-0.05
2011.2	0.50	-0.60	0.02	0.15	0.15	0.00
2012.1	0.47	-0.60	0.53	-0.31	-0.47	-0.31
2012.2	0.33	-0.43	0.51	-0.33	-0.43	-0.40
2013	0.31	-0.56	0.61	-0.35	0.47	-0.52
2014	0.15	-0.44	0.14	0.20	-0.12	-0.45

Table 2

I also computed the correlations for the mean responses of the group, and display the results in the column labeled GroupMeans. Doing so effectively smooths the noise from interpersonal variability with the group.[8] As expected, the correlations are higher for the column GroupMeans than for column Means, thereby reflecting the associated smoothing. Notice that the sign patterns are the same for GroupMeans as for Means, which again is consistent with the rational view.

Table 2 displays mean correlations for the years 1999-2014. As can be seen from Table 2, in some years I conducted the study more than once.[9] As a general matter, the correlation signs for beta, size, and B/M are stable across the sample. The sign for size is uniformly negative, and

[8] Averaging over participants also smooths the integer responses for four of the five questions.

[9] The data collected in 2002 involved a small sample in which participants judged all stocks to be equally risky.

for B/M is mostly positive. Table 2 also displays correlations for prior returns. Notice that there is more variation in sign for the prior return, than for size and B/M.[10]

All in all, I would conclude that the correlation patterns for perceived risk are roughly consistent with the three-factor view of Fama and French.

5. Expected Return and Characteristics

Consider the relationship between investors' expected returns and the six characteristic variables discussed in the previous section. In a rational market, the factors that drive perceived risk should also drive expected return, and in the same direction. Table 3 is the counterpart to Table 2.

The key patterns that are evident in Table 3 are as follows. First, the correlation between expected return and beta tends to be positive for only half the sample. Second, the correlation between expected return and size is almost always positive. Investors expect higher returns from larger stocks, a relationship at odds with the Fama-French three-factor approach. Third, the correlation between expected return and B/M is mostly negative. Investors expect higher returns from growth stocks than value stocks, a relationship at odds with the Fama-French three-factor approach. These results mirror what I reported in Shefrin (2001), and have been reported to hold for individual investors (Amromin and Sharpe, 2013.) Notably, the relationship between expected return and prior returns is variable in sign, but considerably more positive than negative.

All in all, I would conclude that the correlation patterns for expected return are inconsistent with the three-factor view of Fama and French.

[10] In the appendix, I discuss two additional examples, one pertaining to April 2000 and the other to November 2004, denoted 2004.2 in Table 2.

ExpRet	Beta	Size	B/M	Ret6	Ret12	Ret36
1999	-0.10	0.15	-0.05	-0.05	0.02	-0.07
2000	0.01	0.16	-0.16	0.18	0.20	0.04
2001	-0.03	0.52	-0.43	0.26	-0.31	0.11
2002	0.33	0.00	0.07	0.01	0.11	0.29
2003	-0.16	0.26	-0.21	0.27	0.10	0.13
2004.1	-0.15	0.17	-0.09	0.00	-0.10	0.00
2004.2	0.07	0.17	-0.13	-0.02	-0.02	0.04
2005	0.03	0.09	-0.15	0.10	0.10	0.20
2006	0.01	0.13	-0.10	0.01	0.01	0.18
2007.1	0.07	0.11	-0.01	-0.23	0.18	0.08
2007.2	0.01	0.20	-0.12	-0.01	0.07	0.04
2008	0.11	0.11	-0.16	0.00	-0.12	0.01
2009.1	0.12	-0.08	0.10	0.11	-0.12	-0.09
2009.2	-0.11	0.14	0.02	-0.11	0.18	0.14
2010.1	-0.07	0.31	-0.27	-0.27	-0.12	0.13
2010.2	-0.13	0.30	-0.13	0.02	-0.08	0.11
2010.3	-0.31	0.42	-0.23	0.29	0.21	0.38
2011.1	0.08	0.07	0.11	0.03	0.12	-0.19
2011.2	-0.13	0.22	-0.04	0.08	0.07	-0.01
2012.1	0.04	-0.01	-0.16	0.09	0.09	0.15
2012.2	-0.10	0.22	-0.33	0.19	0.29	0.30
2013	-0.03	0.05	-0.07	0.09	-0.11	0.16
2014	-0.02	0.30	-0.30	0.17	0.28	0.48

Table 3

6. Judgments of Expected Return and Perceived Risk: Behavioral Basis

In respect to the Fama-French view, the findings from this study provide a mixed picture in respect to interpreting the relationship between perceived risk and expected return. Roughly speaking, perceived risk appears to conform to the Fama-French view, but not expected return. With expected return, the same variables that are associated with risk also appear to be associated with expected return, but puzzlingly in opposite directions.

In Shefrin (2001), I suggested that the heart of this puzzle is that investors perceive the relationship between risk and return to be negative, not positive. Investors expect higher returns from stocks they perceive to be safer, a result in line with Ganzach (2000). Table 4 displays the average correlation coefficient for each group. With the exception of one year, all correlation coefficients are negative.

In Shefrin (2001) I pointed out that the negative correlation between perceived risk and expected return stems is in line with two behavioral heuristics, one based on representativeness and the other on affect. Representativeness is about reliance on stereotypes for making judgments. Investors who judge that the stocks of good companies are representative of good stocks rely on the representativeness heuristic "good stocks are stocks of good companies" (Solt and Statman, 1989). To that I would add the representativeness counterpart for risk that "stocks of financially sound companies are safe stocks." Affect can be viewed as synonymous with emotion, and in the context of the affect heuristic relates to how people associate degree of positivity or negativity to objects in their memories (Finucane, 2002).

Shefrin and Statman (1995, 2003) used *Fortune* magazine survey responses to study whether investors rely on the "good stocks" heuristic. Their study used ratings for the long-term investment value question (VLTI) as a measure of how good survey respondents regarded the stock of a company, and used variables such as quality of management and quality of product/services as measures of how good is the company. They suggested that high positive correlations between these variables indicate that survey respondents are inclined to judge good stocks to be stocks of good companies.

Before 2003, I included all eight *Fortune* reputation questions as part of my survey. When analyzing the hedge fund data for 1999 through 2002, I set aside the question about VLTI and the question about financial soundness (FS) from the other six questions. I then computed the average of the six responses to provide a score for quality of company (QC). To assess the degree to which investors judge good stocks to be stocks of good companies, I examined the correlation between this measure for QC and VLTI. For 1999, the average correlation was 0.70 and the correlation computed using the group mean smoothing was 0.94. For 2000, the average correlation was 0.51 and the correlation computed using the group mean was 0.95. For 2001, the average correlation was 0.75 and for 2002, it was 0.72.

Correlation	Risk v. Return
1999	-0.223
2000	-0.406
2001	-0.161
2002	#N/A
2003	-0.448
2004.1	-0.103
2004.2	-0.082
2005	-0.084
2006	-0.076
2007.1	-0.060
2007.2	-0.125
2008	-0.043
2009.1	-0.240
2009.2	-0.133
2010.1	-0.272
2010.2	-0.110
2010.3	-0.349
2011.1	0.245
2011.2	-0.174
2012.1	-0.018
2012.2	-0.168
2013	-0.021
2014	-0.245

Table 4

In late 2004, I replaced the six questions with a single question asking about the "quality of the company" (QC). The results using the single question format were qualitatively as when using six separate questions. I first used the single QC question format in an in-company workshop for a large U.S. mutual fund. For this group, the mean correlation was 0.41 and the correlation computed the group mean was 0.76. Mean correlations for the remaining data are displayed in Table 5, and are consistently high and positive.

