Idiosyncratic Risk and the Cross-Section of Stock Returns: Merton (1987) Meets Miller (1977)

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Abstract

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Abstract

Merton (1987) predicts that idiosyncratic risk should be priced when investors hold sub-optimally diversified portfolios, and cross-sectional stock returns should be positively related to their idiosyncratic risk. However, the literature generally finds a *negative* relationship between returns and idiosyncratic risk, which is more consistent with Miller's (1977) analysis of asset pricing under short-sale constraints. We examine the cross-sectional effects of idiosyncratic risk while explicitly recognizing the confounding effects that dispersion of beliefs and short-sale constraints produce in the Merton framework. We find strong support for Merton's (1987) model among stocks that have low levels of investor recognition and for which short selling is limited. For these stocks, the relation between idiosyncratic risk and expected returns is positive, as predicted by Merton (1987).

According to the textbook capital asset pricing model (CAPM), idiosyncratic risk is not priced because investors hold efficiently diversified portfolios. However, the model makes no predictions concerning the effect of idiosyncratic risk on equilibrium returns if investors are constrained from forming diversified portfolios because of transactions costs --- for example, information or trading costs.

In an influential paper, Merton (1987) presents an extension of the CAPM where idiosyncratic risk plays a role in equilibrium. Merton forwards the investor recognition hypothesis (IRH) which posits that, because of incomplete information on security characteristics, investors only hold securities whose risk and returns characteristics they are familiar with. Consequently, they hold under-diversified portfolios and, in the static mean-variance setting considered by Merton, they demand compensation for securities' idiosyncratic risk.[1] Thus, in equilibrium, cross-sectional stock returns are positively related to their idiosyncratic risk.[2]

Direct tests of Merton's (1987) model are rare. Merton's predictions are cross-sectional in nature, but Ang, Hodrick, Xing and Zhang (2004) appears to be the only cross-sectional test of Merton (1987) that directly sorts stocks into portfolios ranked on idiosyncratic volatility. Observing that stocks with high idiosyncratic volatility have "abysmally low average returns," they conclude their results are directly opposite to the implications of Merton's (static) investor recognition hypothesis.

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[1] Levy (1978) and Mayers (1976) produce similar predictions in CAPM extensions where investors hold under-diversified portfolios. Barberis and Huang (2001) produce a prospect-theory model where idiosyncratic risk produces positive expected returns.

[2] Shapiro (2002) generalizes the IRH to a dynamic setting and shows that this conclusion need not hold when the investment opportunity set is stochastically evolving, since higher volatility stocks may still provide a more effective hedge against shifting investment opportunities, compared to lower volatility stocks.

Meanwhile, Diether, Malloy and Scherbina (2002) offer an indirect test of Merton (1987). Since dispersion in analysts' forecasts likely indicates a more volatile, less predictable earnings stream, Diether et al. (2002) suggest that the dispersion of analysts' forecasts reflects the type of idiosyncratic risk to which Merton refers. Their results do not support Merton's theory, and they note "our results clearly reject the notion that dispersion can be viewed as a proxy for risk, since the relation between dispersion and future returns is strongly negative" (page 2139). Similarly, when Gebhardt, Lee and Swaminathan (2001) use forecast dispersion as a risk proxy for estimating cost of capital, they are surprised to find the "wrong sign" on the variable at statistically and economically significant levels.

Thus, both in direct tests using idiosyncratic volatility as a proxy for idiosyncratic risk, and in indirect tests that use analysts' forecast dispersion as a risk proxy, cross-sectional results are incorrectly signed, compared to Merton's (1987) predictions, at high levels of statistical significance. Based on the empirical tests to date, the literature concludes that Merton's hypothesis, while both intuitively appealing and theoretically well grounded, is not supported by the data. Instead, Diether et al. (2002) argue that their results, along with those of Gebhardt et al. (2001), are more consistent with predictions of Miller (1977).

Miller (1977) argues that dispersion of opinion, in the presence of short sale constraints, leads to systematic security overvaluation because the most optimistic market participants set a stock's price. Thus, dispersion of investor opinion is priced at a *premium* when short sale constraints are present. Miller's (1977) theory implies that *if* short sale constraints are binding, there is a negative correlation between risk-adjusted returns and dispersion of beliefs.[3]

Diether et al. (2002) interpret the observed negative correlation between returns and analyst forecast dispersion as supportive of Miller (1977), but contrary to the predictions of Merton (1987), because the dispersion of analysts' forecasts and idiosyncratic volatility are positively correlated. For example, Peterson and Peterson (1982) observe a positive relationship between return volatility and the dispersion of I/B/E/S forecasts.

However, there are strong reasons to question whether Merton (1987) should be viewed as a competing theory to Miller (1977). While Miller (1977) assumes that stocks are short-sale constrained, Merton (1987) models a standard frictionless market, without borrowing and short-selling restrictions (see, page 487). While Merton's IRH applies to low-visibility securities, Miller (1977) makes no low-visibility assumption.

We hypothesize that the previous tests of Merton fail to find that idiosyncratic risk is priced for two reasons. First, Merton's hypothesis applies only to stocks with low visibility, but the existing literature does not condition on visibility. Second, none of the existing studies condition on the level of short interest. Conditioning on short interest is important because short interest is indicative of both dispersion of investor opinion and potential difficulty in shorting. Miller (1977) contends that these conditions are prerequisite for overvaluation. Since dispersion of beliefs has been empirically demonstrated to be positively correlated with idiosyncratic risk, Miller-style dispersion-of-opinion induced overvaluation might obscure evidence of Merton's IRH among more highly shorted stocks.

[3] Indeed, several other theoretical papers derive similar asset pricing predictions. A non-exhaustive set includes Figlewski (1981), Morris (1996), Viswanathan (2002), Chen, Hong and Stein (2002), Danielsen and Sorescu (2001), and Duffie, Garleanu and Pedersen (2002). In contrast, Diamond and Verrecchia (1987) and Jarrow (1980) provide alternative theories of the effects of short-sale constraints on security prices.

It is also possible that negative abnormal returns that follow high observed short interest *are not* driven by Miller-style overvaluation arising from short sale constraints. Instead, high short interest may simply reflect a temporary overvaluation that has been identified by "smart" short sellers who have received negative information ahead of the other investors and sold short in response to negative news not yet reflected in market prices. Either way, numerous studies report that stocks with high levels of short interest are followed by negative abnormal returns.[4] The impact on tests of Merton's IRH is the same irrespective of the mechanism that links short interest to overvaluation. Heavily shorted firms are likely to underperform their benchmarks, and excluding them should prove helpful in detecting evidence supportive of Merton's IRH in the remaining sample. Thus, we propose to exclude stocks with high levels of short interest and focus appropriate tests of Merton (1987) on those stocks which are not heavily shorted.

Because Merton's model applies to stocks with low visibility, in the sense that some investors are unaware of the firm's risk-return parameters, we expect to find empirical support for Merton's investor recognition hypothesis (IRH) only among low-visibility stocks, and more specifically within a subset of low-visibility stocks that are not subject to significant levels of short selling. Accordingly, we analyze the cross-sectional relation between idiosyncratic risk and equity returns for low-visibility firms while controlling for short-sale activity.

Falkenstein (1996) and Aggarwal, Klapper and Wysocki (2005) link institutional ownership (positively) to firm visibility. We utilize this relationship and screen out firms

[4] For example, see Figlewski (1981), Asquith and Meulbroek (1995), Danielsen and Sorescu (2001), Desai, Ramesh, Thiagarajan and Balachandran (2002), Boehme, Danielsen, and Sorescu (2006) and Asquith, Pathak and Ritter (2005)

with high levels of institutional ownership (high-visibility) for whom the investor recognition hypothesis should not apply. Using data on short interest on NYSE and NASDAQ stocks from 1988-2002 and institutional ownership data for the same period, we find that cross-sectional returns are positively correlated with idiosyncratic volatility, as predicted by Merton, for less visible stocks that are not subject to significant short selling. For completeness we also examine the cross-section of volatility for stocks which have greater visibility and/or greater shorting activity. We do not find the positive correlation between volatility and ex-post returns for those firms.

