Cross-sectional performance and investor sentiment in a multiple risk factor model

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This version: October 2011

Abstract

Economists have long recognized the importance of information veracity in valuing risky securities. Market participants concerned about the credibility of information measures may require additional compensation to entice them to hold stocks with less transparent information. These same securities are expected to display greater sensitivities to measures of market sentiment. We find that investor sentiment sensitivities increase directly with multiple measures of opacity in the cross-section. Next we examine the extent to which sentiment sensitivities are priced in an asset pricing context. Using the Jha, Korkie and Turtle (2009) model of conditional performance evaluation, we find an inverse relation between *ex ante* known investor sentiment and the marginal performance of opaque stocks. In contrast, translucent stocks exhibit relatively little variability in performance across levels of sentiment.

JEL classification: G11; G12; G14
Keywords: Investor sentiment; Asset-pricing; Conditional performance

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1. Introduction

If the available information regarding particular stocks is difficult to interpret, economic agents may have difficulty valuing these securities. Further, arbitrageurs and speculators will find it challenging to measure and capitalize on mispricings in these securities, as the veracity of available information may be particularly difficult to resolve. If these securities are prevalent in the economy, and if these risks are difficult to diversify, we might expect these securities to be more sensitive to overall measures of market sentiment. In contrast, if these risks are largely diversifiable, observed premiums on opaque securities should be comparable to those offered by firms with similar risk profiles. We find strong evidence that stock opacity and sentiment sensitivities are closely related, and that both simple and multi-factor risk models do not capture the variability in these stocks' returns over time.

The ability to diversify sentiment risk remains an open and important issue. For instance, if sentiment is important only insofar as it affects other systematic risk sensitivities, economic agents may be largely unconcerned with this area of inquiry. In contrast, if sentiment is an undiversifiable risk source that impacts risk premiums after controlling for systematic risks, this area will be of lasting interest. Initial research by Lee, Shleifer and Thaler (1991) found that small stock returns are positively (and significantly) related to sentiment, relative to portfolios of large stocks, although the relation has weakened over time. In contrast, Elton, Gruber and Busse (1998) provide evidence that sentiment sensitivity is subsumed by other systematic risks. In a simple two-factor model including an equity index and a sentiment factor, Elton, Gruber and Busse find smaller stocks display a positive sensitivity to investor sentiment, exhibiting the strongest returns concurrent with periods in which closed end fund discounts narrow. Conversely, larger stocks are slightly negatively related to this sentiment measure. When they extend their model to consider multiple risk factors they find their results reverse, and sentiment is then negatively related to small stock returns. In sum, Elton, Gruber and Busse (1998) conclude that sentiment is subsumed by other risk factors in a well specified model of asset return behavior.[1] Therefore, from the previous evidence, it appears that sentiment risk may be idiosyncratic. Specifically, returns to a diversified portfolio would reflect the underlying risk factor loadings, but would be otherwise unaffected by investor sentiment. Consequently, from an asset-pricing perspective, investor sentiment would be of little further interest, except to the extent that a researcher was concerned with the relation between investor sentiment and underlying risk sources.

We begin our empirical analysis with an examination of the characteristics of stocks that display the greatest sensitivity to contemporaneous measures of market sentiment. This initial step in our research design examines the extent to which various risk factors may dampen the characteristics of sentiment prone portfolios. For example, if multiple risk factors capture cross-sectional variability in sentiment-prone stocks from a simpler model, there may be little remaining interest in the characteristics of sentiment prone stocks. Our approach is similar in spirit to Lee, Shleifer and Thaler (1991) but we consider a wide number of risk factor specifications. Baker and Wurgler (2006) also study the cross-sectional impact of investor sentiment. Our results allow us to build on their contribution and resolve many of the conflicting results within their study. Focusing on two important firm characteristics relating to opacity, size and research and development, they ultimately find no relation between these characteristics and investor sentiment. Specifically, within the narrow two factor model, they document a negative and marginally significant relation between the orthogonalized sentiment index and subsequent small minus big portfolio returns. However, in their study, and similar to Elton, Gruber and

[1] The evidence in Elton, Gruber, and Busse (1998) is in fact stronger than discussed above in that none of their reported sentiment sensitivities (Table 3) for size decile portfolios are significant at conventional levels. In fact the largest absolute t-statistic is only 1.31 across 20 reported tests.

Busse (1998), this relation disappears within the context of their expanded factor model, suggesting that controlling for additional risk factors eliminates the relation between size and sentiment. Similarly, although their analysis of raw returns with no risk corrections suggests a positive relation between research and development and investor sentiment, their later regression analysis provides no evidence of a relation between sentiment and subsequent returns to their long-short research and development portfolio.

Brown and Cliff (2005) also consider the impact of sentiment on cross-sectional size and book to market portfolios with incongruent findings. They regress long-horizon returns on economic explanatory variables as well as lagged sentiment, and provide evidence that large stocks exhibit greater exposure to investor sentiment, relative to small stocks. As one example, they estimate the long-run response to a one standard deviation shock to sentiment, and find that the small-growth, and small-value portfolios respond positively at the 36 month horizon, with estimates equal to 5.8 and 1.6 percent, respectively, suggesting a negative relation between contemporaneous sentiment and small stock mispricing. In contrast, the comparable estimates of -11.5 and -9.7 percent for the large-growth and large-value portfolios, respectively, suggest these large portfolios exhibit negative subsequent responses to current sentiment levels, providing indirect evidence of a positive relation between contemporaneous sentiment and over-valuation within these stocks. These general findings are contrary to both Elton Gruber and Busse (1998) in that sentiment matters, and especially to Baker and Wurgler (2006) with respect to the role of size and sentiment.

Contrasting with this existing research, we find a strong relation between opaque firms and investor sentiment that is robust across narrow and expanded risk factor models. Our procedure finds that even in the midst of a multiple risk source model, sentiment prone stocks retain their sensitivity to firm based characteristics that are closely aligned with opacity. In particular, sentiment-prone stocks tend to be small, young, volatile, composed of relatively intangible assets, and in general display opaque characteristics. As examples of our sentiment sensitivity results with respect to size and research and development, under the simplest single risk factor model, we find that the average low sentiment sensitivity firm has a market capitalization of 1.1 billion dollars and exhibits research and development spending as a percentage of assets equal to 1.3 percent; the corresponding values for the average high sentiment sensitivity firm are 363 million, and 12.4 percent. Further, these results are robust to the expanded four-factor model, where we find that the average low sentiment sensitivity firm is over 2.5 times larger in terms of market capitalization when compared to the average high sentiment sensitivity firm, and exhibits research and development spending as a percentage of assets that is only 30 percent of the level of spending for the average high sentiment sensitivity firm. These results indicate that, rather than being idiosyncratic, sentiment sensitivities are systematically related within broad cross-sections of equities. Specifically, as opaque companies in which valuations are less certain will exhibit common exposures to investor sentiment, portfolios formed across these equities will be highly exposed to changes in investor sentiment. Consequently, investor sentiment may be non-diversifiable, warranting additional risk premia.

We examine the risk premiums associated with sentiment in the conditional performance framework of Jha, Korkie and Turtle (2009) using *ex ante* sentiment as our known information measure. One benefit of this approach is that the framework admits changes in the conditional mean returns for all assets that evolve with the underlying information variable. The resultant conditional alpha is then a time varying measure of the mispricing in any portfolio. The framework allows for a direct test of the marginal value of sentiment as an information instrument in a model with potentially multiple risk factors including the CAPM, or other extended beta models including both Fama and French (1992, 1993), and Carhart (1997).

Our results differ from Baker and Wurgler (2006) in a number of important dimensions, although many of the general conclusions of their work are preserved. They find that portfolios of firms with opaque characteristics tend to earn large returns. Unfortunately, as there are known correlations between opaque characteristics and systematic risk sources (cf., Elton, Gruber, and Busse (1998), and Schmeling (2009)), these results may be solely due to required risk premiums for these portfolios. In their subsequent analysis (Table V), Baker and Wurgler (2006) examine the sensitivity of long-short portfolios to *ex ante* sentiment after controlling for multiple risk factors. In their four-factor model, they find seven of 16 models have orthogonal sentiment parameters with p-values in excess of 0.35. In contrast, the orthogonalized sentiment factor in a model with only a single risk factor results in eleven of 16 significant cases (with no p-value exceeding 0.30). In sum, these results suggest that correcting for risk has a potentially dramatic effect on the role of sentiment as an information instrument impacting portfolio performance (cf., Elton, Gruber, and Busse (1998)). Jha, Korkie and Turtle (2009) develop a conditional alpha performance measure given by the sum of a simple regression intercept and the product of an information variable coefficient and the *ex ante* level of the information variable. The exclusive focus on the sentiment coefficient has the potential to misspecify economic differences in the marginal performance in these settings. We explicitly measure the intercept, the sensitivity to sentiment, and the *ex ante* known level of sentiment when estimating marginal performance. Our analysis reverses the inferential results in Baker and Wurgler (2006) regarding a lack of significance for all growth opportunity and distress proxies (in all models). In short, sentiment affects asset mispricing.

Our results indicate that measured conditional marginal performance gains may be substantial. Using sentiment as a conditioning information instrument, we find that portfolios of opaque firms exhibit contrarian conditional performance. Portfolios of opaque firms formed after periods of high (low) sentiment offer poor (strong positive) marginal performance. Portfolios of translucent firms exhibit little variation in conditional alpha across all levels of sentiment. Our measure of conditional marginal performance is a natural extension of the unconditional alpha of Jensen (1968) to include both sentiment sensitivities, and evolving sentiment measures. We find consistent results across multiple risk factor specifications. Differences with the extant literature may be due to the importance of sentiment in affecting both unconditional alphas, as well as conditional alphas through variation in both sentiment sensitivities in the cross-section, and realized aggregate sentiment levels in the time series. Using firm age as an example of the results, our sentiment sensitivity analysis indicates that the average low sentiment sensitivity stock is approximately 22 years old. Concomitantly, stocks in the high sentiment sensitivity portfolio are less than 15 years old on average. Extending the example to consider our measure of marginal performance and how sentiment impacts the cross-section of portfolio returns, we find that as sentiment varies from the fifth percentile to the 95th percentile, the portfolio of 'old' stocks has a range of conditional alphas that is less than ten basis points, and equals approximately 0.3 percent per month across all states. For the 'young' portfolio, the conditional alpha exhibits much greater variation, ranging from 0.9 percent to -1.0 percent across the same range of sentiment realizations. Our conditional alpha estimates provide meaningful differences in conditional performance over time and across portfolios with different characteristics, including risk adjustments and inference procedures. The conflicting results of our conditional alpha estimates, relative to the existing research concerning investor sentiment, has important implications for researchers. Specifically, from Jha, Korkie and Turtle (2009), the sole focus on coefficient estimates within the extant sentiment literature does not identify the economic states in which superior or poor performance is obtained. The conditional performance measure employed within the current study is consistent with a model of time varying conditional mean asset returns that evolve linearly with underlying information variables. As evident by the significant findings within our study, and the insignificant multi-factor model results in the earlier literature, our approach offers important advantages when performance varies by economic states, and when averaging over states may obscure important economic relations. In general, for future research, our results show the benefits in using more recent measures of conditional performance.

Our study is also related to the return predictability literature. In the context of return predictability, Welch and Goyal (2008) provide a comprehensive study detailing poor out of sample forecasting performance for frequently studied information variables. They suggest that unconditional historical average returns provide superior forecasting performance, relative to common information variables. In contrast, Campbell and Thompson (2008) show that imposing economically meaningful constraints on estimated coefficients improves forecasting performance. Within the cross-section, our conditional alpha results show that high levels of current sentiment predict below-average risk adjusted returns within opaque firms. In a regression context, our conditional performance measure is intuitively similar to the restricted forecasts in Campbell and Thompson (2008). The orthogonalized sentiment measure is nested within a more structured setting that seems to facilitate test power.

In an asset-pricing context, our sentiment sensitivity analysis reveals a systemic exposure to investor sentiment within opaque equities. Further, we show that this exposure is not subsumed by additional risk factors, and is also non-diversifiable. Therefore, our results are consistent with the notion that equity portfolios with sentiment exposure should offer returns that reflect the average sentiment exposure of the stocks within the portfolio. Further, portfolios of firms with a large proportion of opaque stocks may be especially susceptible to sentiment risk. Finally, within the asset-pricing context, we provide an application of Jha, Korkie and Turtle (2009) conditional performance measure, which may also be of interest using alternative conditioning variables.