	Corr QC VLTI
2005	0.615
2006	0.779
2007.1	0.663
2007.2	0.664
2008	0.773
2009.1	0.842
2009.2	0.574
2010.1	0.674
2010.2	0.695
2010.3	0.548
2011.1	0.662
2011.2	0.633
2012.1	0.809
2012.2	0.681
2013	0.642
2014	0.714

Table 5

The manner in which representativeness leads investors to associate higher returns to safer stocks proceeds through a series of associations. Investors view good stocks as stocks offering high expected returns. Therefore, representativeness leads investors to expect high returns from the stocks of good companies. This implies a high positive correlation for QC and expected return. It is natural to expect that investors would view financial soundness (FS) as the trait of a good company, which implies a high positive correlation for FS and QC.

I suggest that representativeness also leads investors to judge that stocks of financially sound companies are representative of safe stocks. Therefore, representativeness induces a strong negative correlation between FS and perceived risk, and therefore also between QC and perceived risk.

Together, these associations combine to tell an interesting story. Representativeness leads the correlation coefficients for QC and expected return to be positive and for QC and perceived risk to be negative. Therefore investors relying on representativeness are induced to make judgments about expected return and perceived risk in a manner that leads the correlation for these variables to be negative. That is, investors' judgments suggest that they expect higher returns from safer stocks. Table 6 summarizes the relevant correlation coefficients for my sample. Notice that except for the odd exception, the sign patterns are consistent over the sample period.[11]

	Corr QC ExpRet	Corr QC FS	Corr FS Risk	Corr QC Risk	Corr VLTI ExpRet	Corr VLTI Risk
1999	0.37	0.71	-0.36	-0.48	0.55	-0.33
2000	0.10	0.79	-0.01	-0.05	0.28	-0.33
2001	0.63	0.75	-0.18	-0.12	0.63	-0.22
2002	0.25	0.81	#N/A	#N/A	-0.19	#N/A
2003	0.16	-0.07	-0.35	-0.08	0.49	-0.27
2004.1	0.32	0.74	-0.50	-0.48	0.34	-0.48
2004.2	0.26	0.74	-0.38	-0.44	0.36	-0.40
2005	0.14	0.65	-0.34	-0.43	0.35	-0.36
2006	0.29	0.67	-0.49	-0.58	0.36	-0.60
2007.1	0.11	0.70	-0.44	-0.52	0.19	-0.42
2007.2	0.41	0.76	-0.56	-0.58	0.39	-0.51
2008	0.24	0.77	-0.57	-0.68	0.45	-0.48
2009.1	0.22	0.77	-0.64	-0.73	0.39	-0.68
2009.2	0.18	0.73	-0.61	-0.62	0.20	-0.65
2010.1	0.07	0.72	-0.54	-0.57	0.32	-0.53
2010.2	0.36	0.69	-0.33	-0.33	0.44	-0.33
2010.3	0.50	0.81	-0.67	-0.63	0.37	-0.44
2011.1	0.40	0.70	-0.20	-0.26	0.30	-0.30
2011.2	0.40	0.85	-0.60	-0.60	0.37	-0.54
2012.1	0.23	0.64	-0.43	-0.51	0.33	-0.55
2012.2	0.38	0.76	-0.55	-0.59	0.41	-0.52
2013	0.05	0.70	-0.63	-0.62	0.33	-0.62
2014	0.40	0.81	-0.70	-0.62	0.41	-0.64

Table 6

In Shefrin (2001), I noted that before seeing the analysis of their judgments, virtually all participants indicate that in principle they believe that risk and return are positively correlated. Most are astonished to discover that in practice they judge the relationship to be negative. Many who favor investing strategies focused on smaller companies and value stocks are astonished to discover that they expect higher returns from large cap, growth stocks than small cap value

[11] For every group in my data, the correlation between VLTI and expected return is stronger than the correlation between QC and expected return. This feature implies that investors are not rigidly applying the representativeness heuristic. Rather, the representativeness heuristic is a major aspect of the thought process of many, as reflected in the correlation structure. As I point out later in the paper, some participants' responses feature a negative correlation between QC and VLTI.

stocks. I believe that this is because representativeness and affect lie at the heart of their investment processes, and that these operate at the subconscious level.

Kahneman (2011) might say that the judgments of portfolio managers and analysts reflect subconscious System 1 (intuitive) thinking, even though the principles they articulate reflect System 2 (conscious) thinking. Elements of the planning fallacy, also discussed by Kahneman (2011), strike me as being part of this story. These elements involve underweighting or ignoring base rate information (related to characteristics such as size and B/M) when making predictions about future returns, and overweighting singular (firm specific) information.

There is an important framing issue associated with the exercise I use to collect the data. Ganzach (2000) discusses how circumstances impact whether investors' judgments about the relationship between risk and return are positive or negative. In the experimental setup I use, subjects conduct their analysis on a stock-by-stock basis, and are not asked to assemble a table juxtaposing their judgments about risk and expected return. My colleague Meir Statman conducted the experiment I administer differently, asking subjects to complete a table in which a row for judgments about risk was displayed adjacent to a row for judgments about expected return. This added salience had the effect of inducing a positive relationship between perceived risk and expected return. Notably, the alternative procedure offers guidance about how to mitigate some of the bias under discussion.

In respect to the role of characteristics, Statman (2011) differentiates between a *characteristics hypothesis* in which characteristics, such as size and B/M, are the direct drivers of expected returns and a *sentiment hypothesis* in which investors attach a psychological notion of affect to a stock, and it is affect which is the direct driver of expected return. Statman tests this hypothesis by using the name of a company as a proxy for affect and finding that company name is more closely associated with expected return than are characteristics.[12] In my data, the correlation between VLTI and expected return is uniformly greater than the correlation between any characteristic and expected return. This supports the notion that characteristics are related to expected returns indirectly, through their impact on investor affect.

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[12] Corroborating results come from an unpublished study by Malcolm Baker, who undertook a similar exercise as mine with firms that were less familiar. In private correspondence he writes: "I took less familiar firms, and it did not come out as cleanly as a result."

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A key feature of my data is that there is considerable heterogeneity among those who responded, both within groups and across groups. Some respondents appeared to rely mostly on System 1 (intuition) to arrive at their judgments about risk and expected return, as opposed to System 2 which involves taking characteristics into explicit account. Others arrive at their judgments by engaging both System 2 thinking and System 1 thinking. In the appendix, I discuss responses of students, whose judgments more strongly reflect the sentiment hypothesis than investment professionals. In Section 8, I discuss the judgments of sell side analysts in respect to expected returns. Notably, analysts' research reports are public information and provide evidence about the extent to which they rely on System 2 thinking, as well as System 1 thinking.

Beginning in 2004, I ensured that four profitability measures were part of the data available to all study participants. The four measures were ROE, ROA, gross profit margin, and operating profit margin. There are two salient properties in respect to the correlations between profitability measures and judgments. First, the correlations with perceived risk are mostly negative, with means in the range -25% to -34%. Second, the correlations with expected returns are mostly positive, with means in the range 11% to 20%. Therefore, the profitability correlations are similar to those for size and B/M, with opposite signs for perceived risk and expected return. I note that my data are too limited to test for interactions between profitability and other characteristics, which is an important aspect of profitability studies (Novy-Marx, 2012). However, my findings for sign patterns in respect to expected returns appear to be in line with the results for realized return, but are opposite in sign for a risk-based explanation of profitability-based returns.

All in all, I conclude that the correlation patterns for investors' responses are consistent with the hypothesis that investors rely on representativeness and affect to form their judgments about risk and expected return, and that these behavioral elements lead them to expect higher returns from safer stocks. To be sure, a negative relationship between perceived risk and expected return is inconsistent with the rational pricing interpretation of the Fama-French three-factor model.