We conduct similar tests using I/B/E/S sell-side analyst coverage as a proxy for visibility. Aggarwal et al. (2005) note that firms that lack analyst coverage are presumed to lack visibility. Baker, Powell and Weaver (1999) also use analyst coverage as a visibility proxy in testing the impact of NYSE listing on firm visibility. Again, we find that cross-sectional returns are positively correlated with idiosyncratic volatility for firms that lack analyst coverage and do not exhibit significant short selling activity.

Finally, we conduct a series of cross-sectional Fama-MacBeth regressions on monthly returns of various portfolios constructed to isolate the impact of volatility in the presence of low visibility and low short selling activities. Again, the results are supportive of Merton's hypothesis. Among other advantages, the Fama-MacBeth method allows for easy incorporation of risk factors and control variables into the cross-sectional regression analysis.

We organize the rest of this paper as follows. Section I develops the testable hypotheses and discusses our testing methodology and empirical proxies. Section II presents base-line cross-sectional effects. Section III presents empirical tests of Merton

(1987) using institutional ownership as a proxy for visibility, and Section IV repeats the analysis for firms lacking financial analyst coverage. Section V documents further evidence in support of the hypothesis using cross-sectional tests in a Fama-MacBeth framework, and Section VI summarizes and concludes.

I. Hypotheses, Explanatory Variables, and Test Design

Based on the foregoing analysis, we hypothesize that cross-sectional differences in idiosyncratic volatility are positively correlated with subsequent returns when firms have low visibility and low dispersion of beliefs, the latter condition being proxied by low short interest. For more heavily shorted firms, the relationship between idiosyncratic risk and returns is potentially obscure because of the positive correlation between dispersion of beliefs and idiosyncratic risk. In fact, if the countervailing influence of dispersion of beliefs is particularly strong, heavily shorted firms may display a negative correlation between idiosyncratic risk and returns.

We now describe the independent (or explanatory) variables used in the analysis, as well as our methodology for measuring stock returns.

A. Visibility Metrics.

The Merton model applies to stocks with low visibility. That is, the IRH applies to stocks for which some segment of investors is unaware of all the relevant risk-return tradeoff parameters.

We use two proxies for visibility. The first is institutional ownership. Falkenstein (1996) finds that institutional investors (specifically U.S. mutual funds) have a significant preference for stocks with high visibility, as measured by coverage in newspaper articles.

Similarly, Aggarwal et al. (2005) find that institutional ownership is positively correlated with visibility as proxied by the number of analysts following the stock.

We calculate institutional ownership (IO) as the ratio of the total or aggregate number of shares held by institutions (13F filings) to the total number of shares outstanding reported by CRSP for the end of the calendar month of the 13F filing. The 13F records provide institutional holdings on a quarterly basis. Therefore, we use the IO for the month in which the 13F's are filed and for the subsequent two months. For example, if a firm had 40% institutional ownership at the end of March 1996, we use that 40% ownership percentage estimate also for April and May.[5]

Our second proxy for visibility is the presence of analyst coverage. This proxy follows Aggarwal et al. (2005) who observe that analyst following is one "of the strongest determinants of U.S fund investment decisions" (page 2937). Firms lacking analyst coverage in Thompson Financial's I/B/E/S database are deemed to have low visibility. These represent a large fraction of all CRSP firms: over 50% in 1988 and over 36% in 2003, at the end of our study period.

B. Short-Sale Demand

Asquith et al. (2005) proxy for a limited supply of lendable shares using institutional ownership (IO), and they proxy for short-sale demand (i.e. dispersion of opinion) using short interest levels, or "relative short interest" (RSI). They find negative abnormal returns

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[5] Institutional ownership data is missing for some firms in the Thompson Financial database. Most of these missing firms probably have no institutional ownership. However, some omissions are simple errors. For example, a data error seems likely when a firm is covered by 14 analysts but has no reported institutional ownership. We assume that firms with missing institutional ownership data have no institutional ownership in all of the tests reported in the tables. However, excluding missing observations, rather than recoding them as zero values, does not alter any of the substantive results.

for low-IO, high-RSI stocks which they interpret as consistent with Miller (1977). They find no evidence of negative abnormal returns for all other stocks.

The Asquith et al. (2005) argument suggests that the Miller hypothesis should apply *only* to firms with low IO and high RSI. Hence, Miller-style overpricing should not apply to all other firms, i.e., those not subject to low IO and high RSI. And while Merton's IRH should apply whenever firm visibility is low, it should be most easily detected when the RSI does not produce confounding effects. Thus, Merton's IRH should be most easily observed where firms have low visibility (low IO) *and* low dispersion of opinion (low RSI).

We obtain short interest data from the New York Stock Exchange and the NASD. Consistent with Asquith et al. (2005), we divide short interest by shares outstanding to calculate the Relative Short Interest (RSI). Our sample is composed of all firms for which short interest data are electronically available from these sources. For both NYSE and NASDAQ firms, such data are available beginning with January of 1988. We collect all short interest data on a monthly basis for transactions settling by the 15th of each month. We use the ticker symbols shown in the short interest reports to match each observation with CRSP data.[6]

C. Measuring Idiosyncratic Risk (SIGMA)

We measure the idiosyncratic risk (SIGMA) as the standard deviation of weekly excess raw returns (firm return minus CRSP VWRETD index), estimated over the 52 weeks (the ending of the week is defined as of closing on Wednesdays) preceding the first

[6] We noticed short interest data are occasionally missing for firms with valid CRSP data. We do not include such observations in our sample because we are unable to determine if they represent a zero level of short interest, or if short interest data are missing.

day of each month. We perform this estimation method, as opposed to measuring idiosyncratic risk relative to the Fama/French and Carhart four-factor model, because illiquid stocks that are only slightly correlated with the four factors may result in spurious measures of high volatility as a result of asynchronous trading. However, in later tests we observe that our results are robust to the choice of the idiosyncratic risk metric.

D. Measuring Subsequent Stock Returns

Stock returns are obtained from CRSP, and we adopt the standard four-factor, calendar-time portfolio approach for measuring abnormal returns. At the end of June in each year from 1988 to 2002 we use our explanatory variables to classify firms into portfolios. Firms with similar values on each dimension are grouped into equally-weighted portfolios. For each portfolio, we first calculate the monthly raw returns during the 12-month period *subsequent* to the portfolio formation. In other words, the portfolios are constructed on ex-ante information, and the returns are computed ex-post. In a sense, the tests are conducted "out of sample," as in Spiegel and Wang (2005). Specifically, for each portfolio, we estimate the following four-factor regression model:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t} \qquad (1)$$

where, $R_{p,t}$ represents the raw returns of each portfolio, and $R_{f,t}$ is the return of the one-month Treasury Bill. The four independent variables are the excess return on the market portfolio ($R_{m,t}$-$R_{f,t}$); the difference between the returns of value-weighted portfolios of small and big firm stocks (SMB_t); the difference in returns of value-weighted portfolios of high and low book-to-market stocks (HML_t); and, the difference in returns of value-weighted portfolios of firms with high and low prior momentum (UMD_t, or "up" minus "down"). Fama and French (1993) propose the first three factors, while Carhart (1997) proposes the momentum factor. Using the OLS estimation method, we interpret the intercept, α_p, from equation (1) as the mean monthly abnormal return of the calendar-time portfolio.[7]

Our most important tests compare returns between the calendar-time portfolios of stocks having different levels of volatility (SIGMA). As in Mitchell and Stafford (2000) and Boehme and Sorescu (2002), we perform these tests by constructing zero-investment portfolios with long positions in stocks having a certain mix of characteristics (such as low IO, low RSI, and high SIGMA) and short positions in stocks with a different mix (such as low IO, low RSI, and low SIGMA). These portfolios are referred to as long-short portfolios. This example is typical in that only the SIGMA variable is altered between the long and short legs of the portfolio. Thus, we can observe the marginal effect of SIGMA holding the other variables constant. The long-short portfolio returns are regressed on the four factors:

$$R_{high\text{-}SIGMA,t} - R_{low\text{-}SIGMA,t} = \alpha_p + \beta_p(R_{m,t}-R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t} \qquad (2)$$

The intercept obtained in this manner (α_p) represents a measure of the relative abnormal performance of the high-SIGMA portfolio vis-à-vis the shorted low SIGMA portfolio.

In addition to calculating long-short portfolio abnormal returns under the four-factor model, for robustness we consider several alternative pricing model specifications. These include the CAPM, the Fama-French three-factor model, a simple raw-return model, and a

[7] Results throughout the paper also hold using weighted least squares.

five-factor model that augments the four-factor model with a liquidity factor. The liquidity factor deserves some additional comment, because it is relatively new to the literature.