2. Investor sentiment and firm-characteristic data

Consistent with existing literature, we consider sentiment broadly as general optimism or pessimism towards future stock returns. Sentiment can be measured either directly through surveys, or indirectly through economic variables. The direct approach typically uses survey measures to identify levels of sentiment, with periods of high sentiment corresponding to periods in which a majority of economic agents forecast strong future performance.[2] Contrasting the direct approach, a number of studies use observable economic variables to measure levels of sentiment. Lee, Shleifer and Thaler (1991) use the closed-end fund discount. Neal and Wheatley (1998) consider the closed-end fund discount, as well as odd-lot sales and mutual fund redemptions to measure individual investor sentiment. They study the general proposition that

[2] Examples of research using direct measures of sentiment include: Ho and Hung (2009) who use the Investors' Intelligence survey and consumer confidence indices to measure sentiment; Schmeling (2009) who uses consumer confidence indices to measure sentiment across countries; and Verma and Soydemir (2009) who measure individual investor sentiment with the American Association of Individual Investor survey and institutional investor sentiment with the Investors' Intelligence survey.

the best time to buy (sell) is when individual investor sentiment is at its lowest (highest).[3] We adopt the monthly sentiment index of Baker and Wurgler (2006, 2007) who create an aggregate sentiment index based on six sentiment proxies, including the closed-end fund discount, share turnover, the number of IPOs, the first day IPO return, the share of equity issues relative to debt issues, and the dividend premium.[4]

Another strand of recent research expands the direct measures of investor sentiment to consider aggregate market views regarding sentiment across investor type, including both institutional and individual investors. As examples, Brown and Cliff (2004) and Verma and Soydemir (2009) use the Investors Intelligence survey as a measure of institutional sentiment. Brown and Cliff find the relation between institutional sentiment and future market returns is stronger than any relation across individual investor sentiment. The existing research suggests investor sentiment is a contrarian indicator. For example, Brown and Cliff (2005) find evidence of a positive contemporaneous relation across sentiment and pricing errors. In particular, they

[3] Other related studies using individual investors to gauge market sentiment include Frazzini and Lamont (2008) and Green and Hwang (2009). Frazzini and Lamont (2008) classify stocks according to a mutual fund flow related sentiment variable and document that individual investor sentiment has a negative impact on individual investor wealth. Green and Hwang (2009) study price-based comovement and find that the relation across similarly priced stocks is strongest during periods of high sentiment. Their results indicate the impact of sentiment may vary based on the price of a given stock

[4] Brown and Cliff (2004) document a strong relation between many of the proposed indirect sentiment measures and their direct counter-parts in identifying high and low sentiment periods. The Baker and Wurgler sentiment index is also used in Ali and Gurun (2009), and Kurov (2010).

find optimism leads to overvalued stocks and that high levels of sentiment also produce long run future underperformance.[5]

We consider the cross-sectional impact of investor sentiment on equity returns. Our sample covers January 1968 through December 2005, and is based on the universe of CRSP/Compustat stocks with at least 60 months of return data during the sample. We begin with a measurement of size, age, risk, profitability, dividends, tangibility, growth opportunities, and distress, for the stocks within our sample. We winsorize accounting variables at the one, and 99 percent levels to mitigate the impact of outliers. Accounting data from a fiscal year end in month *t* are matched to equity returns during months *t*+6 through *t*+17, to ensure that accounting information is available to investors. We report summary statistics in Table 1.

*** Insert Table 1 about here***

From Table 1, we note that our sample covers a broad cross-section of equities pooled across firms and over time. We note that many firm characteristic variables exhibit significant variability and skewness. For example, average property, plant and equipment is 56 percent of assets with a standard deviation of 39 percent. The median value for property, plant and equipment in the sample is less than 50 percent.

[5] Some additional representative studies examining the impact of sentiment on the aggregate market level include Lee, Jiang and Indro (2002), who find sentiment risk is priced in aggregate; Tetlock (2007), who analyzes the relationship between market returns and media pessimism; and Schmeling (2009) who finds sentiment is priced in 18 national markets.

3. Measuring attributes of sentiment-prone stocks

The impact of investor sentiment may vary in the cross-section. Lee, Shleifer and Thaler (1991) argue individual investor sentiment has the largest impact on small capitalization stocks. In contrast, Brown and Cliff (2005) find evidence that large stocks exhibit the largest exposure to investor sentiment. Baker and Wurgler (2006) hypothesize that small firms will be more opaque, harder to value, and thus will be most sentiment-prone. The results regarding which firms will be most sentiment prone are also dependent on the underlying risk factors considered. In particular, Elton, Gruber and Busse (1998) find that although small stock returns vary positively with contemporaneous sentiment in the context of a simple model, the sign of the sentiment factor reverses in a broader multi-factor risk model.

We examine the role of sentiment in a variety of risk factor models to determine the cross-sectional impact of investor sentiment on firms with different levels of opacity. Our initial empirical analysis provides an alternative approach to examine the relationship between firm characteristics and sentiment. We first estimate sentiment sensitivities within our pooled time-series cross-section of stocks, and then we report average firm characteristics across portfolios formed according to sentiment sensitivities. This approach differs from the raw return analysis in Baker and Wurgler (2006) which uses known information instruments including ex ante sentiment measures -- our sentiment sensitivities are contemporaneous, and net of the other risk factors considered. Our interest is in the characteristics of firms with various sentiment sensitivities after controlling for other systematic risk sources. This approach mitigates the spurious impact of correlations between sentiment measures and risk sources that may be prevalent in the extant literature. If the average firm characteristics of our high-sentiment (low-sentiment) sensitivity portfolios correspond to opaque (translucent) characteristics, we have confirmatory evidence that these portfolios capture sentiment effects. A typical firm in the high sentiment sensitivity grouping is expected to display volatile returns, a small equity base, low-earnings, low-dividends, high distress risk, and have relatively intangible assets.

We estimate sentiment sensitivities at the firm level. Lee, Shleifer and Thaler (1991) use a two-factor model, with the market portfolio and the change in the closed-end fund discount, to estimate sentiment sensitivities across size deciles in their study.[6] We adopt a similar approach, initially utilizing a two-factor model that includes the market portfolio and changes in the measure of investor sentiment. Our regression model may be written as:

$$R_{j,t} = \alpha_j + \beta_{j,m} R_{m,t} + \beta_{j,sent} \Delta Sent_t^{\perp} + e_{j,t}, \qquad (1)$$

for $j = 1, 2, \ldots, N$; $t = 1, 2, \ldots, T$; and where N is the number of cross-sectional observations available and T is the number of time series observations available for each firm; $R_{j,t}$ represents the excess return to asset *j* during period *t*; $R_{m,t}$ represents the excess market return during period *t*; and $\Delta Sent_t^{\perp}$ represents the change in the orthogonalized sentiment index of Baker and Wurgler (2006), during period *t*.[7] Excess market return data is extracted from Ken French's data library. Based on parameter estimates of $\beta_{j,sent}$, we assign stocks to ten sentiment sensitivity portfolios. In the initial analysis, we estimate equation (1) for each unique firm, and assign stocks based on

[6] By estimating sentiment sensitivities at the firm level, our approach may have significant estimation risk. However, this additional noise potentially biases our approach against finding the hypothesized differences across portfolios. Further, parameter estimates are used to sort firms, and statistical tests are conducted across measured firm characteristics. This approach mitigates econometric concerns with tests of betas in cross-sectional regressions (cf. Reinganum (1981)).

[7] We identify firms based on unique PERMNOs. Consequently, *N* is defined for over 12,000 unique firms, and *T* takes a maximum value of 456.

the full-sample $\beta_{j,sent}$ parameter estimate. For some stocks, investor sentiment will have a negligible impact on their return. Further, throughout our sample, some stocks may exhibit returns that vary inversely with investor sentiment. Because most stocks are positively related to investor sentiment and our interest is identification of sentiment prone stocks, we assign any stock j for which the parameter estimate of $\beta_{j,sent}$, is less than zero to the first portfolio, $Port_1$. We then equally split the remaining firms into the nine remaining sentiment sensitivity portfolios, such that all stocks with a positive $\beta_{j,sent}$ estimate are classified into portfolios two, $Port_2$, through ten, $Port_{10}$, where each portfolio has an equal number of stocks, and sentiment betas are increasing across portfolios, respectively.[8] For each firm, we calculate the time series average for each firm characteristic variable, and then pool these averages across sentiment sensitivity portfolios to report the resultant averages in Table 2.

Insert Table 2 about here

Results in Table 2 provide strong support for the hypothesis that firms with high sensitivity to investor sentiment tend to be relatively opaque. Differences across all portfolios, and between the first and 10th portfolio are highly significant and in the expected direction for every specified firm characteristic. For example, the lowest three sentiment sensitivity portfolios show a mean standard deviation of stock returns that ranges between 11 and 12 percent. The average portfolio standard deviation of returns then increases monotonically from 13 to 26 percent for the remaining sentiment sensitivity portfolios. Average firm size differs dramatically across sentiment sensitivity portfolios. The average firm size of stocks assigned to $Port_1$ and

[8] In unreported results, we compare firm characteristics across $Port_2$ and $Port_{10}$. Results from the unreported comparisons are consistent with the results that compare $Port_1$ to $Port_{10}$ presented in Tables 2 through 5.

$Port_2$ is \$1.14 and \$0.75 billion. Average firm size for the highest sensitivity portfolio, $Port_{10}$, is \$0.36 billion. Sample averages relating to earnings, dividends, and tangibility all further suggest that stocks with a high sensitivity to investor sentiment tend to be opaque. Approximately half of our observations indicate positive earnings and positive dividends for the low sentiment sensitivity portfolios. In particular, the proportion of positive earnings observations for $Port_1$ and $Port_2$, are 48 and 53 percent, respectively. The comparable values for positive dividend observations are 52 and 57 percent. These figures compare to 26 and three percent for positive earnings and dividend observations, respectively, for the highest sentiment sensitivity portfolio. Finally, as a percentage of assets, the first three sentiment sensitivity portfolios have property, plant and equipment ranging from 54 to 57 percent, and spend one to two percent on research and development. Firms assigned to the highest sentiment sensitivity portfolio exhibit average property, plant and equipment as 37 percent of assets, and research and development spending of over 12 percent of assets. Overall, the results in Table 2 document a strong relation between the firms that we estimate to have the highest sensitivity to investor sentiment, and the opaque firm characteristics that Baker and Wurgler (2006) hypothesize, after controlling for market risk.

Our initial results from Table 2 are consistent with both Lee, Shleifer and Thaler (1991) and the raw return analysis of Baker and Wurgler (2006), are counter to Brown and Cliff (2005), and do not yet address the concern of Elton, Gruber and Busse (1998) that sentiment results may not be robust to multiple sources of risk. Lee, Shleifer and Thaler (1991) find that small stocks returns exhibit the expected negative relation with changes in closed-end fund discounts in the context of a two-factor model. In contrast Elton, Gruber and Busse (1998) find that the pattern reverses in the context of a five-factor model, including the size and value factors. In particular, the 8th and 10th size decile portfolios exhibit negative loadings on the closed-end fund discount factor. A negative loading on the change in the closed-end fund discount indicates a positive relation between the given portfolio and investor sentiment, as arguably discounts narrow as sentiment increases. Further, the smallest size portfolio exhibits a large and positive loading on the change in the closed-end fund discount under their expanded model. Elton, Gruber and Busse (1998) further compare the relation between market capitalization and sentiment sensitivity across the two separate models. From the two-factor model, the rank correlation across size deciles and loadings on the change in the closed-end fund discount is 0.71, indicating sentiment sensitivity decreases with size. However, in their five factor model, the rank correlation of -0.71 indicates that sentiment sensitivity *increases* with size. The latter finding is consistent with Brown and Cliff (2005) who find a positive relation between size and sentiment. Baker and Wurgler (2006) also document inconsistencies in sentiment sensitivities across model specifications. For example, they find that both the small minus big portfolio and the long-short property, plant and equipment portfolio exhibit marginally significant loadings on lagged sentiment in the two-factor setting, but that the loading on lagged sentiment is insignificant in the expanded model. Therefore, given their expanded risk factor model, Baker and Wurgler (2006) provide no evidence of a relation between investor sentiment and subsequent returns to portfolios formed based on firm size, tangibility, and growth opportunities and distress.

Given the conflicting results across model specifications within the existing research, we expand our model to control for multiple risk sources in our estimation of sentiment sensitivities. This analysis provides robustness results regarding the relationship between firm characteristics and sentiment sensitivities documented in Table 2. We employ a five-factor model that augments the earlier model with the small-minus-big portfolio, high-minus-low portfolio, and the momentum portfolio (cf. Fama and French (1992, 1993), and Carhart (1997)). All risk factor data are from Ken French's data library. Our augmented regression model is given by:

$$R_{j,t} = \alpha_j + \beta_{j,m}R_{m,t} + \beta_{j,smb}R_{smb,t} + \beta_{j,hml}R_{hml,t}$$
$$+\beta_{j,mom}R_{mom,t} + \beta_{j,sent}\Delta Sent_t^{\perp} + e_{j,t}, \qquad (2)$$

where $R_{smb,t}$, $R_{hml,t}$, and $R_{mom,t}$, represent the small minus big, high minus low, and momentum risk factors, respectively, and all other terms are as defined in equation (1). We then repeat the analysis in Table 2, by sorting firms based on $\beta_{j,sent}$ parameter estimates from the augmented model. We report results in Table 3.