7. Baker-Wurgler Sentiment

The sentiment index introduced by Baker and Wurgler (2006, 2007) is the most widely used measure of sentiment in the academic literature. The Baker-Wurgler series SENT (henceforth BW) is derived using a principal component analysis of the following six specific sentiment proxies: turnover on the New York Stock Exchange (NYSE); dividend premium; closed-end fund discount; number and first-day returns on IPOs; and the equity share in new issues. The updated sample range for monthly values of SENT is July 1965 through December 2010, and SENT is normalized over this period to have a mean of zero and a standard deviation of one.

Baker and Wurgler hypothesize that sentiment predicts stock returns in the sense of being conditional on the value of sentiment in the prior month. They report that when past sentiment has been high, subsequent returns to speculative stocks, more difficult-to-arbitrage stocks are lower than returns to safer stocks which are easier to arbitrage. Conversely, when past sentiment has been low, subsequent returns to speculative stocks, more difficult-to-arbitrage stocks are higher than to safer stocks which are easier to arbitrage.

Baker and Wurgler (2007) state: "we view investor sentiment as simply optimism or pessimism about stocks in general …" (p. 132).[13] With this statement in mind, consider Figure 1a. For each date, Figure 1a contrasts BW and expected return (averaged over all stocks that were part of the exercise). Figure 1a only displays data through the end of 2010, as the BW series is only available until December 2010. The correlation between BW and average expected return is 0.57 (t=2.7, p=0.017). See Figure 2a for the scatter plot depiction of these variables. For perceived risk, the corresponding correlation is -0.09 (t=-0.36, p=0.72). The value of BW that is matched to an expected return is the one closest in time to the date the exercise was undertaken.

[13] Barone-Adesi, Mancini, and Shefrin (2014) analyze the degree to which the Baker-Wurgler series reflects excessive optimism and overconfidence about returns for the S&P 500. They find strong evidence that BW reflects excessive optimism, but do not find a statistically significant component for an additional component related to overconfidence, that is not already captured by excessive optimism. They also find that subjective expected returns and risk for the market as a whole are negatively correlated. The results in the present paper are in line with the findings in Barone-Adesi, Mancini, and Shefrin (2014).

Baker and Wurgler's explanation of sentiment impacting the cross-section of realized returns involves the degree to which different stocks are easy to value and easy to arbitrage. Baker and Wurgler suggest that when sentiment increases, stocks which are difficult to value and difficult to arbitrage become overvalued relative to stocks that are easier to value and easier to arbitrage. This is an important issue, given my finding that investors' judgments of expected return are positively correlated with BW.

One of the most intriguing issues that Baker and Wurgler address is the extent to which sentiment impacts the relationship between realized returns and characteristics such as size and B/M. In this regard, Baker and Wurgler (2006) find that the size effect is conditional on sentiment: When sentiment is low (below sample average), small stocks earn particularly high subsequent returns, but when sentiment is high (above average), there is no size effect at all. That is, following a month when sentiment has been negative, the correlation between realized returns and size is negative, whereas following a month when sentiment has been positive, the correlation between realized returns is flat (or slightly positive).

Baker and Wugler also report that several characteristics which do not have any unconditional predictive power display sign-flipping predictive ability, in the hypothesized directions, after conditioning on sentiment. Specifically, when stocks are sorted into deciles by sales growth, book-to-market, or external financing activity, growth and distress firms tend to lie at opposing extremes, with more "stable" firms in the middle deciles.

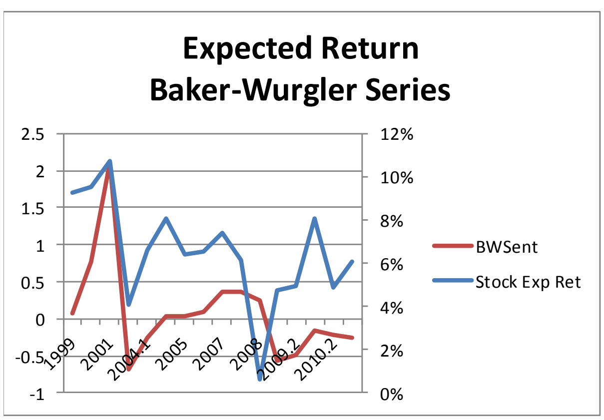

Figure 1a

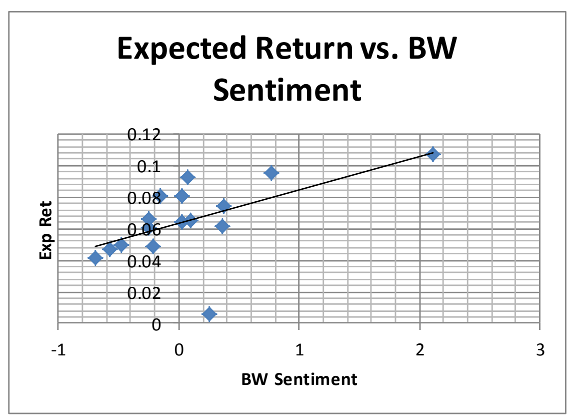

Figure 1b

Given Baker and Wurgler's conditional findings, consider the manner in which correlations involving judgments and characteristics vary, conditional on periods following whether BW has been positive or negative. Table 7 displays the results for beta, size, B/M, past six month returns, and the percentage of investment professionals whose judgments about risk are consistent with Fama-French sign patterns.

Focus on the size effect, beginning with risk. Over the period 1999-2010, the unconditional correlation between judgments of risk and size is -47%. Notably, the negative sign of this correlation is consistent with the Fama-French view that the stocks of small cap firms are judged to be riskier than the stocks of large cap firms. Following periods of positive sentiment, the correlation is -42%, which is weaker than the correlation of -53% associated with periods following negative sentiment. The stronger risk-size effect following periods of negative sentiment is consistent with the pattern for realized returns identified by Baker-Wurgler. However, the associated correlation conditional on negative sentiment does not turn positive, as is the case with realized return.

Over the period 1999-2010, the unconditional correlation between judgments of expected return and size is 19%. Relative to the corresponding correlation involving perceived risk, the expected return-size correlation is both weaker and of the opposite sign. The opposite sign pattern is consistent with investors' reliance on representativeness and affect-based heuristics. Following periods of positive sentiment, the expected return-size correlation is 17%, which is weaker than the correlation of 23% associated with periods following negative sentiment. Therefore, the bias associated with expected return and risk becomes stronger following periods of negative sentiment, thereby enhancing the size effect. However, the magnitudes of the expected return-size correlations are not large enough to explain why the size effect would disappear following periods of positive sentiment.

	Beta		Size		B/M		Ret6		% who are FF
	Risk	Exp Ret	Risk	Exp Ret	Risk	Exp Ret	Risk	Exp Ret	Rational
Unconditional Mean	36.4%	-5.9%	-46.4%	19.4%	20.4%	-11.5%	-1.3%	0.1%	7.0%
Mean if BW > 0	32.3%	-0.1%	-41.6%	16.7%	13.3%	-13.1%	-5.4%	4.3%	7.7%
Mean if BW < 0	41.8%	-13.2%	-52.6%	22.8%	29.6%	-9.4%	3.9%	-5.3%	6.1%

Table 7

Consider the extent to which investors' judgments about there being a size effect change over time. For judgments of risk, there is a marked BW-effect on the percentage of investors who judge that risk and size are negatively correlated. Following periods of positive sentiment, 74% of investment professionals judge that risk and size are negatively correlated, and following periods of negative sentiment, 88% do so. There is no similar pattern for expected return. Following periods of positive sentiment, 32% judge that expected return and size are negatively correlated and following periods of negative sentiment, 30% do so. These results reinforce the correlation findings reported in Table 7 for size.

The conditional sentiment results provide a vehicle for understanding how perceived risk and behavioral bias combine to impact realized returns. In line with the Fama-French view, investors' judgments that small cap stocks are riskier than large cap stocks leads means realized returns for small cap stocks to be greater than mean realized returns for large cap stocks. Moreover, judgments about the risk-size interaction intensify following periods of negative sentiment, leading to a larger size effect during those periods.