Spiegel and Wang (2005) observe that firms with high idiosyncratic risk also have low liquidity, and thus high returns associated with increasing idiosyncratic risk may be due to the illiquidity premium rather than Merton's (1987) hypothesis.[8] We address this concern in robustness tests, where we control for aggregate liquidity risk by constructing a liquidity factor to augment the four-factor Fama/French and Carhart model. We build the liquidity factor using a procedure similar to the LMH (low minus high liquidity) factor estimation in Eckbo and Norli (2005); this estimation technique is similar in spirit to the HML Fama/French factor estimation procedure.

For each calendar month, we assign all NYSE, AMEX, and NASDAQ firms to two market capitalization portfolios (high or low), based on the median NYSE firm market capitalization for that month. Next, for each of these two market capitalization groupings, each month we sort the firms based on turnover (defined as average monthly shares traded divided by shares outstanding over the prior twelve months). For the calendar month following the portfolio formation, we estimate the returns to equally weighted portfolios of firms in the top and bottom 30 percent of prior 12-month turnover, for both the above and below NYSE median market capitalization groups. The low (high) liquidity portfolio is an equally weighted average of the two portfolios in the lowest (highest) 30 percent of turnover from the above and below median NYSE market capitalization firms. We calculate the LMH liquidity factor as the return to a zero investment portfolio holding a

[8] Eckbo and Norli (2005) provide an excellent review of the literature associated with aggregate liquidity risk and expected returns.

long position in the low liquidity portfolio and a short position in the high liquidity portfolio.

E. Descriptive Statistics

Table 1 provides descriptive statistics for the proxy variables used. We provide a snapshot of firms in the dataset at five-year intervals beginning in 1988, the first year for which short interests data is available in digital form. Proxies are estimated for all U.S.-domiciled common stocks listed on the NYSE and NASDAQ.

Both IO and RSI have increased substantially between 1988 and 2002. However, no clear trend in SIGMA is noticeable. Because we form portfolios based on rank-orderings of each of these variables, neither a small number of extreme values, nor the non-stationarity in the time series of a variable introduces any bias to the analysis. Panel B of Table 1 describes the fraction of CRSP firms without analyst coverage. While the fraction has declined over the sample period, over 36% of firms had no I/B/E/S analyst coverage at the end of 2002.

II. Baseline Cross-Sectional Tests

Table 2 presents baseline cross-sectional tests of the effects of volatility on expected returns, without regard to visibility or RSI, for the universe of all CRSP listed common stocks of U.S.-domiciled NYSE and NASDAQ firms. We present the monthly abnormal returns for portfolios formed at the end of each June and held for the next year as a function of idiosyncratic volatility (SIGMA).[9] SIGMA deciles are assigned to each stock by sorting

[9] Longer holding periods are preferable because the Merton's (1987) hypothesis is about long-term steady-state returns. In contrast, Miller (1977) is about the near-term underperformance associated with the initial overpricing and the subsequent convergence to fundamentals. This dichotomy highlights the problem faced when conducting tests intended to disentangle Merton-effects from Miller-effects.

all NYSE and NASDAQ firms on SIGMA. The abnormal returns are computed by forming equally-weighted calendar-time portfolios with twelve-month horizons and regressing the excess portfolio returns ($R_{p,t}$-$R_{f,t}$) on the four Fama-French-Carhart monthly factors. The abnormal return for each sub-sample is the intercept (α_p) from the regression.[10]

The last two columns in Table 2 shows the abnormal return of the long-short portfolio that takes long positions of stocks in the highest SIGMA decile, and short positions in stocks in the lowest SIGMA decile. The t-statistic of the long-short portfolio indicates the statistical significance of the difference of the measured mean return from zero.

There is no evidence in Table 2 of any consistent relationship between abnormal returns and SIGMA: the abnormal return point estimates across the ten SIGMA deciles do not appear to follow any particular trend, and the long-short portfolio returns are not statistically significant. In short, as others have noted, there is no evidence here to provide *unconditional* support for Merton's hypothesis.

III. Idiosyncratic Risk and Return as a function of Institutional Ownership

Having established baseline (unconditional) results for the cross-sectional relationship between SIGMA and abnormal returns, we now focus our analysis on the space in which the assumptions underlying Merton's IRH are best satisfied. In particular, Merton (1987) predicts that idiosyncratic risk will be priced for lower-visibility firms, but not for high-visibility firms. We also hypothesize that Merton's IRH will be difficult to detect among

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[10] These tests are conducted using OLS regressions, but results in this table and elsewhere are not sensitive to the use of the OLS approach. In an alternative specification, we weigh monthly excess returns by the square root of the number of firms in the portfolio each month, These WLS regressions produce very similar point estimates and significance values.

more heavily shorted firms (which tend to have high SIGMA values) because heavily shorted firms are known to produce negative abnormal returns. Unfortunately, although we can state that Merton's hypothesis should be most easily observed where firms have low visibility (low IO) and low dispersion of opinion (low RSI), the IRH does not provide guidance as to how low either of these proxies should be in order for the underlying assumptions to be valid. That is an empirical question.

To address this empirical question, we present Table 3, Panel A. Considering the Institutional Ownership percentage (IO) as our visibility metric, at the end of June in each year, we sort all firms on the Institutional Ownership percentage (IO) and create four IO quartile groups. We next sort each IO grouping into quartiles based on Relative Short Interest (RSI). Firms within each of these sixteen IO/RSI groupings are further sorted into deciles based on idiosyncratic risk (SIGMA). We are left with 160 IO-RSI-SIGMA sorted portfolios. The abnormal return reported for each portfolio is the intercept (α_p) from the four-factor OLS regression. We also report the associated t-statistic. To facilitate our analysis, we also construct long-short (zero-investment) portfolios for each IO-RSI combination. Using the method presented in the Table 2 discussion, these portfolios consisting of a long position in stocks from the highest SIGMA decile and a short position in stocks from the lowest SIGMA decile. These long-short portfolios are presented in the two right-most columns of the Panel.

To facilitate the following discussion, we define all the portfolios in terms of IO quartile and RSI quartile so that (IO=1,RSI=1) refers to the set of firms in the smallest IO quartile and the smallest RSI quartile. Likewise, (IO=4,RSI=4) refers to the set of firms in the largest IO quartile and the largest RSI quartile The space over which Merton's assumptions are best met clearly must include the firms in (IO=1,RSI=1). Likewise, it seems obvious that we must exclude from consideration all those portfolios in the space (IO=4,RSI=1,2,3,4) and all those portfolios in the space(IO=1,2,3,4,RSI=4). Among the remaining portfolios, we observe that (IO=3,RSI=3) has the lowest alpha value. This seems reasonable in that while neither IO nor RSI is in the highest quartile, both IO and RSI are above median for this set of firms. The next lowest alpha among the remaining long-short portfolios is (IO=1,RSI =3). Thus, RSI<3 appears to be a useful point of bifurcation. Otherwise, IO quartiles 1, 2 and 3 each produce positive long-short portfolio alphas.

We note that none of the long-short alphas carry t-statistics that are significant at the five percent level. However, notice that all SIGMA=10 portfolios and all long-short portfolio values are positive after excluding firms in IO quartile 4 and RSI quartile 4. In other words, SIGMA appears to be priced in accordance with Merton's hypothesis for low visibility firms, conditioned on low RSI. Because these portfolios are constructed using three variable sorts, the number of firms in each portfolio is relatively small, rendering the power of the test low. Thus, our effort to find suitable division points in the data must balance (1) the need for defining IO and RSI narrowly enough to satisfy the assumptions of Merton's IRH against (2) the need for adequate portfolio size to ensure sufficient power of the tests.[11]

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[11] This cut of the data excludes the data from (IO=2, RSI=3) which also reports a relatively high long-short portfolio alpha. An alternative cut of the data might define the Merton space to exclude portfolios in the highest quartile of either IO or the highest quartile of RSI, and also exclude the quartile (IO=3, RSI=3), where both proxy variables are relatively high. This definition of the Merton space would extend as far as (IO=2, RSI=3) and (IO=3, RSI=2). This division produces results which are very similar to that described in the body of the paper. In fact, point estimate of the SIGMA=10 portfolio is over 16% annually. However, the t-statistic on the long-short portfolio is significant at only the 10% level. In any event, Panel A provides a great degree of detail for the reader to consider alternative bifurcations of the data.