Insert Table 3 about here

After controlling for additional factors in the return generating process, we again find results that strongly support the hypothesis that sentiment prone stocks display opaque firm-characteristics. Similar to Table 2, the differences across all portfolios, and between the first and tenth portfolios, are all highly significant, and with the hypothesized sign. However, the differences in sample averages of firm characteristics across portfolios are dampened when additional risk factors are considered. For example, in Table 2, research and development spending, as a percentage of assets, is approximately ten times greater for the high sentiment sensitivity portfolio, relative to the low sentiment sensitivity portfolio. From Table 3, this difference across sensitivity portfolios is only three to four times in magnitude. Firm characteristics such as size, property, plant and equipment, volatility, dividends, and earnings also exhibit a similar pattern in which the statistics presented in Table 3 are not as large as in Table 2, but still overwhelmingly document the expected patterns. For example, we find the average size of the high sentiment sensitivity firms (333 million) is approximately 40 percent of the comparable average for high sentiment sensitivity firms (846 million). The analysis of firm size is especially interesting given the contradicting results present in the existing literature with respect to this specific firm-characteristic and investor sentiment discussed above. Our direct approach of estimating sentiment sensitivities and then comparing firm characteristics across levels of sentiment sensitivities reveals that small stocks exhibit the greatest exposure to investor sentiment, and that this exposure is robust across the expanded factor model. In sum, the evidence from Tables 2 and 3 indicates that, for both the two and five risk factor models, highly sentiment-prone stock portfolios exhibit the hypothesized characteristics of being small, intangible, and volatile.[9]

Our unconditional models in Table 2 and Table 3 rely on data throughout the sample period for estimation. To verify that sentiment-sensitivities exhibit similar patterns across firm characteristics with *ex ante* available information, we also estimate sentiment sensitivities utilizing 60-month rolling windows. Specifically, we estimate equation (1) across months *t*-60

[9] Stocks with a negative $\beta_{j,sent}$ parameter estimates are assigned to the first sentiment sensitivity portfolio. Therefore, our analysis allows us to focus on stocks that vary positively with investor sentiment to identify characteristics of sentiment prone stocks. In unreported analyses, stocks are equally assigned into sentiment sensitivity deciles without the adjustment for negative parameter estimates. These results suggest that in the context of the five factor model, some opaque firms vary inversely with investor sentiment. However, the main result that highly sentiment prone stocks exhibit opaque characteristics is robust in these unreported analyses. The finding that sentiment prone stocks tend to be opaque, but some opaque firms also vary inversely with sentiment suggests an explanation for the inconsistent findings when sentiment loadings are estimated across firm characteristic portfolios.

through t-1, to assign stocks to the ten sentiment sensitivity portfolios at time t.[10] For each firm in a given sentiment sensitivity portfolio at a given time t, we calculate average firm characteristics across the previous five years. The five year average matches the estimation period for the rolling regression window, so firm characteristics match sentiment sensitivity estimation. We then pool firm characteristics across each sentiment sensitivity portfolio to create a time-series of average firm-characteristics for each sentiment sensitivity portfolio. In addition to the firm characteristics considered earlier, we also include the root mean square error from the rolling five-year regression, and firm age, defined as the difference in years between a given point in time and the firm's initial appearance in CRSP.[11] We expect younger firms, and firms with a larger root mean square error, to be more opaque and more sensitive to sentiment. Results from the two-factor model are reported in Table 4.

Insert Table 4 about here

Table 4 shows that firm characteristics from our rolling regression estimations exhibit similar patterns to the earlier regression models. For the new variables considered, we find that the root mean square error for firms with the highest sentiment sensitivity is over twice the size of the comparable measure for the lowest sentiment sensitivity firms. In addition, firms in the low sentiment sensitivity portfolio are approximately 1.5 times older than firms in the high sentiment sensitivity portfolio. For the variables considered in prior analysis, we again find that

[10] The sentiment index data is available beginning January 1966. Consequently, rolling window results begin January 1971 to allow five years for estimation. Further, we restrict the analysis at each point in time t, to only include firms with complete return observations from month t-60 through t-1.

[11] A significant percentage of firms list either July 31, 1962 or December 29, 1972 as their initial appearance in CRSP. Omitting the age variable for these firms does not qualitatively change the firm characteristic results.

observed differences across all portfolios, and between the high and low sensitivity portfolios, are highly significant and consistent with the sentiment hypothesis.

To examine the suggestion that sentiment sensitivity is due to missing risk factors, we expand the two-factor conditional model, to include the additional risk factors $R_{smb,t}$, $R_{hml,t}$, and $R_{mom,t}$. Table 5 reports the firm-characteristic results from our sixty-month, five-factor rolling regressions.

Insert Table 5 about here

Consistent with the earlier analyses, firms assigned to the sentiment prone portfolio in Table 5 tend to exhibit the hypothesized firm characteristics. Further, with the exception of the book-to-market analyses, all remaining differences remain strongly significant across portfolios. However, the magnitude of the differences across our portfolios appears to be dampened. For example, earnings, as a percentage of book equity, are 9.0 percent and 7.4 percent across the low and high sentiment sensitivity portfolios, respectively. Further, on average, 67 percent of observations for firms in the low sentiment sensitivity portfolio exhibit positive earnings, compared to 57 percent in the high sentiment sensitivity portfolio. Although significant, this difference is not as large as the earlier documented differences. Differences across the high and low sentiment sensitivity portfolios of approximately 1.7 percent, 6.9 percent, and 2 percent, for research and development, property, plant and equipment, and dividends, respectively, are also smaller, relative to the earlier values. Despite the relative dampening of the magnitude of results in Table 5, overall, we continue to find that sentiment prone stocks exhibit similar firm characteristics. In general, stocks with the highest sensitivity to investor sentiment tend to be opaque or hard to arbitrage. Further, these results are robust to both multiple risk factor models, and conditional rolling-window regressions.

4. Marginal performance conditional on investor sentiment

We investigate the role of investor sentiment as a conditioning information variable. Our analysis to this point documents a robust relation between opacity and sentiment, in models with simple, as well as multiple risk factor specifications. We now shift our analysis to the question as to whether *ex ante* known sentiment measures result in positive portfolio performance. This subsequent analysis considers expected marginal performance during period *t*, given only information available during period *t*-1. We report conditional alphas using sentiment as a conditioning information variable, following the conditional performance evaluation literature including Ferson and Schadt (1996), Christopherson, Ferson, and Glassman (1998), and Jha, Korkie and Turtle (2009). Our resultant conditional alphas provide the marginal performance of a given sentiment portfolio for a given level of systematic risk. Our approach explicitly addresses the concern that sentiment prone portfolios may simply be high risk portfolios warranting additional risk premia.

Berk (1995) and Fama and French (2006) provide an excellent discussion of how firm characteristics may be related to potential risk factors. This general concern applies to much of the sentiment literature as the analysis tends to center on unconditional measures of performance without risk corrections, except potentially under an unconditional model. Our conditional marginal performance measure addresses this concern and examines the marginal performance gain related to *ex ante* known sentiment measures for given risk sources. A potential benefit of the approach is that it can be readily implemented in a simple unconditional regression context.

The model assumes that all underlying conditional asset returns are linearly related to the underlying conditioning variable (cf., Campbell (1987), or Shanken (1990)).

Following Jha, Korkie and Turtle (2009), we estimate the conditional alpha directly from the following simple unconditional regression:

$$R_{j,t} = \alpha_{j,o} + \alpha_{j,sent} Sent_{t-1}^{\perp} + \beta_{j,m} R_{m,t} + e_{j,t}, \qquad (3)$$

where the conditioning information instrument, $Sent_{t-1}^{\perp}$, is known at the beginning of each investment interval and both the portfolio excess return, $R_{j,t}$, and the market excess return, $R_{m,t}$, are contemporaneously measured over the subsequent period. Our earlier analysis indicates a strong relation between sentiment sensitivities and the firm characteristics considered. Therefore, we use these firm characteristics to form portfolios of sentiment prone stocks. Specifically, for each firm characteristic variable, we form ten portfolios based on a firm's ranking of the specific characteristic at that point in time. The portfolio allocations are independent for each firm characteristic such that a firm's portfolio assignment for a given firm characteristic does not influence its ranking for any other firm characteristic.[12] To form portfolios for each month *t*, firms are sorted based on the contemporaneous *age* variable, the standard deviation of monthly returns from month *t*-12 through month *t*-1, and sorted based on all remaining accounting

[12] Firms with missing data for a given firm characteristic are excluded from the specific analysis at that point in time. However, those firms are not excluded from analyses of other firm characteristics, or during alternative time periods in which the data is not missing. Further, values of size, property, plant and equipment, research and development, earnings and dividends that are non-positive are excluded from those specific analyses. Separate analyses based on dividends and earnings are performed across firms with both positive and non-positive entries.

variables that are lagged to match the fiscal year end that falls within months *t*-6 through *t*-17 to ensure that the accounting information is available to investors.[13, 14]

Given a known investor sentiment realization, the conditional alpha may be written as

$$\alpha_{jt} = \alpha_{j,o} + \alpha_{j,sent} Sent_{t-1}^{\perp}, \tag{4}$$

for a given portfolio *j* in period *t*. The resultant conditional alpha measures marginal performance from the conditional regression of the portfolio return against the risk factors where excess returns for all portfolios and factors are linearly related to the underlying information instruments. When no information instruments exist, the intercept is given by a constant, and the regression intercept is then the unconditional Jensen's (1968) alpha.

Inferences for the resultant conditional alpha from equation (3) based on the unconditional regression may be determined by viewing the conditional alpha as a specific forecast of the portfolio excess return when all risk factor coefficients are *a priori* equal to zero. In this special case, the only remaining instrument is the known economic information instrument, $Sent_{t-1}^{\perp}$, and the standard forecast error confidence interval applies. In general, for non-zero risk factors and nonzero coefficient estimates, there are other potential sources of error. In the case of zero risk coefficients and only economic information instruments having nonzero coefficients, the nonstochastic regressor result obtains (cf., Feldstein (1971) for a clear and concise discussion of the issues). Our approach produces conditional alphas that vary over time,

[13] A significant percentage of firms list either July 31, 1962 or December 29, 1972 as their initial appearance in CRSP. We omit these firms from the formation of *age* based portfolios, as these dates likely correspond to an expansion of the database. These firms are not excluded from other characteristic portfolios.

[14] Due to data availability for some accounting variables, the entire conditional alpha analysis is conducted across a monthly sample that spans July 1968 through December 2005.

and with sentiment levels. The conditional alpha estimation procedure also has the ability to provide inference procedures in specific economic states. Comparable measures of average returns or unconditional alphas from the extant literature may provide comparable point estimates in specific cases; although, inference procedures may be impacted by research design procedures. From the unconditional regression equation (3), it is apparent that our measure of marginal performance is dependent upon the regression intercept, $\alpha_{j,0}$, the coefficient on lagged sentiment, $\alpha_{j,sent}$, and the previous sentiment realization. Therefore, our approach identifies states of the world in which significant marginal performance exists, rather than relying solely on static coefficient estimates of investor sentiment. The conditional specification has the potential to capture important cross-sectional and intertemporal variation in conditional performance that may be obfuscated by averaging across firm characteristics, and over time.[15]

Table 6 reports the resultant conditional alpha coefficient estimates, $\alpha_{j,0}$ and $\alpha_{j,sent}$, from equation (3), and tests of differences in $\alpha_{j,sent}$ across decile portfolios formed on firm characteristics.

Insert Table 6 about here

Parameter estimates in Table 6 suggest the expected contrarian nature of sentiment as a conditioning variable for opaque firms. Parameter estimates of $\alpha_{j,sent}$ tend to be negative and significant for these portfolios, with comparable estimates for translucent portfolios that tend to be insignificant, or positive. For example, for portfolios formed on volatility, the estimates of $\alpha_{j,sent}$ are insignificant for the five low-volatility portfolios. In contrast, estimates of $\alpha_{j,sent}$ for

[15] Perhaps more importantly, unconditional results need not be consistent with conditional approaches that make use of *ex ante* known information instruments.

the five high-volatility portfolios are negative, significant, and monotonically increasing in magnitude. The specific estimate for the lowest σ portfolio is insignificant and given by 0.07, and the comparable estimate for the tenth decile σ portfolio is -0.75 and significant at the five percent level. Further, the difference across the first and tenth portfolio is significant at the five percent level. Portfolios formed on market capitalization and age, also show clear patterns across $\alpha_{j,sent}$ parameter estimates. With size, the parameter estimate for the smallest size portfolio is -0.66, and is significant at the five percent level. In contrast, the estimate for the largest size portfolio is positive, although insignificant. Considering age-based portfolios, the $\alpha_{j,sent}$ parameter estimates are negative, and significant, for the five portfolios of the youngest firms, however the remaining estimates for the oldest firm portfolios are insignificant, and much smaller in magnitude. The analysis of portfolios formed from earnings, dividend amounts, and positive or negative dividends, exhibit negative and significant $\alpha_{j,sent}$ parameter estimates for the most opaque portfolio, and significant differences across the first and tenth portfolio in the expected direction.

For each set of coefficient estimates from equation (3), we calculate the conditional alpha according to equation (4) for a given instrument realization, $Sent_{t-1}^{\perp}$. To facilitate reporting, we report the conditional alpha and associated p-value for each firm characteristic based portfolio for investor sentiment at the fifth, 20th, 80th, and 95th percentiles. We report results in Table 7.