However, in line with Baker-Wurgler, perceived risk is not the only driver of realized returns, as judgments of expected return also exert an impact. Moreover, investors expect lower returns from small cap stocks. As a result, investors bid down the prices of small cap stocks to reflect their judgments about expected returns, beyond the impact associated with their judgments of risk. Following periods of negative sentiment, the bias is stronger than following periods of positive sentiment, thereby accentuating the difference in the two conditional size effects.

Table 7 shows that negative sentiment intensifies the correlations of perceived risk with beta and B/M, not just size. For size and B/M, the patterns are consistent with the Fama-French view. For beta, the sign pattern is opposite to the Fama-French view. For past six-month returns, negative sentiment induces a sign pattern shift for risk, in that stocks with higher past returns are considered safer following periods of negative sentiment. For expected return, the flip in sign pattern suggests that investors believe in momentum following periods of positive sentiment and believe in reversals following periods of negative sentiment. At the same time, all correlations pertaining to prior six-month returns are small.

The right-most column in Table 7 shows the impact of sentiment on the percentage of investors whose beliefs come closest to being rational in the Fama-French view. I suggest that

Fama-French rationality requires judgments of both risk and expected return are positively related to beta, negatively related to size, and positively related to B/M; in addition judgments of risk and expected return are positively correlated. Table 7 shows that between 1999 and 2010 approximately 7% of investors satisfied the necessary conditions for Fama-French rationality, with the percentage being higher following periods of positive sentiment. I would note that for my full sample period, 1999-2014, approximately 10% of investors satisfied the necessary conditions for Fama-French rationality.

Finally, consider a possible interaction effect in respect to the conditional size effect. Recall the finding from Table 7 that following periods of positive sentiment, investors judge recent winners to be less risky and to have higher expected returns than recent losers. However, following periods of negative sentiment, the signs reverse: investors judge recent winners to be more risky than recent losers, and to have lower subsequent returns. Therefore, following periods of positive sentiment, if recent winners are more concentrated in small cap stocks, then the impact of past returns would lead to upward pressure on the prices of small cap stocks, thereby lowering subsequent returns and dampening the size effect conditional on BW being positive.

All in all, Baker and Wurgler identify predictable cross-sectional patterns involving BW and realized returns, some of which I find in the relationship between BW and perceived risk.[14] In the time series, BW is significantly correlated with investment professionals' judgments of expected returns. Notably, the latter judgments display strong cross-sectional biases associated with representativeness and affect. Taken together, these associations suggest that the predictable return patterns have a behavioral component, and are not fully rational.

8. Analysts' Target Returns

Brav and Levhavy (2003) analyze the returns implicit in sell side analysts' target prices, which they define as the ratio TP/P, where TP denotes target price and P denotes current market price.

[14] I lack the data to test for the U-shaped patterns, and inverse U-shaped patterns identified by Baker and Wurgler (2006). I also note that Baker and Wurgler find evidence of a negative relationship between total risk and realized returns in periods following positive sentiment, with the relationship being positive after negative sentiment. I find no significant correlation between BW and the mean correlation between judgments of risk and expected return. Likewise, Baker and Wurgler find that the relationship between realized returns and ROE is generally positive following periods of positive sentiment and negative following periods of negative sentiment. I do not find such an effect for perceived risk and ROE, but instead find a negative relationship regardless of whether sentiment has recently been positive or negative.

Brav and Lehavy focus on target price revisions for a large sample of stocks, using data for the period 1997-1999.

My sample of eight-to-ten stocks is of course much smaller than the Brav-Lehavy sample, and in fact is too small for doing meaningful regression analysis involving the three factor Fama-French model or the Carhart four factor model. Nevertheless, it is possible to modify the Brav-Lehavy TP/P approach for my small sample, and examine the correlations between TP/P and the various characteristic variables, just as I have done for expected return in section 5.

Table 8 below displays the average target return for each calendar year beginning in 2004, as well as the correlation coefficient between target return and a series of characteristics. Notice from the table that with two exceptions, the correlation between target return and beta is positive. With two exceptions, the size effect is negative, with two exceptions, the B/M effect is positive, and with three exceptions, the short-term momentum effect is negative. Therefore, in the main, analysts' target prices are in accord with the Fama-French view, but are opposite in respect to momentum. The correlations are respectively for beta (0.37), for size (-0.37), for B/M (-0.04) for Ret6 (-0.64), for Ret12 (-0.59) and for Ret36 (-0.006).

In respect to profitability, Table 8 shows that the pattern features a mix of negative and positive correlation coefficients for all four profitability variables. This mix is at odds with the clear positive pattern in my response data.

In respect to optimism, notice that the magnitude of sell side analysts' expected returns are high. The mean expected return for these stocks over the sample period is about 19%. Given that the average beta is less than 2.0, 19% is consistent with excessive optimism. In contrast, the mean expected return for these stocks over the sample period is about 6%.

For completeness, I include a chart that shows the time series for both analysts' average target return and the Baker-Wurgler index.[15] The correlation coefficient between the two series is 0.26, and the correlation between the analysts' average target return and the average expected return series from my study is 0.31.[16]

[15] A data point for 2000 has been added to the series under discussion, in order to display the character of BW during the early portion of the data series. For the most part, I did not begin to collect data systematically about sell side analysts' implied target returns until 2004.

[16] In Figure 2, I have omitted the observation from 1999 because of missing observations.

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Trgt Ret	25.0%	26.8%	16.1%	9.7%	19.3%	3.6%	29.5%	31.8%	26.6%	8.2%	1.0%
beta	3.8%	-13.0%	6.7%	1.0%	22.6%	-92.7%	64.8%	23.0%	89.6%	48.4%	34.4%
size	-27.3%	-53.0%	-50.8%	45.9%	-41.5%	38.5%	-13.3%	-39.3%	-69.8%	-10.1%	24.5%
B/M	31.1%	16.5%	68.4%	56.7%	34.9%	26.8%	-82.4%	1.7%	5.2%	-58.9%	11.4%
Ret6	-82.6%	-79.7%	-65.7%	-69.3%	-26.4%	3.9%	24.9%	-57.2%	-61.0%	39.2%	-18.4%
Ret12	31.1%	-71.0%	-39.7%	-21.9%	15.8%	3.6%	13.9%	-30.7%	-54.5%	-29.3%	13.6%
Ret36	-27.8%	22.1%	-44.5%	11.1%	44.0%	-56.9%	20.1%	42.6%	-21.3%	42.0%	73.2%
ProfMargin	-6.5%	17.7%	-41.1%	37.5%	6.2%	90.9%	-50.2%	0.8%	-27.4%	7.9%	78.8%
OperMargin	-11.4%	14.1%	-18.2%	29.0%	11.5%	-10.5%	-46.1%	2.3%	-17.0%	18.8%	73.5%
ROA	10.3%	-7.2%	-30.7%	29.6%	-28.6%	28.1%	0.3%	-18.5%	-23.5%	29.1%	66.8%
ROE	14.9%	-17.8%	-60.9%	49.2%	-21.6%	-65.0%	-25.6%	-12.1%	9.2%	4.9%	80.2%

Table 8

From 2004 on, the participants in my workshops had access to sell side analysts' target prices through web-links provided with the instructions about the exercise. In terms of cross-section of stocks, the responses suggest participants varied widely in respect to the weights accorded to target prices: mean correlations for each year tended to be small (approximately 3% on average), but the standard deviations were large (approximately 42%), with the large positive correlations of some being offset by the large negative correlations of others. At the same time, the time series of expected returns, averaged over stocks in each year, are more highly correlated with target returns. The higher time series correlation reflects the fact that both expected returns in my sample and analysts' target returns are both positively correlated with BW-sentiment.