Panel B presents tests for the lowest three IO quartiles By combining the three quartiles, we simplify the following exposition, highlight the economic significance of Merton's IRH by showing that it applies to a large fraction of traded US stocks, and increase the power of the tests. The first line of Panel B presents the results for these lower-visibility firms without conditioning on RSI. This line is labeled "All RSI." These tests are an unconditional test of Merton's IRH on lower-visibility firms without consideration of short interest levels. Subdividing the lower-IO firms into SIGMA deciles, we obtain the 4-factor abnormal return results for each SIGMA-grouped portfolio.

The results in the "All RSI" line are very similar to the baseline results in Table 2. There is limited evidence of a relation between abnormal returns and SIGMA deciles 10 and 9 have higher alpha point estimates than any of the other SIGMA-based portfolios. Otherwise, the point estimates of abnormal returns across the ten SIGMA deciles do not follow a discernable trend. The long-short portfolio return point estimate is positive, but it is not statistically significant.

A. Conditioning on Short Interest

The second and third lines of Panel B subdivide the lower-IO firms between those with low RSI and those with higher RSI, based upon the median RSI level of firms in the low-IO group. We have hypothesized that evidence of Merton's IRH may be difficult to detect among more heavily shorted firms because such firms are known to produce negative abnormal returns, and RSI is positively correlated with SIGMA. Line 2 of Panel B, labeled "Lower RSI half" is composed of low-IO firms with relatively little shorting activity. We expect to find evidence that SIGMA is priced in this subset of firms, and we do. Among these low-RSI firms, firms in the 10th-decile SIGMA portfolio earn monthly abnormal returns of 1.482% per month. This is equivalent to a compounded annual return greater than 19.3%. The 9th-decile portfolio earns the second-highest alpha among all the SIGMA-based portfolios, and portfolios 7 and 8 return the third and fourth-highest alpha values. However, the pattern of abnormal returns across all deciles is not strictly monotonic. Returns decrease slightly from decile 1 through decile 6, but abnormal returns rise sharply as SIGMA increases further. Despite this lack of strict monotonicity, the long-short portfolio constructed by shorting first-decile stocks and purchasing 10th-decile firms earns an economically and statistically significant return of 0.973% monthly (12.3% annually). The long-short portfolio alpha is significant at a 5% level.

The third line of Panel B presents portfolios for the more heavily shorted lower-IO firms. These firms satisfy Merton's low visibility assumption, but the confounding effects of relatively high shorting are present. No pattern is apparent in the SIGMA-based portfolios, and the long-short portfolio return is actually negative, rather than positive as the hypothesis would predict. Thus, no evidence here supports Merton's hypothesis. That idiosyncratic risk is not priced for low-IO, high-RSI firms is consistent with findings of Asquith et al. (2005) who identify these firms as most likely to be overvalued in a Miller sense.

The last three lines of Panel B replicate the first three lines of the table, except that the analysis focuses on the highest-quartile IO firms, rather than the lower-IO firms. Merton's hypothesis suggests that SIGMA should not be priced for these firms because they have high visibility. Consistent with this conjecture, none of the long-short portfolios for high-IO firms produce economically or statistically significant alphas. SIGMA appears to be priced only among low-visibility firms with low short interest.

B. Robustness Tests

For robustness, we present in Table 4 abnormal returns with t-statistics obtained from long-short portfolios under alternative model specifications. Panel A of Table 4 presents results obtained with four alternative asset pricing models: the CAPM, the Fama-French three-factor model, the Fama-French-Carhart four-factor model augmented with the Eckbo-Norli liquidity factor, and a simple risk-free-rate adjusted model. The first column in Panel A restates the long-short portfolio results shown in the last two columns of Table 3, Panel B, for easy reference. The other columns in Panel A show the abnormal returns of the same portfolios under alternative pricing models.

For low-IO firms unconditional on RSI, only the liquidity augmented five-factor model produces statistically significant positive alphas for the long-short portfolios. However, after conditioning on RSI, the alpha is significantly positive only for firms with low levels of short interest, suggesting that the unconditional result actually is driven by this subset. In general, for stocks with low IO and low RSI, the effect of SIGMA on stock returns is significantly positive across the asset pricing models, except for the CAPM where the effect remains positive but does not attain statistical significance. We note that the five-factor model produces the strongest results in a statistical sense, but the raw return model produces the largest alpha point estimates: after accounting for size, book-to-market, momentum, liquidity and the market returns, firms in the highest SIGMA decile earn approximately 1.387% per month (17.9% per year) *more* than firms in the lowest SIGMA decile.

Among firms with low IO but high RSI, long-short abnormal returns are generally negative. Firms in the highest IO quartile also produce no positive and statistically significant long-short intercepts, irrespective of RSI conditioning. The results of Panel A provide clear additional evidence consistent with Merton's Investor Recognition Hypothesis.

Panel B considers alternative portfolio weighting methods, alternative rebalancing frequencies, and alternative investment horizons for the standard four-factor asset-pricing model. Again, for easy reference, the leftmost column of Panel B repeats the results from the leftmost column of Panel A. These portfolios are equally weighted, rebalanced at the end of June each year, and held for a one-year horizon. The next column present results when portfolios are rebalanced every month, and selected stocks are held in the portfolio for a full year. This method necessitates overlapping portfolio formation periods. Portfolios are formed every month, but because the stocks are held for the ensuing 12 months, $1/12^{th}$ of the portfolio changes every month. Stocks which remain low-visibility and lightly shorted for several months will end up included in the portfolio multiple times. However, this method will not bias the result in any particular direction. Moreover, any resulting cross-correlation is automatically accounted for in the calendar time portfolio methodology, because the standard errors are computed from intertemporal (rather than cross-sectional) variation in returns.

Results obtained with monthly rebalancing are consistent with those obtained with annually rebalancing. The point estimate of the long-short alpha for the low-IO, low-RSI firms is economically significant at 0.95% per month (11.4% per year). In untabulated results we also find that more aggressive parsing of the data produces long-short intercepts of greater magnitudes. For example, when the analysis is focused narrowly on firms at the intersection of the lowest IO and lowest RSI quartiles (rather than the lower three-quarters of IO and the lower half of RSI firms), the 10th-decile SIGMA firms earn a highly significant 1.84% monthly abnormal return (24.5% annually).

The third set of results in Panel B corresponds to equally-weighted portfolios with monthly rebalancing and monthly holding periods. For the one-month horizon portfolios, the alpha point estimate is positive (0.66 percent monthly), but the abnormal return does not attain statistical significance at traditional levels. Although this result is short of traditional significance levels, one should consider the possibility that monthly holding periods may not be optimal for this analysis. Merton's hypothesis predicts positive steady-state returns as compensation for bearing risk. It does not predict a mispricing phenomenon (as Miller's theory does) that might be expected to correct over a shorter horizon. As long as firms retain limited visibility, the effect of SIGMA on expected returns should be detected over longer horizons (such as one year).

The right-hand side of Panel B presents results for value-weighted (as opposed to equally weighted) portfolios. Consistent with Ikenberry and Ramnath (2002) we use the natural logarithm of the market capitalization as the weight variable, instead of using the market capitalization directly. Ikenberry and Ramnath explain that "… given the extreme skewness observed in market equity values, strict cap-weighting can lead to perverse investment weights in some months. This assumption not only reflects an unrealistic investment policy, it can lead to less precise point estimates because of the noise in these less diversified portfolios (Loughran and Ritter (2000))" (page 519). We follow Ikenberry and Ramnath and use log-value weighting to obtain much of the benefit of value weighting, while mitigating problems driven by extreme skewness in market values. Each of the three log-value weighted robustness tests produces results that remain consistent with prior findings.[12] For robustness, we have also measured idiosyncratic risk using the residuals from the four-factor Fama/French-Carhart model, rather than weekly excess raw returns (firm return minus CRSP VWRETD index). The results are very similar.

Taken as a whole, the results in Tables 3 and 4 are broadly consistent with Merton's IRH. Idiosyncratic risk is priced for low-visibility firms when short selling is not prevalent. This result is economically important. We find evidence that idiosyncratic risk is priced for the least-shorted half of the stocks of the lowest three IO quartiles, i.e. about 38% of US stocks.