Insert Table 7 about here

Conditional measures of marginal performance indicate that opaque portfolios tend to vary inversely with investor sentiment, at the same time as translucent firms exhibit little variation in marginal performance across levels of sentiment. For example, the conditional alpha for the high volatility portfolio is 1.3 and -1.2 percent, when sentiment is at the fifth, and 95th percentiles, respectively. Thus, the difference in conditional alpha for the high volatility portfolio across these extreme sentiment percentiles is approximately 2.5 percent. The comparable values of conditional alpha are 0.3 and 0.5 percent for the low volatility portfolio, resulting in a range of less than 0.3 percent across the same extreme sentiment percentiles. Further, the conditional alpha for the high volatility portfolio decreases monotonically with investor sentiment. In contrast, the low volatility portfolio exhibits the opposite pattern. Many of the other firm characteristic analyses exhibit similar patterns within the opaque and translucent portfolios. For example, variation in conditional alpha across the fifth and 95th percentiles of investor sentiment is 2.2 and 1.8 percent for the small and young portfolios, respectively. The comparable variation is approximately 0.3 and 0.1 percent for the large and old portfolios, respectively. Thus, we observe large variation in marginal performance for opaque firms across levels of investor sentiment, with little variation in marginal performance for translucent firms across the same levels of investor sentiment. The analysis in Baker and Wurgler (2006) can be interpreted as a comparison of the $\alpha_{j,sent}$ coefficients between portfolios that sort high versus low on a given characteristic. Our analysis of $\alpha_{j,o} + \alpha_{j,sent} Sent_{t-1}^{\perp}$ captures these differences in the measured coefficient $\alpha_{j,sent}$, as well as differences related to $\alpha_{j,o}$ and to how observed sentiment impacts performance through $\alpha_{j,sent}$. Many of the insignificant findings in Baker and Wurgler's (2006) long-short analysis may be due to the inability of their research design to capture important cross-sectional variation in $\alpha_{j,o}$, and temporal variability in $Sent_{t-1}^{\perp}$. Our approach also provides an *ex ante* point estimate of marginal performance that will be more economically informative than a t-test of differences in $\alpha_{j,sent}$ across portfolios. Our results demonstrate that many of the findings in these long-short portfolios are due to the opaque constituents of these portfolios.

Interestingly, all book-to-market portfolios show a strong sentiment impact for all decile portfolios. In high sentiment periods, book-to-market portfolios tend to generate a full percent less in marginal performance relative to low sentiment periods. As examples, the low book-to-market portfolio exhibits a performance differential of 1.7 percent (-1.28 - 0.38) across the fifth and 95th percentiles of sentiment, and the performance differential is a comparable 1.6 percent for the high book-to-market portfolio across the same range of sentiment. In addition, the book-to-market effect is readily apparent when comparing marginal performance across decile portfolios for a given sentiment percentile. For example, when sentiment is at the 80th percentile we find a performance difference in excess of 1.5 percent (-0.75 - 0.79) between the lowest and highest deciles of book-to-market firms. Similarly, when sentiment is at the 20th percentile we again find a performance difference of 1.5 percent (-0.03 – 1.48) across these portfolios, indicating the book-to-market effect persists across all sentiment percentiles, which suggests a lesser impact for opacity in this instance.

To further illustrate the cross-sectional variation in marginal performance conditional on investor sentiment, we plot conditional alpha across portfolios and levels of sentiment in Panels 1a through 1i of Figure 1. Specifically, we illustrate the point estimates of conditional alpha detailed in Table 7.

*** Insert Figure 1 about here ***

Within Figure 1, reading left to right across a given plot, reveals the variation in the conditional alpha, across portfolios, for a given level of sentiment. Comparing various plot lines vertically the plots reveal variation in conditional alpha, across levels of sentiment, for a given portfolio. As opacity increases we expect to observe greater variability in marginal performance measures across portfolios. The plots for volatility, age, size, dividend, and research and development portfolios all detail a large and inverse relation between marginal performance and investor sentiment for the opaque portfolios, and little, or positive, variation in marginal performance across sentiment for translucent firms. For example, in Panel 1e we report conditional alphas for the lowest dividend paying firms on the left and for the highest dividend paying firms in the right most results. A greater relative dividend stream should facilitate valuation certainty and increase firm transparency. This is consistent with the observed sentiment sensitivity in the panel. As we move from left to right in the plot, transparency increases and we observe a general convergence towards a smaller range of conditional alpha measures. The sales growth deciles in Panel 1i provide interesting evidence of much greater variability in conditional alphas for both the smallest and largest sales growth firms. This is consistent with an increase in transparency for moderate growth firms.[16]

A potential explanation for the variation in conditional alpha across firm characteristics documented above could be varying sensitivities to additional risk factors. To control for this possibility, we expand equation (3) and specify

$$R_{j,t} = \alpha_j + \alpha_{j,sent} Sent_{t-1}^{\perp} + \beta_{j,m} R_{m,t} + \beta_{j,smb} R_{smb,t} \\ + \beta_{j,hml} R_{hml,t} + \beta_{j,mom} R_{mom,t} + e_{j,t}, \quad (5)$$

with all variables as previously defined. With the expanded specification, the conditional alpha for a given portfolio is still given by equation (4). Table 8 reports the resultant conditional alpha

[16] This finding is likely related to the impact of correlations across firm characteristics. For example, dynamic high growth firms in portfolio 10 are likely to be opaque with difficult to value future cash flow streams. Similarly, very low sales growth firms may include firms in decline with poor future prospects and large real risks associated with required strategic decisions.

across firm characteristic decile portfolios and levels of investment sentiment from the expanded model that includes additional risk factors.

Insert Table 8 about here

Reported conditional alpha estimates in Table 8 confirm that the earlier results are robust to a model with additional risk factors. Conditional alpha varies inversely with investor sentiment within opaque firms, and conversely translucent firms vary positively with investor sentiment, or exhibit little variation. For example, considering portfolios formed from volatility deciles, conditional on investor sentiment at the fifth percentile, conditional alpha increases monotonically from 0.3 to 0.8 for the fourth through tenth decile. Corresponding estimates for the three low volatility portfolios are smaller in magnitude and insignificant. Conversely, with sentiment at the 95^{th} percentile, the three low volatility portfolios exhibit significant conditional alphas approximately equal to 0.3, while point estimates are negative, but insignificant, for the three high volatility portfolios. Further, for the small, young, and zero-dividend portfolios, differences in conditional alpha are approximately 1.0 or greater as sentiment ranges from the fifth to 95^{th} percentile. The comparable range for the large portfolio is 0.2, and the variation in conditional alpha is less than 0.1 for the old, and positive-dividend portfolios. Therefore, conditional alpha results from the expanded model confirm that sentiment is a contrarian indicator for opaque firms.

5. Conclusion

We study the impact of investor sentiment on the cross-section of equity returns in a model with multiple risk factors with conditional measures of marginal performance. We find that the most sentiment-prone stocks tend to exhibit opaque characteristics – they tend to be volatile, small, young, and intangible. Further, and in contrast to the mixed evidence in the extant literature, portfolios with opaque firm characteristics offer the greatest marginal performance when previous sentiment levels are lowest. In general, opaque portfolios exhibit much greater variation in conditional alpha estimates across levels of investor sentiment relative to translucent portfolios. Our results are both economically and statistically significant, and suggest that variability in marginal performance is due to cross-sectional differences in unconditional alphas, cross-sectional differences in sentiment sensitivities, and to time series variability in sentiment measures.

Our results have important implications for further research. Because portfolios formed from firms with opaque (translucent) characteristics exhibit high (low) exposure to investor sentiment, and because this risk appears non-diversifiable, future research may seek to incorporate investor sentiment as a priced risk factor. In addition, because sentiment may display interesting patterns of persistence with potentially sudden changes, we are currently examining the feedback and decay mechanisms describing how sentiment patterns impact stock returns. In particular, our empirical results are consistent with periods of positive sentiment persistence producing poor stock returns, especially for opaque firms. Our current line of inquiry investigates the pattern of returns following long periods of sentiment persistence that often characterize business cycles. Finally, many of the firm characteristics that we consider relate to existing asset-pricing anomalies. Our results, which detail systematic relations between sentiment and firm characteristics may lead to additional research within asset mispricing.

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Table 1
Summary Statistics.

Variable	Mean	Median	St Dev	N
$Size$	871.453	81.098	2788.140	171047
E	8.010	5.063	9.942	174036
E^{+}	58.841	100.000	49.212	174630
D	2.326	0.000	3.747	152143
D^{+}	51.759	100.000	49.969	174630
PPE	56.080	49.166	38.984	149538
RD	2.778	0.000	7.197	164037
BE/ME	87.395	69.266	86.754	149950
SG	18.845	9.842	62.077	159777
R	1.026	-0.310	16.590	1935739
σ	13.118	10.764	10.068	1715044

We present summary statistics for our monthly dataset from January 1968 through December 2005. We include the universe of CRSP/Compustat stocks with at least 60 months of return data. We define $Size$ as the market value of equity ($ million), given by shares outstanding multiplied by share price. Earnings and dividends are defined by E and D, where both are scaled by book equity. We also define dummy variables defining positive realizations of earnings and dividends as E^{+} and D^{+}, respectively. Property, plant and equipment, and research and development, are given by PPE and RD, respectively, where both are scaled by total assets. We define BE/ME as the ratio of book equity to market equity and sales growth, SG, is defined as the percentage change over the previous years' sales. Excess returns are denoted by R, with associated sample standard deviation of the previous twelve months' raw return given by σ. With the exception of $Size$, all variables are reported as percentages. For month t, accounting variables represent values from the fiscal year end falling in month t-17 through month t-6. Reported statistics are based on annual accounting variables, and monthly return related variables.

Table 2
Unconditional Sentiment Sensitivity and Firm Characteristics.

	$Port_1$	$Port_2$	$Port_3$	$Port_4$	$Port_5$	$Port_6$	$Port_7$	$Port_8$	$Port_9$	$Port_{10}$	F	t_{1-10}
σ	11.656	10.967	11.670	13.055	13.825	14.848	16.225	17.416	19.797	26.550	542.93	-36.05
											(0.000)	(0.000)
$Size$	1135.625	747.331	764.979	470.176	430.806	436.127	407.499	436.354	468.092	363.318	30.29	13.67
											(0.000)	(0.000)
E	6.934	7.500	8.169	7.739	7.597	7.785	7.405	6.641	5.643	3.954	37.41	15.73
											(0.000)	(0.000)
E^+	47.582	53.133	57.539	56.568	56.902	56.358	52.304	47.129	40.107	26.203	77.51	21.70
											(0.000)	(0.000)
D	2.700	2.754	2.598	2.073	1.582	1.451	1.133	0.754	0.328	0.203	123.91	34.59
											(0.000)	(0.000)
D^+	51.995	56.758	54.015	45.228	39.394	32.698	24.712	18.453	8.155	3.001	328.670	70.35
											(0.000)	(0.000)
PPE	56.891	56.125	53.880	52.333	53.398	50.539	50.922	45.181	40.788	37.308	37.29	16.30
											(0.000)	(0.000)
RD	1.295	1.228	1.515	1.956	2.235	2.504	3.140	4.721	6.825	12.396	322.72	-25.73
											(0.000)	(0.000)
BE/ME	77.694	88.598	89.747	92.343	91.057	91.258	87.700	76.692	64.467	47.946	45.71	13.63
											(0.000)	(0.000)
SG	21.672	17.627	19.795	19.936	20.138	20.891	23.411	27.984	31.088	46.890	69.25	-12.50
											(0.000)	(0.000)

We estimate the following model:

$$R_{j,t} = \alpha_j + \beta_{j,m} R_{m,t} + \beta_{j,sent} \Delta Sent_t^{\perp} + e_{j,t},$$

for $j = 1, 2, \dots, N$; $t = 1, 2, \dots, T$; and where $R_{j,t}$ represents the excess return to asset j during period t; $R_{m,t}$ represents the excess market return during period t; and $\Delta Sent_t^{\perp}$ represents the change in the orthogonalized sentiment index of Baker and Wurgler, during period t. Based on parameter estimates of $\beta_{j,sent}$, we assign stocks to 10 sentiment portfolios, defined as $Port_i$, for $i = 1, 2, \dots, 10$. Stocks for which the $\beta_{j,sent}$ parameter estimate is negative, are assigned to the first portfolio, $Port_1$. The remaining stocks are assigned equally to the remaining nine sentiment portfolios, such that $Port_2$ and $Port_{10}$ contain stocks with the smallest and largest magnitude positive parameter estimates, respectively. We calculate average firm characteristics for each stock within our sample. We then pool these averages and report statistics across the sentiment sensitivity portfolios. We report F-statistics and t-statistics in the final two columns testing that the given average firm characteristic is equal across all sentiment portfolios, and between the 1st and 10th sentiment portfolios, respectively. Variables are as defined in Table 1.

Table 3
Unconditional Sentiment Sensitivity and Firm Characteristics.