All in all, the sign patterns for sell side analysts' implicit expected returns are in line with the Fama-French three-factor model. This suggests that sell side analysts are more inclined to engage System 2 thinking than the investors in my data. However, there is considerable noise in analysts' expected returns, a belief in reversal rather than momentum, and strong optimism bias.

In the appendix, I investigate the manner in which the correlations of analysts' target returns with characteristics vary with BW. I find that an increase in BW generally magnifies virtually every effect with the exception of market beta. Therefore, an increase in BW sentiment generally amplifies the tendency for analysts' target returns to conform to the Fama-French view, and also to have stronger beliefs about short-term reversals and long-term continuation.

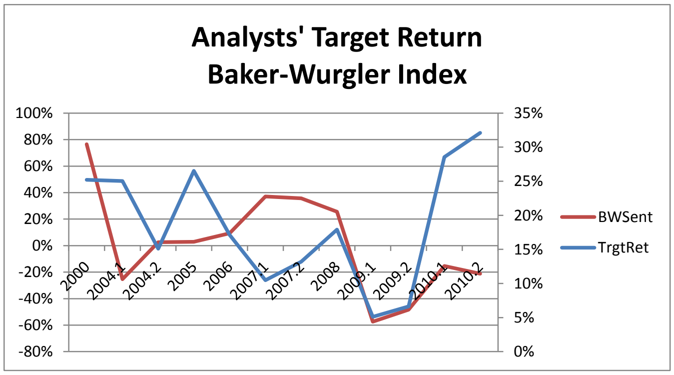

Figure 2

9. Robustness

Most of the correlation signs in my data are highly consistent over time. Still, with at most ten stocks, many correlations are not statistically significant. In additions, the number of degrees of freedom is too small to allow for meaningful regression analysis. These limitations raise questions about robustness, which I address in this section by focusing on the variable VLTI, and in the appendix by focusing on a Bayesian approach.

Shefrin and Statman (1995, 2003) use VLTI as a proxy for expected return. Table 6 shows the average correlation of VLTI and expected return over time, as well as its sign which is consistently positive. These findings lend support to the use of VLTI as a proxy for expected return. At the same time, VLTI is also negatively correlated with perceived risk. Indeed after 2004, the strength of the VLTI-correlation for risk is higher than for expected return. This implies, therefore, that VLTI reflects both risk and return.[17]

Keep in mind that as a general matter, expected return is positively correlated with size, and perceived risk is negatively correlated with size. As a result, given the correlations involving expected return and size, and perceived risk and size, there is good reason to expect that VLTI will be positively correlated with size and negatively correlated with B/M.

Shefrin and Statman (1995, 2003) use multiple regression analysis to investigate the relationship between VLTI and characteristics such as beta, size, B/M, and past returns. Their data spans the period 1982 through 1994 with 1982 marking the date of the first *Fortune*

[17] Regressing VLTI on both expected return and perceived risk shows that before 2005, perceived risk was not statistically significant. From 2005 on, perceived risk is statistically significant, and in 2009 and 2012, expected returns is not statistically significant.

magazine survey of corporate reputation. A specific survey is denoted by the symbol "t/t+1," with data collection in year t, and the results reported during t+1. Statman, Fisher, and Anginer (2008), Anginer and Statman (2010), and Statman (2011) discuss the *Fortune* survey data for the period 1982/83 through 2005/06, and finds that the same general patterns hold as in the data ending in 1995.

	beta	size	B/M	Ret12	Constant	Observations	R-squared
1982	0.278	0.389***	-0.165*	0.169	3.434***	77	0.493
1983	-0.195	0.414***	-0.469***	0.097	3.854***	102	0.545
1984	-0.379**	0.314***	-0.896***	-0.073	5.314***	114	0.546
1985	-0.048	0.267***	-0.699***	0.459	4.898***	126	0.354
1986	-0.202	0.237***	-0.743***	0.251	5.247***	135	0.350
1987	-0.206	0.240***	-1.379***	-0.375*	5.721***	140	0.433
1988	-0.162	0.283***	-0.891***	-0.778**	4.915***	139	0.339
1989	0.082	0.233***	-1.038***	-0.150	5.283***	149	0.374
1990	0.438*	0.154***	-0.291**	1.414***	5.170***	152	0.409
1991	-0.022	0.276***	-0.862***	0.186	4.710***	158	0.424
1992	-0.155	0.217***	-0.322***	0.122	5.028***	161	0.304
1993	0.046	0.228***	-0.497***	-0.129	4.843***	195	0.305
1994	0.097	0.275***	-0.659***	-0.214	4.433***	199	0.304
1995	-0.038	0.290***	-0.208	0.446**	4.172***	203	0.373
1996	0.022	0.266***	-0.309*	0.698***	4.279***	216	0.382
1997	-0.026	0.287***	-0.674***	0.210*	4.179***	251	0.381
1998	0.130	0.291***	0.000***	0.167	3.753***	258	0.335
1999	-0.169	0.290***	-0.306**	0.246**	3.926***	264	0.409
2000	-0.314***	0.288***	-0.139**	0.278***	3.896***	303	0.410
2001	-0.041	0.272***	-0.180***	0.135	3.779***	306	0.292
2002	-0.001	0.303***	-0.018	0.797***	3.461***	346	0.277
2003	-0.232***	0.327***	-0.066	0.149	3.606***	388	0.278
2004	-0.181***	0.314***	-0.363***	0.222*	3.836***	389	0.316
2005	-0.189***	0.321***	-0.485***	0.139	3.712***	347	0.342
Pooled Data	-0.041*	0.284***	0.000***	0.317***	3.935***	5,118	0.245

Table 9

Table 9 provides the results of year-by-year regressions for these surveys, for VLTI regressed on beta, size, and B/M. Table 9 covers the period 1982 through 2005.[18] Notice that the regression coefficients for size and B/M are consistent in sign from year-to-year, and statistically

[18] I thank Deniz Anginer for providing the updated data for these regressions.

significant.[19] The coefficient for size is positive in every year and for B/M is negative in every year. The coefficient on beta varies between being positive and being negative, and is not statistically significant.

	beta	size	B/M	Ret6	Ret12	Ret36
1999	-0.46	0.52	-0.11	-0.07	0.13	-0.17
2000	-0.15	0.45	-0.37	0.20	0.18	0.09
2003	0.05	0.33	-0.04	-0.06	-0.05	-0.05
2004.1	-0.39	0.63	-0.34	0.29	-0.17	0.22
2004.2	0.25	0.77	-0.37	-0.40	0.38	-0.40
2005	-0.27	0.50	-0.41	0.27	0.37	0.17
2006	-0.34	0.61	-0.44	0.26	0.13	0.25
2007.1	-0.05	0.42	0.27	-0.30	0.09	0.12
2007.2	-0.07	0.49	0.02	0.05	-0.05	0.13
2008	-0.29	0.42	-0.40	0.22	0.09	0.18
2009	-0.59	0.68	-0.51	-0.53	0.66	0.65
2010.1	-0.47	0.56	-0.47	-0.08	-0.38	0.47
2010.2	-0.17	0.49	-0.27	0.00	-0.19	0.19
2010.3	-0.30	0.48	-0.15	0.23	0.06	0.41
2011.1	-0.34	0.47	-0.09	-0.01	-0.08	-0.11
2011.2	-0.29	0.46	0.04	0.01	-0.07	-0.12
2012.1	-0.58	0.73	-0.66	0.54	0.64	0.50
2012.2	-0.34	0.50	-0.49	0.34	0.45	0.40
2013	-0.26	0.51	-0.46	0.42	-0.56	0.51
2014	-0.18	0.50	-0.18	-0.11	0.14	0.54

Table 10

Table 10 displays the time series of correlation coefficients in my survey data. Table 11 contrasts regression coefficients from Table 9. Notice that the same general pattern holds in respect to the signs of the correlations in Table 15 and the signs of the regression coefficients in Table 9. I would argue that this strong consistency in signs is indicative of the relationships being robust through time.