IV. Idiosyncratic Risk and Return for Firms without Analyst Coverage

Another reasonable proxy for firm visibility is the level of analyst coverage. More than half the firms in our sample had no sell-side analyst coverage reported by IBES at the beginning of 1988. Even at the beginning of 2003, this fraction remained relatively high, at 36 percent. A lack of sell-side analyst scrutiny certainly seems consistent with low visibility in an IRH sense. Accordingly, we repeat our Merton tests on firms lacking analyst coverage by mirroring the tests previously performed on low-IO firms. Table 5 reports these results for our standard method; annual rebalancing, one year investment horizon, and four-factor asset-pricing model.

The first row in Table 5 shows the cross-section of monthly abnormal returns for all zero-analyst firms. Although these firms are not presorted on RSI, there is some evidence of a positive relation between SIGMA and abnormal returns. Specifically, the abnormal

[12] For completeness, we also examine results based on "strict" value weighting (i.e. without taking the natural log of the market capitalization). The results (not tabulated) do not attain statistical significance, consistent with Ikenberry and Ramnath's (2002) conjecture.

returns are monotonically increasing for SIGMA deciles 4 through 10. However, the long-short portfolio t-statistic does not denote statistical significance.

Once we control for RSI, we find results consistent with the IRH that are both economically and statistically significant. The second and third rows of Panel A report results for zero-analyst firms that have been further segregated into portfolios of low-RSI and high-RSI firms each month. Again, we segment these firms into deciles based on SIGMA ranking. Thus, the twenty portfolios presented in the second and third row of Panel A have an equal number of firms in each month of the analysis.

For zero-analyst firms that also have low RSI, the results strongly support Merton's hypothesis. Abnormal returns rise in a near-monotonic manner from the third SIGMA decile to the tenth decile. The tenth decile's abnormal return is 1.462% per month, which compounds to 19.0% annually. This is significantly higher than the abnormal return of the first decile (0.461% per month or 5.6% per year). The long-short portfolio abnormal return is also positive and statistically significant. In contrast, for zero-analyst firms with high RSI (relative to other zero-analyst firms); long-short portfolio returns are actually negative.

Table 6 presents robustness measures for the long-short portfolio alphas in Table 5. As we will show, the results observed in Table 5 prove to be quite robust to methodological variations. Table 6 follows the same format as Table 4. In Panel A the zero-analyst, low-RSI firms produce statistically significant positive long-short abnormal returns for all pricing models considered. In contrast, high-RSI firms do not exhibit significantly positive abnormal long-short returns; in fact, some of the intercepts are negative. Moreover, although these zero-analyst firms are likely to be lightly traded, the results do not appear to be liquidity driven. The addition of a liquidity factor does not change the main conclusion from Table 5.

In Panel B we use the four-factor asset-pricing model and explore alternative portfolio weighting methods, rebalancing frequencies, and investment horizons. The first two columns of Panel B duplicate the long-short results from Table 5. For low-RSI firms, each alternative specification presented in Panel B produces an even more positive intercept of greater statistical significance, when compared to the leftmost equally-weighted, annually rebalanced, 12-month portfolios. For example, when portfolios are rebalanced monthly and held for a one-year investment horizon, the log-value weighted long-short returns approach 1.8% per month (23.8% annually).[13]

None of the portfolios of more heavily shorted firms produce statistically-significant positive alphas. In fact the alphas are often negative. In sum, the results of Tables 5 and 6 provide very strong support for Merton's IRH.

V. Cross-Sectional Analysis (Fama-MacBeth Regressions)

In Sections III and IV, we see the positive effect of SIGMA on expected returns for low visibility stocks, i.e., stocks that are in the lower half of the sample based on the RSI level. However, these results are based on portfolio selection methods that, of necessity, are somewhat arbitrary. To overcome this concern, we conduct a set of cross-sectional Fama-MacBeth regressions of returns on continuous visibility metrics, RSI, SIGMA, and various

[13] For robustness, we also measure idiosyncratic risk using the residuals from the four-factor Fama/French-Carhart model, with similar results throughout.

control variables. The results of this analysis significantly strengthen the evidence in favor of Merton's IRH.

There are at least two important advantages of the Fama-MacBeth analysis relative to the long-short-portfolio calendar-time analysis. First, the information from all firms is considered in the Fama-MacBeth framework. The long-short calendar-time portfolios compare only the lowest and highest SIGMA deciles. Second, the Fama-MacBeth method easily incorporates additional risk factors and control variables into the cross-sectional analysis.

Our regressions deviate slightly from Fama and MacBeth's original method in that we use continuous variables rather than portfolio grouped variables. However, the following results are also evident using portfolio groupings. In the following tests, for each firm we measure future equally-weighted raw returns for the one-month holding period. Each month, these future raw returns are regressed on continuous proxies for visibility, short sale constraint, idiosyncratic volatility, as well as several control variables that are related to the cross-section of stock returns. These right-hand-side variables are all measured at t=0. The regression loadings are averaged intertemporally (across all months in the sample), and the results are presented in Table 7.

Column (1) presents results from the following specification:

$$ret_{i,t+1} = \alpha_0 + \alpha_1 IO_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY_t$$
$$\alpha_5 (MERTON\_DUMMY*SIGMA)_t + \varepsilon_t \qquad (3)$$

The continuous variables used are as follows: IO (Institutional Ownership), the proportion of shares held by institutions, RSI is the Relative Short Interest for the firm, our proxy for dispersion of opinion. SIGMA is the idiosyncratic risk of the firm. Because each of these three variables is interrelated in Merton's hypothesis, we create an interaction term to capture the marginal effect of SIGMA when firms otherwise reside in the Merton space. Because interactions of three variables makes the coefficient estimate difficult to interpret, we construct the variable MERTON_DUMMY that is equal to 1 if the firm is both in the lowest three quartiles of IO and the lower half of RSI, and equal to zero otherwise. We include MERTON_DUMMY both as a stand-alone variable and also interacted with SIGMA. The stand-alone variable ensures that the coefficient of the interaction term conveys information about the effect of SIGMA on stock returns over the Merton region of the security space.

The coefficient of interest in the above regression is α_5, which is the marginal impact of SIGMA on returns when visibility and RSI are both low. In column (1) the coefficient on this interaction term is positive and statistically significant at better than the one percent level. This result conforms to Merton's IRH.

The model used in column (2) incorporates several additional control variables. LOG_SIZE is the logarithm of the firm's market capitalization, B/M is the book to market ratio of the firm, PRIOR_RET is the prior year raw holding period return (momentum), and ILLIQUIDITY is the Amihud (2002) illiquidity measure of the firm.[14] The IL measure is estimated for each firm over the previous 250 days, using the following model:

[14] In this section, our Fama-MacBeth results are presented using Amihud's illiquidity measure as opposed to the turnover-based measure embedded in the LMH factor. For robustness, we verify that our results (untabulated) remain substantially unchanged when *turnover* is used in place of the Amihud measure. We present this section's results using Amihud's metric since this proxy is more commonly used in Fama-MacBeth regressions.

$$IL_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} |R_{i,d}| / VOL_{i,d}$$

Here, $|R_{i,d}|$ is the absolute value of the daily percentage return for firm *i* on day *d*, $VOL_{i,d}$ is the total dollar trading volume (no. shares times price) for firm *i* on day *d*, in millions USD, and D_t equals the number of trading days of nonzero volume. High values of IL denote illiquidity. The results in column (2) are qualitatively identical to those reported in column (1). We conclude that SIGMA is positively correlated with returns for firms in the Merton space, even after controlling for the usual asset-pricing factors.

The models in columns (3) and (4) are identical to those in columns (1) and (2), except that the IO visibility metric is now replaced by NO_ANALYSTS. This variable equals unity when the firm lacks sell-side analyst coverage in IBES; zero otherwise. For these regressions, the MERTON_DUMMY is unity for firms with no analysts and below median RSI. We hypothesize that the coefficient on MERTON_DUMMY*SIGMA will be positive. For both models (3) and (4), we find that the point estimate of this interaction is positive and statistically significant, consistent with Merton's IRH.

In untabulated tests we repeat the analysis in Table 7 using a holding period equal to one year instead of one month. The regressions are still performed monthly, resulting in overlapping returns. We correct for the resulting cross-correlation using the Newey-West procedure. The results are qualitatively similar to those reported in the table. We also examine additional specifications and find that the inclusion or deletion of various combinations of control variables does not change the sign or level of significance for coefficient of interest. In addition, results remain unchanged when the monthly portfolio returns are value-weighted with the log of the market capitalization of each stock.