	$Port_1$	$Port_2$	$Port_3$	$Port_4$	$Port_5$	$Port_6$	$Port_7$	$Port_8$	$Port_9$	$Port_{10}$	F	t_{1-10}
σ	13.429	10.633	11.211	12.262	13.103	14.102	15.939	16.398	19.029	24.216	238.60	-26.40
											(0.000)	(0.000)
$Size$	845.910	939.884	792.688	728.515	676.072	709.147	512.118	607.272	609.660	333.068	6.10	8.89
											(0.000)	(0.000)
E	7.232	6.484	6.712	7.214	7.232	7.652	6.732	6.869	6.380	4.424	17.42	13.55
											(0.000)	(0.000)
E^+	50.628	46.420	49.188	53.114	52.173	53.768	48.645	47.821	42.166	28.946	36.71	20.56
											(0.000)	(0.000)
D	2.122	2.713	2.792	2.375	1.989	1.763	1.184	0.905	0.703	0.232	60.71	30.58
											(0.000)	(0.000)
D^+	43.959	59.380	56.222	49.262	42.920	39.333	26.593	22.617	13.751	4.585	180.33	52.58
											(0.000)	(0.000)
PPE	52.816	54.468	52.882	54.270	54.001	52.173	49.699	49.948	44.289	42.229	10.10	7.25
											(0.000)	(0.000)
RD	2.573	1.452	1.800	2.004	2.048	2.734	3.018	3.578	5.171	8.545	74.72	-13.63
											(0.000)	(0.000)
BE/ME	78.765	91.340	92.411	89.622	85.692	85.109	82.967	78.419	68.900	56.386	20.01	8.43
											(0.000)	(0.000)
SG	22.668	18.459	17.158	17.147	23.228	22.291	26.754	25.308	32.158	43.493	45.34	-9.30
											(0.000)	(0.000)

We estimate the following model:

$$R_{j,t} = \alpha_j + \beta_{j,m}R_{m,t} + \beta_{j,smb}R_{smb,t} + \beta_{j,hml}R_{hml,t} + \beta_{j,mom}R_{mom,t} + \beta_{j,sent}\Delta Sent_t^{\perp} + e_{j,t},$$

where $R_{smb,t}$, $R_{hml,t}$, and $R_{mom,t}$, represents the small minus big, high minus low, and momentum risk factors, respectively, and all other terms are as defined in Table 2. Based on parameter estimates of $\beta_{j,sent}$, we assign stocks to 10 sentiment portfolios as in Table 2, with the portfolios defined as $Port_i$, for *i*=1,2,…10. We calculate average firm characteristics for each stock within our sample. We then pool these averages and report statistics across the sentiment sensitivity portfolios. We report F-statistics and t-statistics in the final two columns testing that the given average firm characteristic is equal across all sentiment portfolios, and between the 1st and 10th sentiment portfolios, respectively. Variables are as defined in Table 1.

Table 4
Rolling Regression Sentiment Sensitivities and Firm Characteristics.

	$Port_1$	$Port_2$	$Port_3$	$Port_4$	$Port_5$	$Port_6$	$Port_7$	$Port_8$	$Port_9$	$Port_{10}$	F	t_{1-10}
$RMSE$	9.750	8.752	9.213	9.849	10.535	11.377	12.495	13.647	15.389	20.789	565.99	-32.34
											(0.000)	(0.000)
$Size$	1269.261	866.304	822.752	778.611	699.821	626.413	513.659	457.220	302.620	147.062	221.14	32.18
											(0.000)	(0.000)
Age	22.254	21.880	21.581	21.362	20.773	19.808	18.457	17.312	15.859	14.063	671.04	72.24
											(0.000)	(0.000)
E	9.228	8.911	9.152	9.408	9.507	9.547	9.308	9.059	8.360	6.583	105.24	19.24
											(0.000)	(0.000)
E^+	66.529	65.534	67.731	70.163	72.197	73.290	71.630	69.664	64.805	52.946	91.63	13.79
											(0.000)	(0.000)
D	3.713	3.821	3.603	3.365	2.980	2.602	2.157	1.802	1.335	0.712	938.46	80.57
											(0.000)	(0.000)
D^+	73.580	77.336	75.221	71.366	66.829	61.987	53.875	46.998	36.671	21.760	561.87	63.82
											(0.000)	(0.000)
PPE	66.369	63.228	61.958	60.534	59.241	57.431	55.073	53.774	50.886	49.177	303.99	39.87
											(0.000)	(0.000)
RD	1.431	1.309	1.447	1.685	1.888	2.143	2.606	3.232	4.214	5.971	155.58	-15.60
											(0.000)	(0.000)
BE/ME	89.822	92.453	93.560	94.174	95.835	97.874	98.482	98.100	98.969	95.715	3.75	-2.39
											(0.000)	(0.017)
SG	14.489	13.521	13.691	13.777	14.116	15.079	15.916	16.892	18.355	19.478	110.77	-12.99
											(0.000)	(0.000)

We estimate the following model:

$$R_{j,t} = \alpha_j + \beta_{j,m}R_{m,t} + \beta_{j,sent}\Delta Sent_t^{\perp} + e_{j,t},$$

across rolling 60 month windows. Based on parameter estimates of $\beta_{j,sent}$ from months t-60 through t-1, we assign stocks to 10 sentiment portfolios as in Table 2, for each month t. We calculate average five year firm characteristics for each stock within our sample at each point in time. We then calculate sentiment portfolio averages at each point in time and report statistics across the sentiment sensitivity portfolios through time. We report F-statistics and t-statistics in the final two columns testing that the given average firm characteristic is equal across all sentiment portfolios, and between the 1st and 10th sentiment portfolios, respectively. Variables are as earlier defined, with the addition of $RMSE$, the root mean square error from the rolling five year regression, and Age, defined as the difference in years between period t, and the firm's first appearance in CRSP. Given the 60-month rolling window, we report results from January 1971, through December 2005.

Table 5
Rolling Regression Sentiment Sensitivity and Firm Characteristics.

	$Port_1$	$Port_2$	$Port_3$	$Port_4$	$Port_5$	$Port_6$	$Port_7$	$Port_8$	$Port_9$	$Port_{10}$	F	t_{1-10}
$RMSE$	10.450	8.535	8.644	8.973	9.408	9.953	10.672	11.695	13.265	18.404	775.51	-30.81
											(0.000)	(0.000)
$Size$	965.749	1048.358	1014.585	974.582	967.644	910.582	785.878	627.995	464.456	211.071	119.02	21.93
											(0.000)	(0.000)
Age	20.558	21.952	22.154	22.055	21.901	21.348	20.393	19.329	17.468	15.003	585.70	56.56
											(0.000)	(0.000)
E	9.011	8.985	9.084	9.256	9.459	9.572	9.531	9.283	8.892	7.433	55.36	13.46
											(0.000)	(0.000)
E^+	67.298	66.799	67.528	69.169	70.267	71.211	70.959	70.023	67.178	57.170	49.19	11.43
											(0.000)	(0.000)
D	3.068	3.743	3.710	3.578	3.363	3.097	2.755	2.359	1.893	1.060	976.84	53.38
											(0.000)	(0.000)
D^+	65.605	76.372	76.207	74.196	71.537	67.738	63.267	57.095	46.818	28.418	660.31	41.09
											(0.000)	(0.000)
PPE	61.718	62.810	61.903	60.802	60.741	59.273	58.509	57.462	55.381	54.850	95.97	17.10
											(0.000)	(0.000)
RD	1.998	1.469	1.471	1.531	1.695	1.836	2.078	2.355	2.904	3.712	141.42	-12.36
											(0.000)	(0.000)
BE/ME	94.316	93.358	92.955	93.912	94.058	94.216	95.370	96.821	96.636	97.797	1.46	-1.61
											(0.158)	(0.108)
SG	15.049	13.714	13.505	13.803	14.166	12.209	14.967	15.410	17.176	18.377	95.64	-12.33
											(0.000)	(0.000)

We estimate the following model:

$$R_{j,t} = \alpha_j + \beta_{j,m}R_{m,t} + \beta_{j,smb}R_{smb,t} + \beta_{j,hml}R_{hml,t} + \beta_{j,mom}R_{mom,t} + \beta_{j,sent}\Delta Sent_t^{\perp} + e_{j,t},$$

across rolling 60 month windows. Based on parameter estimates of $\beta_{j,sent}$ from months *t*-60 through *t*-1, we assign stocks to 10 sentiment portfolios as in Table 2, for each month *t*. We calculate average five year firm characteristics for each stock within our sample at each point in time. We then calculate sentiment portfolio averages at each point in time and report statistics across the sentiment sensitivity portfolios through time. We report F-statistics and t-statistics in the final two columns testing that the given average firm characteristic is equal across all sentiment portfolios, and between the 1st and 10th sentiment portfolios, respectively. Variables are as earlier defined, with the addition of $RMSE$, the root mean square error from the rolling five year regression, and Age, defined as the difference in years between period *t*, and the firm's first appearance in CRSP. Given the 60-month rolling window, we report results from January 1971, through December 2005.

Table 6

Parameter Estimates Across Firm Characteristic Portfolios with Sentiment as an Information Variable.

		$Port_1$	$Port_2$	$Port_3$	$Port_4$	$Port_5$	$Port_6$	$Port_7$	$Port_8$	$Port_9$	$Port_{10}$	F_{10-1}	$F_{i=j}$
σ	$\alpha_{j,o}$	0.381	0.445	0.415	0.406	0.420	0.332	0.393	0.270	0.231	0.155		
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.029)	(0.024)	(0.209)	(0.367)	(0.636)		
	$\alpha_{j,sent}$	0.074	0.014	-0.012	-0.134	-0.167	-0.326	-0.386	-0.526	-0.624	-0.753	6.36	1.59
		(0.423)	(0.881)	(0.906)	(0.229)	(0.181)	(0.031)	(0.026)	(0.014)	(0.015)	(0.022)	(0.012)	(0.117)
$Size$	$\alpha_{j,o}$	1.515	0.622	0.361	0.247	0.122	0.105	0.088	0.122	0.116	0.088		
		(0.000)	(0.010)	(0.091)	(0.201)	(0.480)	(0.485)	(0.482)	(0.261)	(0.148)	(0.091)		
	$\alpha_{j,sent}$	-0.655	-0.570	-0.504	-0.456	-0.384	-0.234	-0.207	-0.134	-0.016	0.082	5.70	1.22
		(0.028)	(0.018)	(0.018)	(0.018)	(0.026)	(0.119)	(0.098)	(0.216)	(0.840)	(0.116)	(0.017)	(0.282)
Age	$\alpha_{j,o}$	0.040	0.223	0.126	0.264	0.322	0.495	0.439	0.380	0.319	0.291		
		(0.849)	(0.294)	(0.509)	(0.148)	(0.062)	(0.002)	(0.001)	(0.002)	(0.007)	(0.001)		
	$\alpha_{j,sent}$	-0.539	-0.581	-0.508	-0.506	-0.340	-0.219	-0.205	-0.123	-0.027	-0.016	7.43	2.52
		(0.010)	(0.006)	(0.008)	(0.005)	(0.047)	(0.168)	(0.130)	(0.317)	(0.815)	(0.849)	(0.007)	(0.008)
E	$\alpha_{j,o}$	0.401	0.470	0.438	0.379	0.351	0.357	0.312	0.259	0.226	0.244		
		(0.041)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.007)	(0.026)	(0.068)	(0.069)		
	$\alpha_{j,sent}$	-0.503	-0.346	-0.231	-0.253	-0.239	-0.207	-0.125	-0.171	-0.163	-0.248	4.33	1.36
		(0.010)	(0.029)	(0.090)	(0.044)	(0.054)	(0.081)	(0.274)	(0.138)	(0.187)	(0.064)	(0.038)	(0.203)
E^+	$\alpha_{j,o}$	0.311									0.343		
		(0.094)									(0.007)		
	$\alpha_{j,sent}$	-0.403									-0.253	1.84	
		(0.029)									(0.045)	(0.176)	
D	$\alpha_{j,o}$	0.361	0.281	0.456	0.375	0.393	0.369	0.386	0.372	0.339	0.190		
		(0.014)	(0.036)	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.090)		
	$\alpha_{j,sent}$	-0.282	-0.224	-0.192	-0.145	-0.115	-0.139	-0.025	-0.051	0.030	0.098	13.39	1.98
		(0.053)	(0.093)	(0.126)	(0.226)	(0.321)	(0.190)	(0.800)	(0.581)	(0.744)	(0.377)	(0.000)	(0.040)
D^+	$\alpha_{j,o}$	0.310									0.360		
		(0.175)									(0.001)		
	$\alpha_{j,sent}$	-0.627									-0.082	9.00	
		(0.006)									(0.433)	(0.003)	
PPE	$\alpha_{j,o}$	0.087	0.168	0.226	0.278	0.372	0.417	0.471	0.385	0.415	0.591		
		(0.662)	(0.438)	(0.261)	(0.147)	(0.032)	(0.011)	(0.002)	(0.009)	(0.001)	(0.000)		
	$\alpha_{j,sent}$	-0.402	-0.523	-0.468	-0.412	-0.379	-0.315	-0.355	-0.290	-0.212	-0.225	1.11	0.81
		(0.042)	(0.015)	(0.020)	(0.031)	(0.028)	(0.051)	(0.020)	(0.047)	(0.084)	(0.074)	(0.294)	(0.607)