[19] These regressions are based on GroupMeans, not individual responses. Recall that using GroupMeans has the benefit of smoothing noise from individual variation, and therefore yielding higher t-statistics.

	Regression Coefficients				Correlation Coefficients			
	beta	size	B/M	Ret12	beta	size	B/M	Ret12
1999	-0.169	0.290	-0.306	0.246	-0.457	0.523	-0.109	0.130
2000	-0.314	0.288	-0.139	0.278	-0.155	0.448	-0.373	0.183
2001	-0.041	0.272	-0.18	0.13	-0.030	0.523	-0.429	0.257
2002	-0.001	0.303	-0.018	0.797	0.334	-0.004	0.074	0.014
2003	-0.232	0.327	-0.066	0.149	0.048	0.329	-0.035	-0.046
2004.1	-0.181	0.314	-0.363	0.222	-0.386	0.632	-0.341	-0.172
2004.2					0.254	0.771	-0.367	0.379
2005	-0.189	0.321	-0.485	0.139	-0.268	0.502	-0.414	0.372

Table 11

All in all, the correlation patterns for VLTI are mostly consistent with the *Fortune* magazine survey VLTI data, suggesting that these patterns are robust, significant, and extend well beyond the small sample of stocks I used in my studies. In addition, my findings buttress the assumptions made in Shefrin and Statman (1995, 2003), Statman, Fisher, and Anginer (2008), Anginer and Statman (2010), and Statman (2011) where VLTI is used as a proxy for expected return.

10. Discussion and Conclusion

Investors are a mixed lot. Some form judgments about both risk and expected return that are generally in line with the Fama-French three factor model. Some only form judgments about risk that are in line with the Fama-French three factor model, but form judgments about expected return that are not in line with Fama-French.[20]

The results from this paper suggest that most investors' judgments about risk are roughly in line with the Fama-French view, but not their judgments about expected return. That is, a majority of investors perceive that risk is negatively related to size and positively related to B/M, but judge that expected return is positively related to size and negatively related to B/M. These investors form judgments as if they believe that risk and expected return are negatively related, with a negatively sloped security market line and negatively sloped capital market line.

There are important lessons to be learned from applying these insights about financial judgments to the contributions of both Fama-French and Baker-Wurgler. First, that in most but not all years, a majority of investment professionals' judgments about risk conform to the Fama-

[20] As for Carhart (1997), the evidence is mixed in respect to the momentum factor.

French view is of great significance, especially as Fama and French offer no justification for why size and B/M should be the basis for two of the risk factors underlying their framework.

Second, a case can be made that perceived risk is a major contributor to realized returns. Correlations involving beta, size and B/M are much stronger for judgments of risk than for expected returns. Moreover, Baker-Wurgler report that predictability patterns in realized returns are conditional on recent sentiment. For example, the size effect appears to occur only in periods following negative sentiment, but not positive sentiment. I find that perceived risk exhibits some of the same predictability patterns. For example, following periods of negative sentiment (as measured by BW), investment professionals become more inclined to judge stocks associated with smaller firms and higher B/M as riskier than they do following periods of positive sentiment. The results from my data are consistent with the size effect being stronger following periods of positive sentiment than following periods of negative sentiment; however, my results do not provide a clear explanation for why the size effect should disappear following periods of positive sentiment.

Third, investment professionals' judgments of expected returns are significantly correlated with Baker-Wurgler sentiment. Therefore, judgmental biases have both a time series component and a cross-sectional component. The most pronounced cross-sectional bias is that judgments of risk and expected return are negatively correlated over most of the sample.

Fourth, the combination of the above three lessons suggests that judgments of risk are major drivers of realized returns whose influence is mediated by judgments of expected returns. As a general matter, irrational investors expecting higher returns from safer stocks bid down the prices of riskier stocks by amounts unwarranted by fundamentals. As a result, their actions lead these stocks to generate positive abnormal future returns. I suggest that this can explain why low beta stocks, value stocks, and the stocks of small firms are associated with positive abnormal returns.[21]

Fama and French (2004) argue that it is not possible to differentiate between the position that prices are rational and the position that prices reflect behavioral elements. Fama (2008) is

[21] Think about Warren Buffet, whose track records suggests a positive alpha strategy. Frazzini and Kabiller (2013) suggest that the success of Buffett's strategy stems from his overweighting of low beta value stocks in combination with leverage. That explanation is consistent with my evidence about risk perceptions and expected returns. Moreover, investors and security analysts are prone to predicting reversals rather than continuation. Therefore stocks with positive momentum are prone to being underbid by unwarranted amounts, thereby leading momentum stocks to be associated with positive abnormal returns.

clear that he accepts the idea that some investors behave irrationally. Nevertheless, he maintains that one cannot jump to the conclusion that in the aggregate the existence of some individual irrationality implies that market prices must be irrational.

I agree with Fama's view that the existence of some irrationality is not a sufficient condition for prices to be irrational. One of the main themes in Shefrin (2005, 2008) is to identify conditions under which the presence of bias at the level of individual investors leads to prices that are less than fully rational.[22]

In an average year, approximately 50% of investors' judgments about risk are in line with the Fama-French view, meaning that they judge that risk is positively correlated with beta, negatively correlated with size, and positively correlated with B/M. The percentage is higher (55% vs. 48%) following periods of negative sentiment than following periods of positive sentiment. If we only focus on size and B/M, the average is 63%, (55% following periods of positive sentiment and 74% following periods of negative sentiment). The magnitude of these correlations suggests that investors' judgments of risk are closely associated with the cross-section of realized returns. Their conditional dependence on sentiment suggests that prices are not fully rational, but instead reflect a behavioral component.

A necessary condition for an investor's judgments to be rational from a Fama-French perspective is to judge that both risk and expected return are positively related to beta, negatively related to size, and positively related to B/M. In addition, it seems reasonable to require that they judge risk and expected return to be positively correlated. The judgments of approximately 10% of the investors in my sample satisfy this rationality requirement.[23] Hence, most investment professionals form judgments that do not reflect the Fama-French view. For the 10% minority, prices might appear to be rational, but not so for the 90% majority with identifiable biases. To argue that prices are fully rational is to argue that the 90% have no net impact on asset prices. And yet, the sentiment conditioning results for realized returns from Baker-Wurgler, and the

[22] In Shefrin (2008) I argue that investors' biases can wash out in the aggregate, even in the presence of systematic errors on the part of investors. This happens when error-wealth covariances are equal in magnitude but opposite in sign to aggregate investor biases. I also point out that this washing out effect constitutes a knife edge case, and conclude that systematic biases interfere with rational pricing most of the time. Notably, error cancellation in the presence of systematic bias is not the result of investors who are free of bias. Their presence only dilutes the degree of bias in market prices. Complete elimination of errors in market prices, in the presence of systematic bias, stems from investors making offsetting errors and having just the right mix of different wealth levels.

[23] The intertemporal standard deviation is 12%.

presence of sentiment conditioning in my data on judgments, suggests that the biases of the 90% are neither self-cancelling nor arbitraged away.

Moreover, in addition to investment professionals, there are also individual investors whose judgments need to be taken into account. As a proxy for individual investors, I use data involving judgments by students of finance at the undergraduate and MBA levels. Based on results reported in Statman, Fisher, and Anginer (2008) and Anginer and Statman (2010), I suggest that students' responses reflect those of general individual investors.