VI. Summary and Conclusions

Merton (1987) presents an "investor recognition hypothesis" (IRH) which extends the standard CAPM model under the assumption that investors only hold securities whose risk and returns characteristics they are familiar with. Because these investors hold under-diversified portfolios, they demand compensation for idiosyncratic risk. Accordingly, ex-post returns are positively related to firms' idiosyncratic risk.

Direct tests of Merton's predicted positive correlation between idiosyncratic risk and returns are relatively rare. Those which have been undertaken have concluded that stocks with high idiosyncratic volatility have "abysmally low average returns," an opposite conclusion to the implications of Merton (1987). Previous studies have noted that the low returns to idiosyncratic risk seem to be more consistent with the predictions of Miller (1977). Miller theorized that short sale constraints will result in poor returns for stocks with high dispersion of investor opinion, an attribute known to be positively correlated with trading volatility.

We hypothesize that these previous tests of Merton fail to find that idiosyncratic risk is priced for two reasons. First, Merton's hypothesis applies only to stocks with low visibility (those stocks not "recognized" by investors). Prior studies have not explicitly controlled for visibility. Second, firms with high levels of short selling are likely either to have high dispersion of investor opinion such that the conditions for Miller's hypothesized overvaluation are present, or to have negative information that is not yet incorporated in prices. Our tests control for both visibility and short selling activities.

Using low institutional holdings as a proxy for low visibility, we examine firms which also have relatively low short sales activity. These firms are unlikely to possess

Miller's requisite dispersion of beliefs and are also unlikely to have negative information that is not immediately priced. Using the calendar-time portfolio approach, we compare the returns of high volatility firms against firms with low volatility. We find idiosyncratic risk is priced for the least-shorted half of stocks belonging to the lowest three quartiles of institutional ownership. In other words, idiosyncratic risk appears to be priced for an economically significant fraction of US stocks.

These findings are robust to alternative asset pricing model specifications, alternative portfolio weighting methods, alternative rebalancing frequencies, and alternative investment horizons. Each of these findings is qualitatively replicated when we consider the lack of sell-side analyst coverage, rather than low institutional ownership, as the indicator of low visibility.

For robustness we also conduct a set of cross-sectional Fama-MacBeth regressions of monthly portfolio returns using alternative visibility metrics. Consistent with the calendar-time approach, the Fama-MacBeth regressions reveal that idiosyncratic risk is priced for low visibility firms that are not subject to high levels of short selling, again with high levels of statistical significance. The regression results hold whether visibility is proxied using institutional ownership or the lack of analyst coverage.

Thus, except where firms possess high visibility (inconsistent with Merton's assumptions) or where firms have high short selling (consistent with Miller's requisite dispersion of beliefs), we find that idiosyncratic risk is priced in accordance with the investor recognition hypothesis forwarded by Merton (1987).

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Table1: Descriptive statistics

Panel A presents a description of each proxy variable for various calendar dates: January 1988, January 1993, January 1998, and December 2002. Proxies are estimated for all U.S.-domiciled common stocks listed on the NYSE and NASDAQ. For each calendar date, the *Idiosyncratic Risk* (*SIGMA*) is the standard deviation of the excess weekly returns (firm return minus CRSP value weighted return) computed over the prior 52 weeks (week ending defined as of Wednesday's close). The *I/B/E/S Analyst Forecast Dispersion* is the standard deviation of I/B/E/S earnings per share forecasts for the next fiscal year end, scaled by the forecast mean. The *Relative Short Interest (RSI)* is measured as the short interest divided by the number of outstanding shares. The *Institutional Ownership (IO)* is measured by dividing the reported number of shares held by institutions (SEC 13F filings obtained from Thomson Financial) by the total number of outstanding shares reported by CRSP. Panel B lists the total number of U.S. domiciled common stocks listed on CRSP, along with both the number and percentage without analyst coverage on I/B/E/S.

Panel A: Descriptive statistics for SIGMA, RSI, and IO

Dependent Variable	Date	N. Obs.	Mean	First Percentile	First Quartile	Median	Third Quartile	99th Percentile
Idiosyncratic Risk: *SIGMA*	198801	5179	0.0748	0.0277	0.0454	0.0637	0.0919	0.2175
	199301	4930	0.0771	0.0182	0.0423	0.0639	0.0953	0.2719
	199801	6414	0.0733	0.0221	0.0414	0.0628	0.0917	0.2317
	200212	4794	0.0835	0.0249	0.0461	0.0689	0.1060	0.2648
Relative Short Interest (%): *RSI*	198801	1145	0.0083	0.0000	0.0009	0.0026	0.0071	0.0981
	199301	4166	0.0105	0.0000	0.0006	0.0023	0.0086	0.1236
	199801	6111	0.0157	0.0000	0.0005	0.0038	0.0163	0.1605
	200212	4413	0.0266	0.0000	0.0013	0.0096	0.0213	0.2333
Institutional Ownership (%): *IO*	198801	4701	0.2131	0.0008	0.0463	0.1527	0.3314	0.7323
	199301	4962	0.2687	0.0010	0.0666	0.2114	0.4305	0.8195
	199801	6551	0.3197	0.0009	0.1000	0.2658	0.5151	0.9006
	200212	4686	0.4007	0.0009	0.1238	0.3676	0.6494	0.9934

Panel B: I/B/E/S analyst coverage of CRSP listed firms

	Date	Total no. CRSP firms	% without analyst coverage
Analyst coverage on I/B/E/S	198801	5923	51.12
	199301	5607	43.25
	199801	7132	31.35
	200212	4971	36.07

Table 2: Abnormal returns as a function of idiosyncratic risk

Calendar time portfolio abnormal returns are shown as a function of idiosyncratic risk (SIGMA) for all CRSP listed common stocks (CRSP share codes 10 and 11) of U.S. domiciled NYSE and NASDAQ firms. SIGMA is the standard deviation of the excess weekly returns (firm return minus CRSP value weighted return) computed over the prior 52 weeks (week ending on Wednesday's close). SIGMA deciles are assigned annually at the end of June, beginning with June 1988 and ending with June 2002) by sorting all NYSE and NASDAQ firms on SIGMA. The abnormal returns are computed by forming equally-weighted calendar-time portfolios of 12 month horizon and regressing the excess portfolio returns ($R_{p,t}$ - $R_{f,t}$) on a four factor model containing the three Fama and French (1993) risk factors (R_m - R_f, SMB, HML) as well as the momentum factor of Carhart (1997) (UMD). Calendar time portfolios are re-balanced once per year at the end of June. The estimation method is OLS. The abnormal return for each sub-sample is the intercept (α_p) from the following regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + e_{p,t}.$$

We also report the long-term abnormal return of a long-short (or zero-investment) portfolio, consisting of long positions of stocks in the highest SIGMA decile and short positions of stocks in the lowest SIGMA decile. The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of 12-month horizon and regressing the difference in portfolio returns ($R_{sigma\ 10,\ t}$ - $R_{sigma\ 1,\ t}$) on the four factor model: The abnormal return for each sub-sample is the intercept or alpha (α_p) from the following regression:

$$R_{high\text{-}sigma,t} - R_{low\text{-}sigma,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + e_{p,t}.$$

Monthly abnormal returns are expressed in decimal point notation. For example, an abnormal return of 0.00290 represents 29.0 bps per month. For each portfolio, the monthly mean number of firms is reported as "Mean No. obs." The t-statistics (one-tail test) reporting positive statistical significance are shown in brackets below the intercepts and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. Results are for the July 1988 to June 2003 period.