RD	$\alpha_{j,o}$	0.186	0.198	0.327	0.357	0.408	0.422	0.504	0.608	0.521	0.678		
		(0.217)	(0.172)	(0.021)	(0.029)	(0.018)	(0.044)	(0.023)	(0.017)	(0.075)	(0.067)		
	$\alpha_{j,sent}$	-0.303	-0.297	-0.293	-0.304	-0.243	-0.386	-0.277	-0.338	-0.486	-0.603	0.86	0.55
		(0.044)	(0.039)	(0.037)	(0.062)	(0.158)	(0.063)	(0.206)	(0.179)	(0.095)	(0.101)	(0.355)	(0.840)
BE/ME	$\alpha_{j,o}$	-0.375	-0.167	0.003	0.118	0.305	0.388	0.531	0.584	0.778	1.146		
		(0.104)	(0.331)	(0.984)	(0.420)	(0.029)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)		
	$\alpha_{j,sent}$	-0.484	-0.415	-0.338	-0.308	-0.272	-0.193	-0.278	-0.353	-0.272	-0.465	0.01	2.11
		(0.035)	(0.016)	(0.029)	(0.034)	(0.049)	(0.167)	(0.057)	(0.024)	(0.123)	(0.035)	(0.918)	(0.027)
SG	$\alpha_{j,o}$	0.634	0.557	0.589	0.497	0.504	0.486	0.434	0.294	0.066	-0.486		
		(0.020)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.029)	(0.672)	(0.020)		
	$\alpha_{j,sent}$	-0.570	-0.398	-0.216	-0.190	-0.113	-0.145	-0.214	-0.222	-0.417	-0.704	0.84	2.53
		(0.036)	(0.030)	(0.152)	(0.123)	(0.349)	(0.214)	(0.083)	(0.098)	(0.008)	(0.001)	(0.360)	(0.008)

We estimate the following model

$$R_{j,t} = \alpha_{j,o} + \alpha_{j,sent} Sent_{t-1}^{\perp} + \beta_{j,m} R_{m,t} + e_{j,t},$$

across firm characteristic deciles. For each firm characteristic, we assign stocks to a decile for month t based on accounting data from the fiscal year end that falls in month t-17 through month t-6. We then estimate the above equation for equal weighted excess returns across each firm characteristic decile, and report parameter estimates of $\alpha_{j,o}$ and $\alpha_{j,sent}$, along with the associated p-values. We report F-statistics in the final two columns testing that the reported parameter is equal between the 1st and 10th sentiment portfolios, F_{10-1},and across all 10 sentiment portfolios, $F_{i=j}$. The sample is monthly from July 1968 through December 2005.

Table 7
Conditional Alphas with Sentiment as an Information Variable.

	$Sent_{t-1}^{\perp}$	$Port_1$	$Port_2$	$Port_3$	$Port_4$	$Port_5$	$Port_6$	$Port_7$	$Port_8$	$Port_9$	$Port_{10}$
σ	*5%*	0.266	0.423	0.433	0.614	0.681	0.838	0.993	1.088	1.200	1.326
		(0.128)	(0.027)	(0.029)	(0.006)	(0.007)	(0.006)	(0.004)	(0.011)	(0.019)	(0.041)
	20%	0.328	0.435	0.423	0.501	0.540	0.564	0.668	0.646	0.675	0.692
		(0.008)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.004)	(0.023)	(0.045)	(0.099)
	80%	0.439	0.456	0.406	0.303	0.291	0.080	0.094	-0.136	-0.251	-0.426
		(0.000)	(0.000)	(0.002)	(0.034)	(0.066)	(0.363)	(0.361)	(0.348)	(0.289)	(0.227)
	95%	0.520	0.472	0.393	0.157	0.109	-0.274	-0.325	-0.709	-0.929	-1.244
		(0.010)	(0.023)	(0.063)	(0.314)	(0.364)	(0.270)	(0.262)	(0.109)	(0.083)	(0.072)
$Size$	*5%*	2.534	1.507	1.144	0.956	0.719	0.468	0.410	0.331	0.140	-0.039
		(0.000)	(0.002)	(0.007)	(0.013)	(0.036)	(0.103)	(0.090)	(0.109)	(0.258)	(0.369)
	20%	1.983	1.028	0.721	0.572	0.396	0.272	0.236	0.218	0.127	0.030
		(0.000)	(0.001)	(0.011)	(0.025)	(0.076)	(0.143)	(0.131)	(0.113)	(0.179)	(0.359)
	80%	1.009	0.181	-0.027	-0.105	-0.174	-0.075	-0.072	0.019	0.103	0.151
		(0.009)	(0.330)	(0.397)	(0.361)	(0.284)	(0.367)	(0.358)	(0.395)	(0.228)	(0.024)
	95%	0.297	-0.438	-0.575	-0.600	-0.592	-0.329	-0.296	-0.127	0.086	0.240
		(0.354)	(0.269)	(0.167)	(0.126)	(0.099)	(0.225)	(0.205)	(0.339)	(0.347)	(0.032)
Age	*5%*	0.879	1.126	0.916	1.051	0.850	0.835	0.757	0.571	0.361	0.316
		(0.035)	(0.008)	(0.016)	(0.004)	(0.013)	(0.009)	(0.005)	(0.020)	(0.105)	(0.062)
	20%	0.425	0.637	0.489	0.625	0.564	0.651	0.585	0.467	0.338	0.302
		(0.111)	(0.024)	(0.051)	(0.010)	(0.014)	(0.002)	(0.001)	(0.005)	(0.029)	(0.009)
	80%	-0.376	-0.226	-0.266	-0.127	0.059	0.326	0.281	0.285	0.298	0.278
		(0.137)	(0.273)	(0.208)	(0.338)	(0.383)	(0.099)	(0.095)	(0.068)	(0.045)	(0.013)
	95%	-0.962	-0.858	-0.819	-0.678	-0.311	0.088	0.059	0.151	0.268	0.260
		(0.033)	(0.057)	(0.045)	(0.076)	(0.270)	(0.385)	(0.390)	(0.333)	(0.212)	(0.135)
E	*5%*	1.183	1.008	0.797	0.772	0.722	0.679	0.507	0.525	0.479	0.629
		(0.002)	(0.002)	(0.004)	(0.002)	(0.004)	(0.004)	(0.026)	(0.023)	(0.049)	(0.019)
	20%	0.760	0.717	0.603	0.559	0.521	0.505	0.402	0.381	0.342	0.421
		(0.004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.009)	(0.014)	(0.036)	(0.018)
	80%	0.013	0.203	0.259	0.183	0.166	0.197	0.216	0.127	0.101	0.053
		(0.398)	(0.231)	(0.121)	(0.197)	(0.219)	(0.160)	(0.122)	(0.267)	(0.319)	(0.379)
	95%	-0.534	-0.173	0.008	-0.093	-0.093	-0.029	0.080	-0.059	-0.076	-0.217
		(0.164)	(0.346)	(0.399)	(0.374)	(0.373)	(0.396)	(0.376)	(0.386)	(0.381)	(0.292)

E^+	*5%*	0.937									0.736
		(0.011)									(0.004)
	20%	0.598									0.523
		(0.015)									(0.002)
	80%	0.000									0.147
		(0.399)									(0.254)
	95%	-0.438									-0.128
		(0.205)									(0.353)
D	*5%*	0.800	0.629	0.754	0.600	0.571	0.584	0.425	0.451	0.293	0.037
		(0.006)	(0.018)	(0.003)	(0.012)	(0.014)	(0.006)	(0.033)	(0.015)	(0.094)	(0.393)
	20%	0.563	0.441	0.592	0.478	0.475	0.468	0.404	0.408	0.318	0.120
		(0.004)	(0.013)	(0.000)	(0.003)	(0.002)	(0.001)	(0.003)	(0.001)	(0.009)	(0.278)
	80%	0.144	0.108	0.308	0.263	0.304	0.262	0.366	0.332	0.362	0.266
		(0.289)	(0.320)	(0.054)	(0.080)	(0.041)	(0.053)	(0.005)	(0.006)	(0.002)	(0.061)
	95%	-0.163	-0.135	0.099	0.106	0.179	0.111	0.339	0.277	0.394	0.373
		(0.344)	(0.353)	(0.370)	(0.364)	(0.300)	(0.350)	(0.104)	(0.137)	(0.043)	(0.106)
D^+	*5%*	1.284									0.488
		(0.005)									(0.020)
	20%	0.757									0.419
		(0.013)									(0.003)
	80%	-0.174									0.296
		(0.328)									(0.029)
	95%	-0.855									0.207
		(0.075)									(0.252)
PPE	*5%*	0.712	0.981	0.954	0.918	0.961	0.906	1.022	0.836	0.744	0.941
		(0.066)	(0.023)	(0.018)	(0.016)	(0.005)	(0.005)	(0.001)	(0.004)	(0.002)	(0.000)
	20%	0.374	0.541	0.560	0.572	0.642	0.641	0.723	0.592	0.566	0.751
		(0.130)	(0.056)	(0.035)	(0.024)	(0.005)	(0.003)	(0.000)	(0.002)	(0.001)	(0.000)
	80%	-0.224	-0.237	-0.135	-0.040	0.080	0.173	0.197	0.161	0.252	0.417
		(0.260)	(0.267)	(0.343)	(0.393)	(0.371)	(0.272)	(0.229)	(0.266)	(0.097)	(0.011)
	95%	-0.662	-0.805	-0.643	-0.488	-0.332	-0.169	-0.189	-0.154	0.022	0.172
		(0.106)	(0.076)	(0.118)	(0.183)	(0.256)	(0.350)	(0.333)	(0.349)	(0.397)	(0.319)

RD	*5%*	0.657	0.660	0.783	0.829	0.785	1.021	0.935	1.134	1.275	1.615
		(0.028)	(0.022)	(0.006)	(0.011)	(0.022)	(0.014)	(0.033)	(0.024)	(0.028)	(0.028)
	20%	0.402	0.410	0.537	0.573	0.581	0.697	0.702	0.849	0.867	1.108
		(0.042)	(0.032)	(0.004)	(0.008)	(0.011)	(0.012)	(0.017)	(0.012)	(0.025)	(0.024)
	80%	-0.048	-0.032	0.101	0.122	0.221	0.124	0.289	0.347	0.146	0.213
		(0.385)	(0.392)	(0.336)	(0.330)	(0.230)	(0.354)	(0.224)	(0.213)	(0.367)	(0.357)
	95%	-0.377	-0.355	-0.218	-0.207	-0.043	-0.295	-0.012	-0.021	-0.382	-0.442
		(0.189)	(0.194)	(0.300)	(0.329)	(0.396)	(0.314)	(0.399)	(0.398)	(0.325)	(0.336)
BE/ME	*5%*	0.377	0.477	0.528	0.597	0.728	0.688	0.964	1.133	1.200	1.869
		(0.274)	(0.136)	(0.078)	(0.038)	(0.009)	(0.014)	(0.001)	(0.000)	(0.001)	(0.000)
	20%	-0.030	0.128	0.244	0.338	0.499	0.525	0.730	0.836	0.972	1.478
		(0.397)	(0.334)	(0.182)	(0.074)	(0.007)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
	80%	-0.749	-0.488	-0.258	-0.120	0.095	0.238	0.316	0.312	0.568	0.787
		(0.012)	(0.027)	(0.158)	(0.317)	(0.341)	(0.152)	(0.085)	(0.105)	(0.013)	(0.006)
	95%	-1.275	-0.938	-0.625	-0.456	-0.201	0.028	0.013	-0.072	0.273	0.282
		(0.010)	(0.012)	(0.057)	(0.124)	(0.310)	(0.397)	(0.398)	(0.389)	(0.300)	(0.328)
SG	*5%*	1.520	1.175	0.926	0.792	0.681	0.712	0.768	0.639	0.715	0.609
		(0.005)	(0.001)	(0.002)	(0.001)	(0.005)	(0.002)	(0.002)	(0.017)	(0.022)	(0.122)
	20%	1.041	0.841	0.744	0.633	0.585	0.590	0.587	0.453	0.364	0.016
		(0.004)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.073)	(0.398)
	80%	0.193	0.250	0.422	0.350	0.417	0.374	0.269	0.123	-0.256	-1.029
		(0.337)	(0.215)	(0.030)	(0.028)	(0.008)	(0.014)	(0.084)	(0.301)	(0.163)	(0.000)
	95%	-0.426	-0.182	0.187	0.143	0.293	0.216	0.036	-0.118	-0.710	-1.794
		(0.297)	(0.354)	(0.332)	(0.340)	(0.199)	(0.266)	(0.395)	(0.364)	(0.034)	(0.000)

We report parameter estimates for the conditional alpha with associated p-values, for deciles of firm characteristic portfolios, for various percentiles of lagged sentiment. All estimates are based on the following model

$$R_{j,t} = \alpha_{j,o} + \alpha_{j,sent} Sent_{t-1}^{\perp} + \beta_{j,m} R_{m,t} + e_{j,t},$$

across firm characteristic deciles. The conditional alpha from this model is defined as

$$\alpha_{jt} = \alpha_{j,o} + \alpha_{j,sent} Sent_{t-1}^{\perp}.$$

Table 8
Conditional Alphas with Sentiment as an Information Variable.