I find that both undergraduate business students and MBA students are prone to rely on a combination of representativeness and affect in making judgments about risk and expected return.[24] One indication of this is the high and positive correlation in their responses between quality of company (QC) and the long-term investment value of the company's stock (VLTI). For investment professionals, the correlation is considerably lower. As discussed in the appendix, the strength of the correlations involving size and B/M is actually stronger for the students than for the investment professionals. I suggest that this is because investment professionals are more likely than students to exhibit expected return correlations that are in line with the Fama-French view. As a result, the sign patterns for investment professionals are more mixed than they are for students.

The expected returns associated with sell side analysts' consensus target prices are generally in line with the Fama-French three factor model, albeit with biases pertaining to optimism and to short-term reversals. From 2004 on, the participants in my workshops had access to sell side analysts' target prices through web-links provided with instructions about the exercise. The responses suggest that participants varied widely in respect to the weights they accorded target prices: mean correlations for each year tended to be small, but the standard deviations were large, with the large positive correlations of some being offset by the large negative correlations of others.

All in all, my findings suggest that size and B/M are relevant for empirical asset pricing to the extent that they impact the judgments investors make about the risks and expected returns

[24] In this view, the relationship involving characteristics on the one hand, and perceived risk and expected return on the other, is indirect and related to associations between company-specific affect and these characteristics. In this context, representativeness and affect-based heuristics state that "good stocks are stocks of good companies" and "stocks of financially sound companies are safe stocks." The results from data suggest that investors' judgments are strongly consistent with these heuristics, but are not the exclusive drivers.

associated with specific companies and their stocks. In addition, the results for how profitability measures correlate with judgments about risk and expected return are in line with this perspective. As for momentum, the findings based on my workshop data paint a mixed picture, and are conditional on sentiment, although not for sell side analysts who set target prices as if they believe in short-term reversal, not momentum.

Making a case that prices are fully rational without having a well specified notion of risk is tenuous at best. Doing so in the face of data about strong, persistent, systematic biases in investors' judgments of risk and return over time is even more tenuous, especially when these biases are closely linked to sentiment-based predictability in realized returns that have been documented in the existing literature.

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Appendix

This appendix contains several sections. Section A1 provides a list of job titles for workshop participants. Section A2 contains additional details about some of the workshops. Section A3 compares the responses of investment professionals with business school students at the undergraduate and MBA levels. Section A4 provides some additional details about the nature of sell side analysts' target returns. Section A5 provides a Bayesian interpretation of the overall results.

A1. Job Descriptions

Below is a subset of typical job descriptions for workshop participants.

- Director of research, chief investment officer, hedge fund
- Quantitative analyst, investment research, insurance firm
- Senior portfolio manager, investment bank
- Head of research, institutional asset management
- Equity analyst, investment bank
- Senior portfolio manager, pension fund
- Portfolio manager, pension fund
- Senior strategist, research and investment services, consulting firm
- Senior sales manager, investment bank
- Sales advisor, equities, investment bank
- Head of account group, regulatory agency
- Senior economist, central bank
- Senior consultant, investment consulting firm
- Proprietary trader, investment firm
- Senior financial manager, external funds, sovereign fund
- Portfolio manager, equities, investment bank
- Investment manager, insurance firm
- Chief executive officer, investment bank
- Senior portfolio manager, equity management, investment bank
- Professor, finance, university
- Vice president, corporate clients, investment bank
- Economist, statistician, central bank
- Portfolio construction, asset management, investment bank
- Director equities, private trading, investment bank
- Group vice president, risk management, investment bank
- Head of global emerging markets, equity management, investment bank
- Business analyst, investment firm
- Equity trader, investment bank
- Economist and portfolio manager, investment bank
- Certified financial planner, wealth management firm

- Assistant to head of department, products and trading, private bank
- Portfolio manager, small caps, investment bank
- Portfolio manager, alternative investments, investment bank
- Investment analyst, emerging markets, investment bank
- Dealer and technical analyst, investment bank
- Director, distressed assets, investment bank
- Investment manager, CFO, industrial firm
- Treasury and trading, equities, industrial firm

A2. Additional Workshop Details

In April 2000, I repeated the workshop exercise with the same hedge fund as I did in 1999, but only for portfolio managers and analysts. Table A1 displays the resulting correlations.

Risk	Mean	Median	StDev	Min	Max	GroupMeans
Beta	9.7%	9.6%	23.4%	-23.9%	50.0%	25.3%
Size	-0.6%	-9.3%	47.9%	-55.8%	86.7%	6.9%
B/M	-16.0%	-25.4%	53.4%	-97.4%	69.9%	-45.8%

Sample size	9

Table A1

Table A1 contained some surprises about size and B/M. The biggest surprise involved the negative coefficients associated with B/M. The findings for size in respect to GroupMeans were also surprising, but explainable by large outliers. In this respect, the size coefficient for the Median column is consistent with the rational view.

Because six of the portfolio managers and analysts participated in both the July 1999 workshop and April 2000 workshop, I was able to test the degree to which their perceived risk scores for the eight stocks varied along with changes in beta, size, and B/M. Table A2 displays the correlation coefficients, averaged across the six respondents, for differences in risk scores and differences in beta, size, and B/M. Notably, the puzzling sign patterns pertaining to size and B/M, which I discussed in the preceding paragraph, surface here as well.

Risk		
Beta	Size	B/M
40.5%	21.8%	-25.4%

Table A2

A possible explanation for the puzzling pattern involves a combination of the particular time period and the impact of other variables such as momentum. The dates of the workshops, July 1999 and April 2000 bracket the period August 1999 through March 2000, which marked the dramatic rise and climax of the technology stock bubble. I note that for both samples, perceived risk is positively correlated with prior returns over the past six months and twelve months. At the same time, these correlations are significantly weaker than the correlations for beta, size, and B/M. Nevertheless, in April 2000, several weeks after the peak of the technology stock bubble, the correlation for change (between the two periods) for perceived risk and past six month return is 0.45: This is higher than for any other of the variables under discussion, and suggests that the drop in past six month return from July 1999 to April 2000 was the major driver associated with an increase in perceived risk.

Table A3 displays correlations for portfolio managers and analysts from an in-company workshop for a major U.S. mutual fund firm that I conducted in November 2004. One issue of note is that the correlations for prior 6 month return, Ret6, is negative while the correlations for the other two prior return variables is positive.

Risk	Mean	Median	StDev	Min	Max	GroupMeans
Beta	40.2%	49.1%	35.4%	-59.2%	80.6%	69.3%
Size	-49.4%	-69.1%	41.7%	-90.7%	61.5%	-84.6%
B/M	11.4%	16.4%	32.4%	-66.2%	71.1%	25.0%
Ret6	-3.0%	-5.1%	29.5%	-47.8%	52.7%	-9.5%
Ret12	24.2%	22.9%	26.5%	-24.5%	77.0%	37.7%
Ret36	23.6%	28.6%	33.4%	-51.2%	83.5%	38.5%

Sample size	30

Table A3

Table A4 provides summary data for correlations associated with Group means in specific examples. As I mentioned in Section 4, group averaging smooths individual variation across investors.

ExpRet	1999	2000	2004
Beta	-52.0%	-58.2%	-26.2%
Size	18.2%	32.1%	52.8%
B/M	-14.2%	-32.2%	-15.6%
Ret6	16.4%	33.5%	29.5%
Ret12	20.9%	36.9%	-16.4%
Ret36	4.4%	2.7%	-27.4%

Table A4

A3. Correlation Comparisons: Investment Professionals vs. Undergraduate and Master's Business Students

Beginning in 1997, I began administering the workshop exercise used to collect the data for this study. My initial subjects were business students. Beginning in 1999, I used the same exercise with as with investment professionals. There are four years in which I administered the same survey to both students and to investment professionals, namely 2002, 2004, 2006, and 2008. The responses from students enable me to ascertain the degree to which professionals' responses are similar to students. The students who participated in the exercise had all taken at least two finance courses, of which one was a course in investments. In some years the students were undergraduates and in other years the students were enrolled in an MBA program.