	Idiosyncratic Risk Decile (SIGMA)											
	1st decile (lowest)	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile (highest)	Long-short portfolio: deciles 10 minus 1	*t-statistic* of long-short portfolio
Abnormal return	0.00290 *[1.89]*****	0.00223 *[1.44]**	0.00155 *[1.04]*	0.00094 *[0.67]*	-0.00015 *[-0.13]*	-0.00058 *[-0.57]*	-0.00100 *[-0.96]*	0.00200 *[1.46]**	0.00387 *[1.65]*****	0.00837 *[1.96]*****	0.00547	*[0.98]*
Mean No. obs.	537	533	530	524	526	523	518	515	503	461		

*, **, *** denotes positive statistical significance at the 10, 5, and 1 percent levels, respectively

Table 3: Abnormal returns as a function of idiosyncratic risk, conditioned on institutional ownership and relative short interest

For each end of June, beginning with 1988 and ending with 2002, all common stocks of U.S. domiciled NYSE and NASDAQ firms are first sorted on the Institutional Ownership percentage (IO) into quartiles. In Panel A below, we next sort each IO quartile into quartiles based on the Relative Short Interest (RSI), and then further sort each of these sixteen IO/RSI groups into deciles based on the idiosyncratic risk (SIGMA).

In Panel B below, the three lowest IO quartiles (1, 2, and 3) are grouped together, while quartile 4 (highest) remains a separate group. We next sort each IO grouping into halves based on Relative Short Interest (RSI). Next, firms within each of these four IO/RSI groupings are further sorted into deciles based on idiosyncratic risk (SIGMA). We also perform a sorting (unconditional of RSI) of these two IO groupings into SIGMA deciles. In both Panels A and B, we report the long-term abnormal returns for each portfolio. These are computed by forming equally-weighted calendar-time portfolios of 12-month horizon and regressing the excess portfolio returns ($R_{p,t}$-$R_{f,t}$) on the three Fama and French (1993) risk factors (R_m-R_f, SMB, HML) as well as Carhart's (1997) momentum factor (UMD). The abnormal return for each portfolio is the intercept (α_p) from the following regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

We also report the long-term abnormal return of long-short (or zero-investment) calendar-time portfolios, consisting of a long position in stocks with the highest SIGMA decile and a short position in stocks from the lowest SIGMA decile. The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of 12-month horizon and regressing the difference in portfolio returns ($R_{sigma\ 10,\ t}$ - $R_{sigma\ 1,\ t}$) on the same four factors. The abnormal return is the intercept or alpha (α_p) from the following regression:

$$R_{sigma\ 10,\ t} - R_{sigma\ 1,\ t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_p SMB_t + h_p HML_t + u_p UMD_t + e_{p,t}.$$

Calendar-time portfolios are re-balanced once per year at the end of June. The estimation method is OLS. Monthly abnormal returns expressed in decimal point notation. For example, an abnormal return of 0.00467 corresponds to 46.7 bps. per month. The t-statistics (one-tail test) reporting positive statistical significance are shown in the last column and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. Results are for the July 1988 to June 2003 period.

Panel A: Firms sorted into Institutional Ownership (IO) quartiles; with each IO quartile sorted into Relative Short Interest (RSI) halves; and each IO/RSI group further sorted into Idiosyncratic Risk (SIGMA) deciles.

Institutional Ownership (IO) quartile	Relative Short Interest (RSI) group	*Idiosyncratic Risk decile (SIGMA)* 1st decile (lowest)	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile (highest)	Long-short portfolio [decile 10] – [decile 1] abnormal returns	Long-short portfolio *t-statistic*
1 (lowest quartile)	RSI1	0.00467	0.00750	0.00104	0.00832	0.00114	0.00728	0.01480	0.01109	0.01385	0.00828	0.00361	*[0.48]*
	RSI2	0.00520	0.00314	0.00691	0.00317	0.00072	0.00591	0.00321	0.00106	0.01542	0.00883	0.00363	[0.41]
	RSI3	0.00392	0.00129	-0.00142	-0.00397	-0.00123	-0.00255	0.00127	0.00691	0.00213	0.00750	0.00358	*[0.40]*
	RSI4	0.00108	-0.00367	-0.00205	-0.00313	-0.00837	-0.01281	-0.00151	-0.00840	0.00178	-0.00810	-0.00919	*[-0.93]*
2	RSI1	0.00421	0.00591	0.00693	0.00184	0.00585	0.00138	0.00279	0.01220	0.00782	0.01322	0.00901	*[1.34]**
	RSI2	0.00754	0.00651	0.00443	0.00445	0.00090	0.00110	0.00320	0.00749	0.00910	0.01693	0.00940	*[1.28]**
	RSI3	0.00322	0.00416	0.00362	-0.00130	0.00213	0.00353	0.00108	0.00605	0.01451	0.01574	0.01252	*[1.64]**
	RSI4	-0.00181	-0.00446	-0.00635	-0.00410	-0.00446	-0.00319	-0.00426	-0.00360	0.00040	-0.00663	-0.00482	*[-0.65]*
3	RSI1	0.00403	0.00283	0.00094	-0.00045	0.00382	-0.00132	-0.00141	-0.00290	0.00380	0.00983	0.00580	*[1.26]*
	RSI2	0.00271	0.00145	0.00207	0.00199	0.00116	0.00458	0.00273	0.00416	0.00405	0.00951	0.00680	*[1.47]**
	RSI3	0.00071	0.00198	-0.00034	0.00312	-0.00053	-0.00420	0.00140	-0.00256	0.00505	0.00202	0.00130	*[0.27]*
	RSI4	-0.00026	0.00167	-0.00197	0.00253	0.00004	-0.00723	-0.00562	-0.00414	-0.00087	-0.00211	-0.00185	*[-0.32]*
4 (highest quartile)	RSI1	0.00191	0.00190	0.00088	-0.00019	0.00294	0.00019	0.00325	-0.00186	-0.00002	0.00104	-0.00086	*[-0.24]*
	RSI2	0.00273	0.00099	0.00051	0.00117	0.00045	0.00061	0.00059	-0.00110	-0.00013	0.00168	-0.00105	*[-0.30]*
	RSI3	0.00096	0.00148	0.00241	0.00115	0.00010	0.00054	0.00326	-0.00120	-0.00164	0.00441	0.00345	*[0.83]*
	RSI4	-0.00029	-0.00181	-0.00290	-0.00362	0.00074	-0.00117	0.00058	0.00348	0.00376	-0.00424	-0.00395	[-0.82]

*, **, *** denotes positive statistical significance at the 10, 5, and 1 percent levels, respectively

Panel B: Institutional Ownership (IO) quartiles 1 through 3 grouped together, quartile 4 (highest) kept separate; with each IO grouping also further sorted into Relative Short Interest (RSI) halves

Institutional Ownership (IO) quartile	Relative Short Interest (RSI) group	*Idiosyncratic Risk decile (SIGMA)* 1st decile (lowest)	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile (highest)	Long-short portfolio [decile 10] – [decile 1] abnormal returns	Long-short portfolio t-statistic
1, 2 and 3 (lowest three quartiles)	All RSI	0.00346	0.00277	0.00268	0.00016	-0.00119	-0.00127	0.00179	0.00288	0.00456	0.00764	0.00418	*[0.73]*
	Lower RSI half	0.00509	0.00512	0.00355	0.00291	0.00107	0.00005	0.00675	0.00616	0.00919	0.01482	0.00973	*[1.66]***
	Upper RSI half	0.00132	0.00037	0.00125	-0.00287	-0.00179	-0.00310	-0.00228	-0.00035	0.00091	-0.00130	-0.00262	*[-0.42]*
4 (highest)	All RSI	0.00191	0.00115	0.00042	0.00014	0.00017	-0.00029	0.00109	-0.00080	0.00077	0.00137	-0.00054	*[-0.18]*
	Lower RSI half	0.00201	0.00159	0.00081	0.00118	0.00025	0.00147	0.00171	-0.00023	-0.00173	0.00194	-0.00007	*[-0.02]*
	Upper RSI half	0.00081	0.00107	-0.00065	-0.00108	-0.00140	0.00152	-0.00003	0.00130	0.00187	-0.00032	-0.00114	*[-0.28]*

*, **, *** denotes positive intercepts with statistical significance at the 10, 5, and 1 percent levels, respectively

Table 4: Robustness tests of long-short portfolios conditioned on institutional ownership

This table presents robustness tests of the long-short portfolio regressions presented in Table 3. Only long-short portfolio results are reported below. In Panel A, we examine robustness across various alternative calendar time pricing models, while maintaining the equally-weighted portfolio, annual portfolio holding periods, and annual portfolio rebalancing procedure of Table 3. In Panel B, we only present the four-factor model, while varying the portfolio holding periods and frequency of portfolio rebalancing, and we also present results where the firms are weighted by the logarithm of market capitalization.