	$Sent_{t-1}^{\perp}$	$Port_1$	$Port_2$	$Port_3$	$Port_4$	$Port_5$	$Port_6$	$Port_7$	$Port_8$	$Port_9$	$Port_{10}$
σ	*5%*	-0.025	0.135	0.108	0.251	0.306	0.446	0.588	0.666	0.745	0.780
		(0.392)	(0.212)	(0.261)	(0.045)	(0.020)	(0.003)	(0.000)	(0.003)	(0.012)	(0.068)
	20%	0.057	0.183	0.154	0.217	0.274	0.323	0.455	0.464	0.506	0.496
		(0.323)	(0.030)	(0.058)	(0.010)	(0.002)	(0.001)	(0.000)	(0.002)	(0.011)	(0.080)
	80%	0.202	0.268	0.234	0.157	0.218	0.106	0.220	0.107	0.084	-0.006
		(0.025)	(0.001)	(0.004)	(0.052)	(0.010)	(0.205)	(0.038)	(0.296)	(0.358)	(0.399)
	95%	0.308	0.329	0.293	0.112	0.177	-0.053	0.048	-0.155	-0.224	-0.373
		(0.040)	(0.016)	(0.028)	(0.274)	(0.168)	(0.376)	(0.383)	(0.319)	(0.304)	(0.282)
$Size$	*5%*	1.822	0.851	0.545	0.423	0.240	0.049	0.081	0.095	0.037	0.081
		(0.000)	(0.006)	(0.026)	(0.038)	(0.114)	(0.366)	(0.291)	(0.252)	(0.371)	(0.218)
	20%	1.545	0.604	0.341	0.245	0.105	0.019	0.042	0.089	0.074	0.132
		(0.000)	(0.003)	(0.036)	(0.068)	(0.232)	(0.388)	(0.328)	(0.159)	(0.206)	(0.011)
	80%	1.057	0.168	-0.019	-0.070	-0.133	-0.035	-0.026	0.080	0.139	0.222
		(0.000)	(0.268)	(0.395)	(0.342)	(0.160)	(0.360)	(0.369)	(0.183)	(0.033)	(0.000)
	95%	0.700	-0.151	-0.283	-0.300	-0.307	-0.074	-0.076	0.073	0.187	0.288
		(0.107)	(0.355)	(0.212)	(0.145)	(0.070)	(0.338)	(0.315)	(0.316)	(0.079)	(0.001)
Age	*5%*	0.604	0.698	0.451	0.642	0.335	0.373	0.399	0.289	0.036	0.091
		(0.020)	(0.007)	(0.032)	(0.001)	(0.060)	(0.034)	(0.013)	(0.053)	(0.382)	(0.262)
	20%	0.368	0.435	0.233	0.402	0.220	0.350	0.356	0.299	0.117	0.097
		(0.033)	(0.012)	(0.087)	(0.002)	(0.063)	(0.003)	(0.001)	(0.003)	(0.144)	(0.135)
	80%	-0.049	-0.030	-0.151	-0.022	0.018	0.310	0.279	0.318	0.261	0.109
		(0.380)	(0.392)	(0.201)	(0.392)	(0.394)	(0.007)	(0.008)	(0.001)	(0.002)	(0.095)
	95%	-0.355	-0.369	-0.433	-0.333	-0.130	0.280	0.222	0.331	0.366	0.117
		(0.165)	(0.152)	(0.055)	(0.103)	(0.313)	(0.121)	(0.161)	(0.042)	(0.009)	(0.220)
E	*5%*	0.614	0.511	0.342	0.350	0.340	0.322	0.175	0.219	0.205	0.327
		(0.004)	(0.001)	(0.010)	(0.004)	(0.008)	(0.008)	(0.150)	(0.090)	(0.146)	(0.058)
	20%	0.383	0.378	0.278	0.252	0.254	0.263	0.178	0.186	0.192	0.249
		(0.007)	(0.000)	(0.002)	(0.002)	(0.003)	(0.001)	(0.041)	(0.036)	(0.055)	(0.032)
	80%	-0.027	0.144	0.164	0.079	0.104	0.159	0.183	0.128	0.169	0.112
		(0.390)	(0.129)	(0.051)	(0.227)	(0.166)	(0.039)	(0.031)	(0.118)	(0.077)	(0.231)
	95%	-0.326	-0.027	0.081	-0.047	-0.006	0.083	0.187	0.085	0.153	0.012
		(0.128)	(0.393)	(0.333)	(0.372)	(0.398)	(0.318)	(0.153)	(0.329)	(0.247)	(0.398)

E^+	*5%*	0.504									0.345
		(0.020)									(0.003)
	20%	0.349									0.262
		(0.016)									(0.001)
	80%	0.075									0.116
		(0.340)									(0.102)
	95%	-0.126									0.010
		(0.339)									(0.397)
D	*5%*	0.351	0.199	0.319	0.224	0.222	0.256	0.112	0.173	0.039	-0.264
		(0.031)	(0.167)	(0.026)	(0.107)	(0.106)	(0.052)	(0.276)	(0.146)	(0.379)	(0.080)
	20%	0.233	0.112	0.254	0.180	0.193	0.201	0.120	0.156	0.084	-0.133
		(0.031)	(0.216)	(0.008)	(0.058)	(0.042)	(0.024)	(0.153)	(0.063)	(0.234)	(0.158)
	80%	0.026	-0.044	0.138	0.104	0.141	0.103	0.135	0.126	0.164	0.097
		(0.386)	(0.361)	(0.118)	(0.202)	(0.110)	(0.181)	(0.111)	(0.110)	(0.046)	(0.237)
	95%	-0.126	-0.157	0.053	0.048	0.104	0.032	0.145	0.105	0.223	0.265
		(0.300)	(0.251)	(0.374)	(0.379)	(0.311)	(0.388)	(0.235)	(0.291)	(0.097)	(0.099)
D^+	*5%*	0.778									0.120
		(0.002)									(0.228)
	20%	0.506									0.111
		(0.002)									(0.136)
	80%	0.026									0.095
		(0.393)									(0.172)
	95%	-0.326									0.084
		(0.172)									(0.316)
PPE	*5%*	0.384	0.648	0.630	0.591	0.609	0.519	0.624	0.428	0.359	0.535
		(0.062)	(0.005)	(0.002)	(0.003)	(0.001)	(0.002)	(0.000)	(0.005)	(0.019)	(0.004)
	20%	0.264	0.462	0.473	0.471	0.489	0.433	0.485	0.326	0.272	0.408
		(0.055)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.008)	(0.001)
	80%	0.052	0.133	0.195	0.259	0.277	0.282	0.241	0.147	0.118	0.185
		(0.367)	(0.254)	(0.123)	(0.042)	(0.014)	(0.008)	(0.019)	(0.116)	(0.180)	(0.102)
	95%	-0.102	-0.108	-0.009	0.103	0.122	0.172	0.062	0.015	0.005	0.022
		(0.356)	(0.359)	(0.398)	(0.350)	(0.317)	(0.238)	(0.371)	(0.397)	(0.398)	(0.396)

RD	*5%*	0.302	0.260	0.422	0.528	0.544	0.750	0.729	0.953	1.075	1.182
		(0.107)	(0.116)	(0.010)	(0.005)	(0.012)	(0.002)	(0.007)	(0.003)	(0.003)	(0.018)
	20%	0.165	0.130	0.304	0.440	0.525	0.668	0.751	0.957	1.003	1.081
		(0.164)	(0.198)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	80%	-0.077	-0.099	0.097	0.283	0.490	0.525	0.788	0.963	0.877	0.902
		(0.325)	(0.259)	(0.251)	(0.019)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.006)
	95%	-0.253	-0.267	-0.055	0.168	0.465	0.420	0.816	0.968	0.785	0.771
		(0.181)	(0.131)	(0.378)	(0.272)	(0.044)	(0.098)	(0.005)	(0.005)	(0.044)	(0.130)
BE/ME	*5%*	0.250	0.367	0.311	0.291	0.388	0.273	0.520	0.624	0.601	1.167
		(0.280)	(0.044)	(0.040)	(0.039)	(0.006)	(0.032)	(0.000)	(0.000)	(0.000)	(0.000)
	20%	0.088	0.228	0.213	0.199	0.303	0.248	0.422	0.468	0.533	0.960
		(0.361)	(0.059)	(0.035)	(0.034)	(0.001)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)
	80%	-0.196	-0.018	0.041	0.036	0.153	0.206	0.248	0.192	0.412	0.594
		(0.237)	(0.394)	(0.363)	(0.365)	(0.081)	(0.013)	(0.006)	(0.030)	(0.000)	(0.000)
	95%	-0.404	-0.198	-0.085	-0.082	0.044	0.174	0.121	-0.009	0.324	0.326
		(0.182)	(0.230)	(0.344)	(0.340)	(0.381)	(0.164)	(0.276)	(0.398)	(0.073)	(0.184)
SG	*5%*	0.957	0.657	0.466	0.359	0.290	0.336	0.410	0.313	0.442	0.430
		(0.007)	(0.002)	(0.003)	(0.002)	(0.017)	(0.004)	(0.001)	(0.013)	(0.003)	(0.067)
	20%	0.749	0.498	0.420	0.301	0.304	0.327	0.355	0.281	0.274	0.076
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.007)	(0.352)
	80%	0.381	0.218	0.340	0.198	0.328	0.312	0.259	0.224	-0.023	-0.551
		(0.084)	(0.095)	(0.001)	(0.008)	(0.000)	(0.000)	(0.001)	(0.006)	(0.387)	(0.000)
	95%	0.111	0.012	0.281	0.123	0.346	0.300	0.189	0.183	-0.240	-1.009
		(0.380)	(0.398)	(0.086)	(0.233)	(0.009)	(0.016)	(0.135)	(0.146)	(0.119)	(0.000)

We report parameter estimates for the conditional alpha with associated p-values, for deciles of firm characteristic portfolios, for various percentiles of lagged sentiment. All estimates are based on the following model

$$R_{j,t} = \alpha_{j,o} + \alpha_{j,sent}Sent_{t-1}^{\perp} + \beta_{j,m}R_{m,t} + \beta_{j,smb}R_{smb,t} + \beta_{j,hml}R_{hml,t} + \beta_{j,mom}R_{mom,t} + e_{j,t},$$

across firm characteristic deciles. The conditional alpha from this model is defined as

$$\alpha_{jt} = \alpha_{j,o} + \alpha_{j,sent}Sent_{t-1}^{\perp}.$$

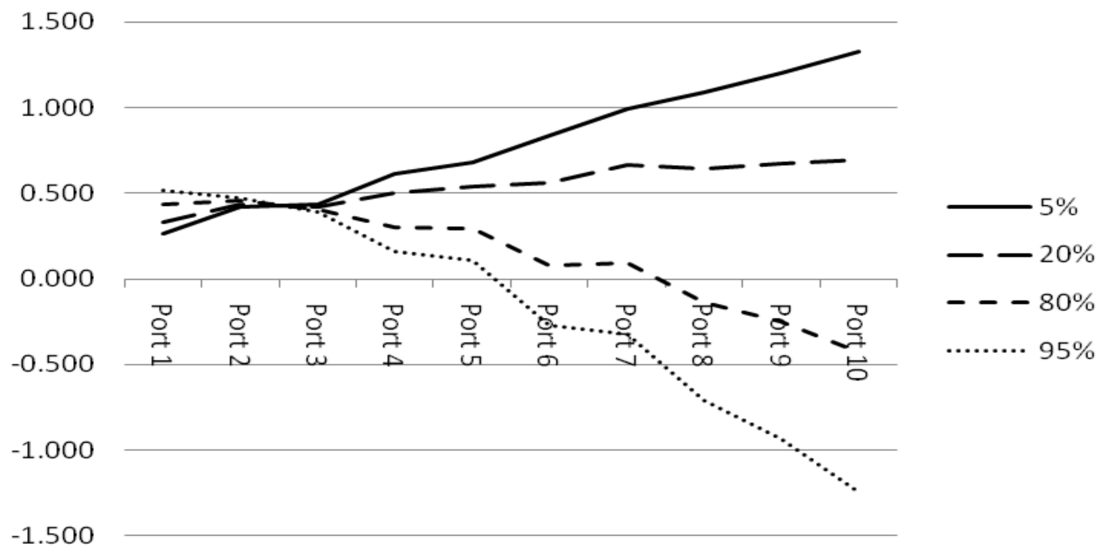

Fig. 1a. Conditional alpha across volatility portfolios.

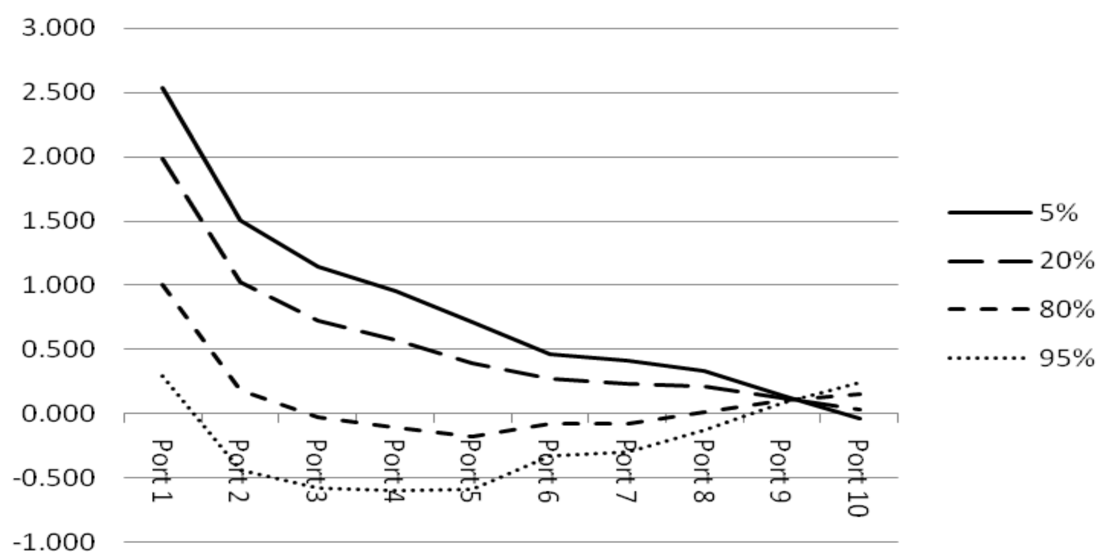

Fig. 1b. Conditional alpha across size portfolios.