Table A5 below contrasts responses for key correlations.[25] The entries in Table A5 are all mean correlations across the responding groups. For example, for Return v. Market Beta, the average (mean) correlation (across the ten stocks) between expected return and beta was -21.3%, whereas for the investment professionals who completed the same exercise within the same calendar quarter, the corresponding average correlation was -12%.

[25] Table A5 does not include the student data from 2002 because the sample size for the corresponding investment professionals is too small to provide a valid comparison.

	UG 2004	Prof 2004	MBA 2006	Prof 2006	MBA 2008	Prof 2008
Return v. Market Beta	-21.3%	-12.0%	-11.5%	1.2%	-9.4%	11.2%
Return v. Natural Log of Mkt Cap	28.9%	19.4%	31.1%	13.2%	45.0%	10.8%
Return v. Book-to-Market	-34.8%	-8.9%	-33.8%	-10.3%	-32.8%	-16.0%
Return v. 6 Month Returns	27.2%	8.4%	-5.5%	0.7%	34.4%	-0.2%
Return v. 12 Month Returns	23.9%	-1.1%	-17.8%	1.0%	30.3%	-12.4%
Return v. 36 Month Returns	26.4%	-1.3%	1.0%	17.7%	33.7%	1.4%
Corr QC ExpRet	45.8%	25.4%	59.4%	28.6%	55.1%	23.7%
Corr QC FS	79.1%	77.1%	82.2%	67.1%	80.4%	77.1%
Corr FS Risk	-44.9%	-36.7%	-64.4%	-48.5%	-56.8%	-57.3%
Corr QC Risk	-49.6%	-39.6%	-63.8%	-57.5%	-63.2%	-67.7%
Corr VLTI ExpRet	55.6%	37.9%	65.8%	36.3%	66.0%	44.8%
Corr VLTI Risk	-59.1%	-39.7%	-56.3%	-59.8%	-54.6%	-48.4%
Long-Term Value v. Quality of Company	70.0%	43.0%	71.4%	77.9%	69.1%	77.3%
Risk v. Return	-31.9%	-8.5%	-39.4%	-7.6%	-22.6%	-4.3%
Risk v. Market Beta	48.5%	41.9%	44.9%	58.6%	50.3%	71.1%
Risk v. Natural Log of Mkt Cap	-54.7%	-51.9%	-57.4%	-55.3%	-64.5%	-62.4%
Risk v. Book-to-Market	27.0%	13.9%	45.0%	41.4%	37.4%	42.3%
Risk v. 6 Month Returns	-19.8%	-5.2%	-2.7%	-29.6%	-59.5%	-21.3%
Risk v. 12 Month Returns	-2.0%	23.3%	14.3%	-20.2%	-62.5%	-14.5%
Risk v. 36 Month Returns	-7.9%	24.2%	2.4%	-20.0%	-55.5%	-12.4%

Table A5

All three comparisons in Table A5 show a similar pattern. In terms of similarity, signs of the correlation coefficients for the students are the same as for the professionals. In terms of differences, the strength of the correlations is greater for the students than for the professionals. I suggest that this is because investment professionals are more likely than students to exhibit expected return correlations that are in line with Fama-French.

These findings lead me to suggest that as groups, both students and professionals rely on representativeness-based thinking to arrive at their judgments. However, students are much more prone to do so, especially in respect to B/M.

A4. Sell Side Analysts

During 2004, the weblinks in my workshop instructions included the target prices of sell side analysts. Before 2004, target prices were only included sporadically. Table A6 displays two sets of figures for the period 2004-2010. The first row contains the mean values of correlations between analysts' target returns and specific characteristics. The second row displays correlations between Baker-Wurgler sentiment and these characteristic correlations. The second row indicates how an increase in BW impacts the strength and direction of the characteristic relationships.

	Trgt Ret	Beta	Size	B/M	Ret6	Ret12	Ret36
Mean	18.6%	-1.0%	-14.5%	21.7%	-42.1%	-9.7%	-4.6%
Corr With BW	12.2%	52.9%	-20.7%	32.8%	-42.8%	-34.5%	64.2%

Table A6

In Table A6, the column for Target Return indicates that the mean annual target return for all ten stocks over the period 2004-2010 was 18.6%. Putting aside magnitude, the 12.2% correlation with BW indicates that when BW increased, analysts' target return tended to increase. For the Beta column, the mean correlation of beta and Target Return over the period 2004-2010 was virtually zero (-1%). However, an increase in BW is associated with an increase in Target Return. The columns for Size and B/M show that Target Return generally conformed to the Fama-French view, with an increase in BW amplifying this feature.[26] The column for Ret6 shows that sell side analysts generally believed in short-term reversal, with an increase in BW amplifying this effect. The column for Ret36 shows a small long-term reversal effect, which moves in the opposite direction when BW increases.

[26] In 2000 at the height of the dot.com bubble, the correlation between target returns and size was strongly positive for the eight stocks that were part of the study at that time. There were also two other years in my data where this exception was the case.

A5. Bayesian Approach to Judgments about Sign Patterns

In respect to the magnitude of the correlation coefficients discussed above, I place less emphasis on the t-statistics used as measures of statistical significance,[27] and more emphasis on a Bayesian approach, in so far as interpreting the significance of the findings.[28] Beginning with a diffuse prior, a Bayesian analysis conditional on the data presented in this paper would attach high probabilities to the correlation signs associated with size and B/M conforming to the historical patterns in respect to VLTI, perceived risk, and expected return.

A formal Bayesian approach for the sign of a single variable uses a beta distribution, and conditions Bayesian updating on whether the sign of a particular correlation is positive or nonpositive (Robert, 2001). With a flat prior, the implied posterior density, conditional on the sequence of sign patterns, is tightly distributed around the historical relative frequencies.

For example, beginning with a flat prior, the posterior distribution that the sign of the correlation between expected return and size will be positive for a group, without conditioning on group size, is 0.84. In respect to the correlation between expected return and B/M, the corresponding posterior probability that the correlation will be negative is 0.80. The corresponding probability in respect to beta is 0.56, which implies that it is pretty much of a tossup as to whether a new group would view the slope of the security market line as being positive.

Of course, for someone with a very tight prior, suggesting a perspective held with great conviction, the evidence I have presented might not induce much of an adjustment in subjective probability. Very tight priors can also stem from confirmation bias.

For combinations of sign patterns, a Dirichlet density is used. The number of combinations is akin to the number of degrees of freedom, in the sense that a larger number of observations is required to achieve tightening of the posterior density. For example, the posterior probability that the correlation between expected return and size will be positive AND the

[27] One exception is the t-statistic and associated p-value for the strength of the correlation between expected returns and BW, Baker-Wurgler's sentiment variable SENT.

[28] Most of the correlations I report are averages across individual respondents. These tend to be lower in absolute value than the correlations associated with group means. To take an example, for the 2011.2 study, the average correlation between expected return and size is 0.23, which appears weak with a t-statistic of 0.48. In contrast the corresponding correlation for the group mean is 0.6 with a t-statistic of 2.1. For these data, t-statistics are misleading because they understate the consistency of the sign patterns. The t-statistic of 2.1 does not appear to be especially strong, and yet a glance at Table 3 shows that the sign pattern for size is remarkably consistent.

correlation between expected return and B/M will be negative, for a group without conditioning on size, is 0.67.[29]

[29] The Bayesian probabilities described in this section are based only on data from investment professionals and financial economists in academia (faculty and Ph.D. students). Adding data from business students at the undergraduate and MBA level, discussed in the appendix, only increases the probabilities, as all of these groups make judgments in which expected return is positively related to size and negatively related to B/M.