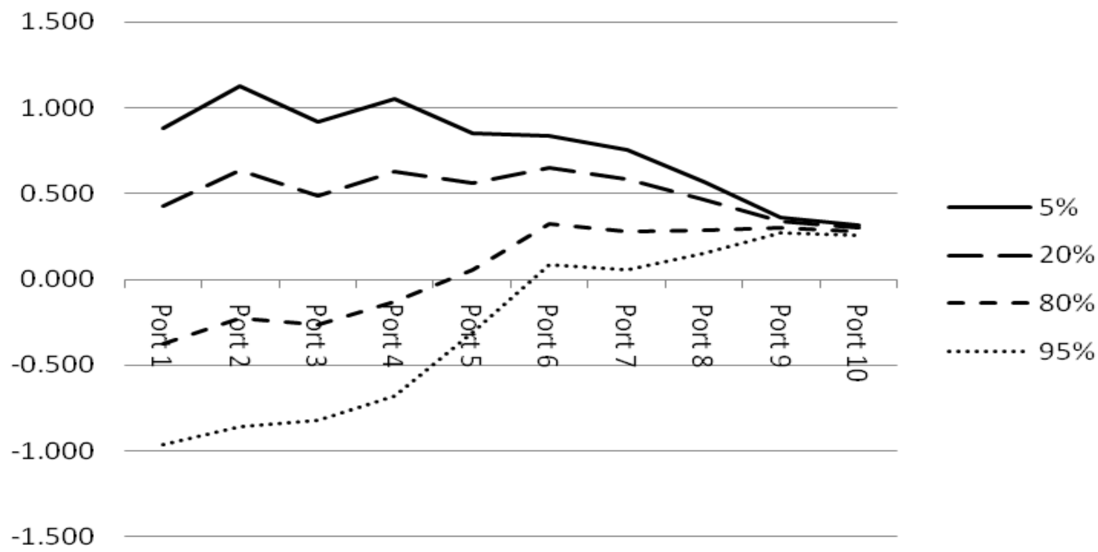

Fig. 1c. Conditional alpha across age portfolios.

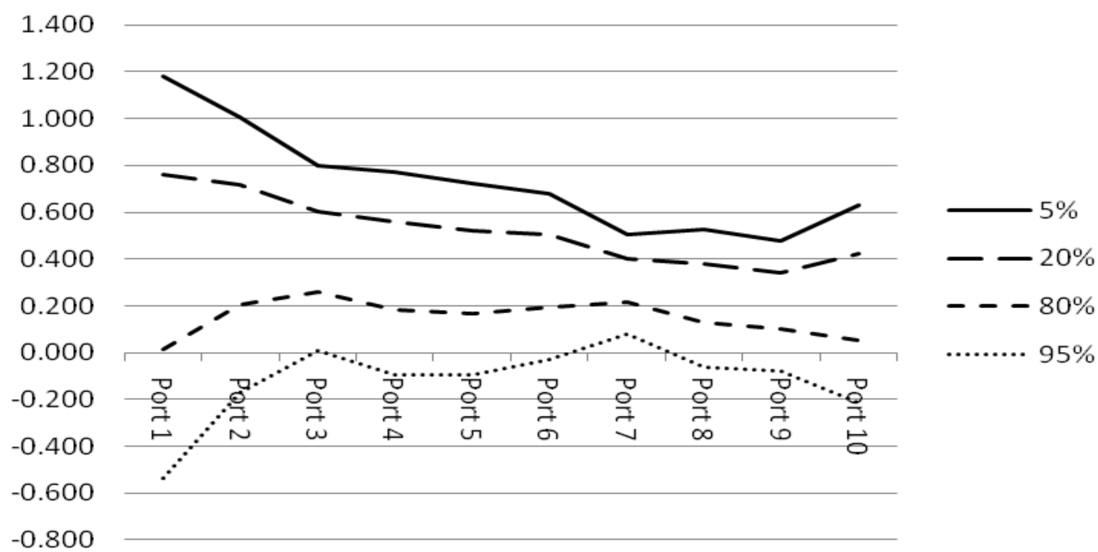

Fig. 1d. Conditional alpha across earnings portfolios.

Fig. 1e. Conditional alpha across dividend portfolios.

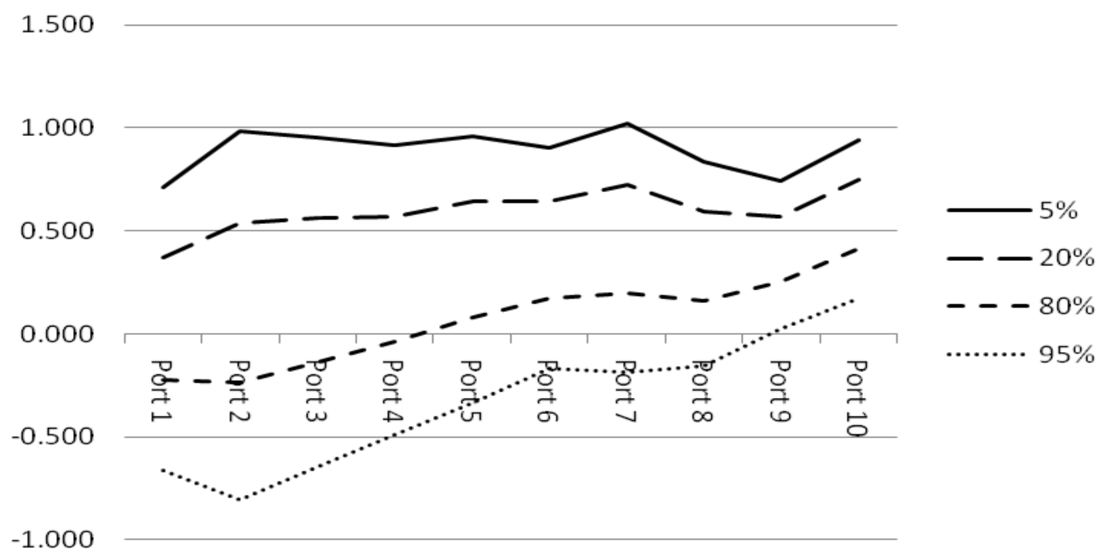

Fig. 1f. Conditional alpha across property, plant and equipment portfolios.

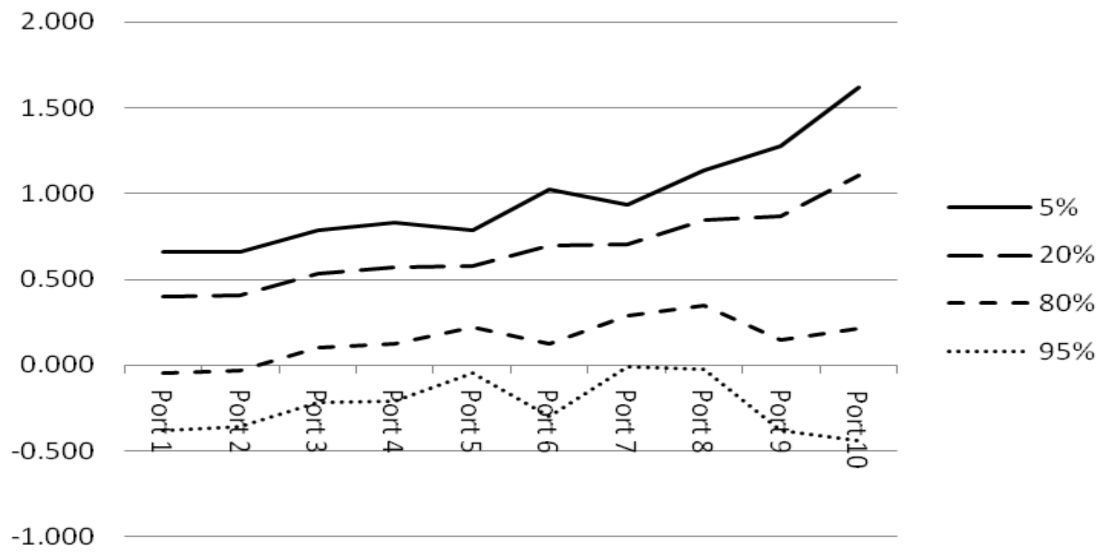

Fig. 1g. Conditional alpha across research and development portfolios.

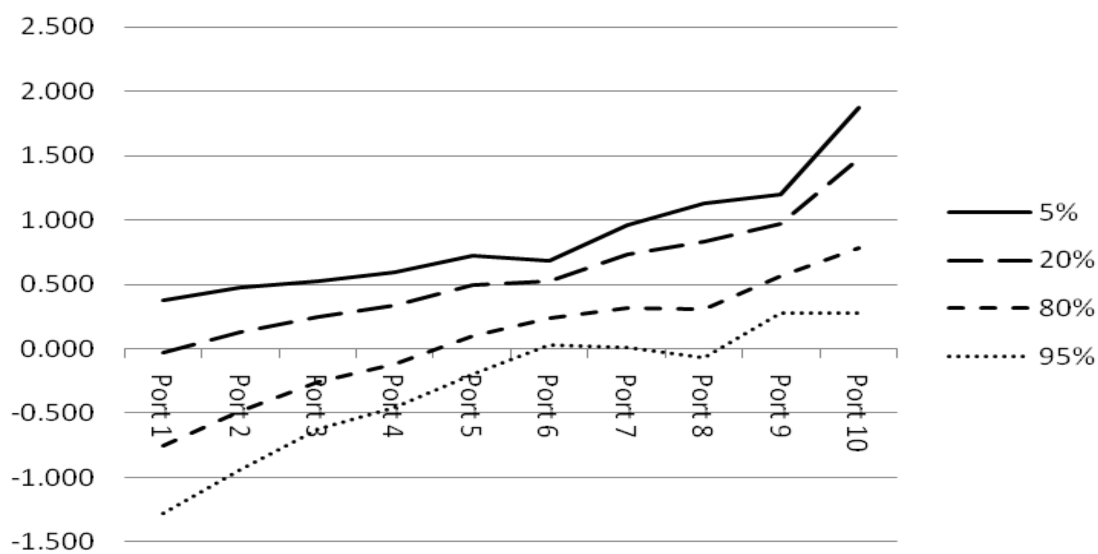

Fig. 1h. Conditional alpha across BE/ME portfolios.

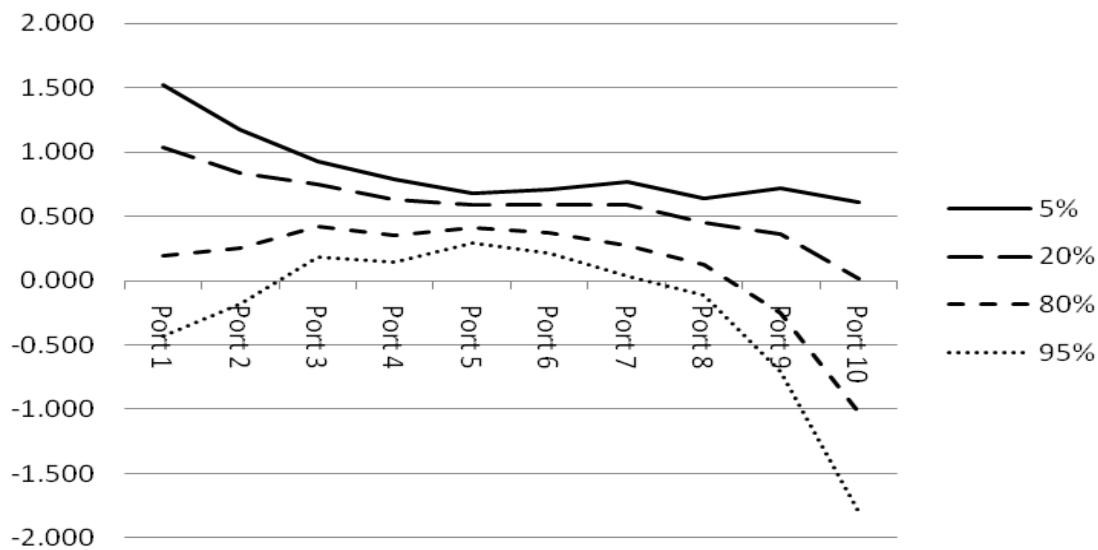

Fig. 1i. Conditional alpha across sales growth portfolios.