We report the long-term abnormal return of long-short (or zero-investment) calendar time portfolios, consisting of a long position in stocks with the highest SIGMA decile and a short position in stocks with the lowest SIGMA decile. The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of either 12-month horizon (both in Panels A and B) or one-month horizon (Panel B only), and regressing the difference in portfolio returns ($R_{sigma\ 10,\ t}$ - $R_{sigma\ 1,\ t}$) on four -factor, five factor, Fama/French three-factor, CAPM, and Raw return models: The five factor model augments the four factor model with the LMH liquidity risk factor factor of Eckbo and Norli (2005), where LMH is the monthly difference in returns between low and high liquidity firms. In Panel A we utilize equally weighted portfolios, while in Panel B we utilize both equally and log-of-market-capitalization weighted portfolios. The abnormal return for each sub-sample is the intercept, t (α_p) from the following regression (five factor model shown):

$$R_{sigma\ 10,\ t} - R_{sigma\ 1,\ t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + l_pLMH_t + e_{p,t}.$$

For Panel A, we repeat the Table 3 process where calendar-time portfolios are re-balanced once per year at the end of June, and the results are for the July 1988 to June 2003 period. In Panel B, we explore (1) one-month holding periods with monthly rebalancing and (2) twelve month holding periods with monthly rebalancing, where results of (1) and (2) are presented for the February 1988 to December 2002 periods. The estimation method is OLS. An abnormal return of 0.00418 below is to be interpreted as an abnormal return of 41.8 bps. per calendar month. The t-statistics (one-tail test) reporting positive statistical significance are shown in brackets beside the intercepts and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. For expositional convenience, the first columns of both Panel A and Panel B (4-factor results) restate long-short-portfolio results from Table 3.

Panel A: Alternative Asset Pricing Models

Institutional Ownership (IO) quartile	Relative Short Interest (RSI) group	Asset Pricing Model									
		4-factor		5-factor		3-factor		CAPM		Raw Returns	
		Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*
1, 2 and 3 (lowest three quartiles)	All RSI values	0.00418	*[0.73]*	0.00936	*[1.70]***	-0.00101	*[-0.18]*	-0.00520	*[-0.91]*	0.00812	*[0.88]*
	Lower RSI half	0.00973	*[1.66]***	0.01387	*[2.46]****	0.00805	*[1.58]*	0.00515	*[0.97]*	0.01652	*[1.99]***
	Upper RSI half	-0.00262	*[-0.42]*	0.00302	*[0.51]*	-0.01037	*[-1.70]*	-0.01568	*[-2.42]*	-0.00092	*[-0.09]*
4 (highest)	All RSI values	-0.00054	*[-0.18]*	0.00311	*[1.10]*	-0.00540	*[-1.75]*	-0.01122	*[-2.78]*	-0.00118	*[-0.17]*
	Lower RSI half	-0.00007	*[-0.02]*	0.00218	*[0.78]*	-0.00348	*[-1.25]*	-0.00774	*[-2.25]*	0.00018	*[0.03]*
	Upper RSI half	-0.00114	*[-0.28]*	0.00306	*[0.81]*	-0.00548	*[-1.40]*	-0.01241	*[-2.49]*	-0.00159	*[-0.21]*

*, **, *** denotes positive statistical significance at the 10, 5, and 1 percent levels, respectively

Panel B: Alternative rebalancing periods, investment horizons, and portfolio weighting

Institutional Ownership (IO) quartile	Relative Short Interest (RSI) group	Portfolio weighting method											
		Equally-weighted						Log-value-weighted					
		Rebalancing frequency											
		Annual		Monthly		Monthly		Annual		Monthly		Monthly	
		Investment Horizon											
		One year		One year		One month		One year		One year		One month	
		Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*
1, 2 and 3 (lowest three quartiles)	All RSI values	0.00418	*[0.73]*	0.00300	*[0.51]*	-0.00175	*[-0.29]*	0.01197	*[1.91]***	0.01048	*[1.63]**	0.00514	*[0.78]*
	Lower RSI half	0.00973	*[1.66]***	0.00905	*[1.55]**	0.00662	*[1.12]*	0.01683	*[2.64]****	0.01612	*[2.51]****	0.01289	*[1.96]***
	Upper RSI half	-0.00262	*[-0.42]*	-0.00364	*[-0.58]*	-0.01090	*[-1.60]*	0.00617	*[0.93]*	0.00476	*[0.71]*	-0.00295	*[-0.41]*
4 (highest)	All RSI values	-0.00054	*[-0.18]*	0.00069	*[0.24]*	-0.00143	*[-0.43]*	0.00106	*[0.35]*	0.00198	*[0.68]*	-0.00022	*[-0.07]*
	Lower RSI half	-0.00007	*[-0.02]*	0.00226	*[0.86]*	0.00321	*[1.00]*	0.00163	*[0.56]*	0.00381	*[1.44]**	0.00570	*[1.75]***
	Upper RSI half	-0.00114	*[-0.28]*	-0.00037	*[-0.11]*	-0.00335	*[-0.81]*	-0.00022	*[-0.06]*	0.00077	*[0.23]*	-0.00223	*[-0.55]*

*, **, *** denotes positive statistical significance at the 10, 5, and 1 percent levels, respectively

Table 5: Abnormal returns as a function of idiosyncratic risk, conditioned on relative short interest and absence of analyst coverage

This table considers only common stocks with no I/B/E/S analyst coverage. These stocks are sorted into deciles based on SIGMA, and abnormal returns based on SIGMA-decile groups are presented as the first row of the table. We also sort stocks into halves based on Relative Short Interest (RSI). Next, firms within each RSI grouping are further sorted into deciles based on SIGMA, producing a final sorting into 20 (2x10) portfolios. The portfolio assignments are conducted annually at the end of June (from 1988 to 2002). Abnormal returns for these portfolios are presented in the second and third rows. Abnormal returns are computed by forming equally-weighted calendar-time portfolios of 12-month horizon and regressing the excess portfolio returns ($R_{p,t}$-$R_{f,t}$) on the three Fama and French (1993) factors (R_m-R_f, SMB, HML) as well as Carhart's (1997) momentum factor (UMD). The abnormal return for each portfolio is the intercept or alpha (α_p) from the following regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + e_{p,t}.$$

We also report the long-term abnormal return of long-short (or zero-investment) calendar-time portfolios, consisting of long positions in stocks with the highest-SIGMA decile and short positions in stocks from the lowest-SIGMA decile. The long-short portfolio abnormal returns are computed by forming equally-weighted calendar-time portfolios of 12-month horizon and regressing the difference in portfolio returns ($R_{sigma\ 10,\ t}$ - $R_{sigma\ 1,\ t}$) on the same four factors. The abnormal returns of each long-short portfolio are the intercepts (α_p) from the following regression:

$$R_{sigma\ 10,\ t} - R_{sigma\ 1,\ t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + e_{p,t}.$$

Calendar-time portfolios are re-balanced once per year at the end of June. The estimation method is OLS. Results are presented for the July 1988 to July 2003 period. Monthly abnormal returns expressed in decimal point notation. For example, an abnormal return of 0.00328 corresponds to 32.8 bps. per month. The t-statistics (one-tail test) reporting positive statistical significance are shown in the last column and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. Results are for the July 1988 to June 2003 period.

	Idiosyncratic Risk decile (SIGMA)											
Relative Short Interest (**RSI**) half of firms with zero I/B/E/S analyst coverage	1st decile (lowest)	2nd decile	3rd decile	4th decile	5th decile	6th decile	7th decile	8th decile	9th decile	10th decile (highest)	Long-short portfolio: deciles 10 minus 1	*t-statistic* of long-short portfolio
All RSI values	0.00328	0.00220	0.00059	-0.00080	-0.00062	0.00150	0.00281	0.00624	0.00752	0.00941	0.00613	[0.97]
Lower RSI half	0.00461	0.00442	0.00229	0.00483	0.00251	0.00481	0.00819	0.00717	0.01003	0.01462	0.01001	[1.75]**
Upper RSI half	0.00199	-0.00032	-0.00498	-0.00317	-0.00477	-0.00237	0.00201	0.00397	-0.00049	0.00070	-0.00128	[-0.18]

*, **, *** denotes positive statistical significance at the 10, 5, and 1 percent levels, respectively

Table 6: Robustness tests of long-short portfolios using analyst coverage as proxy for visibility

This table presents robustness tests of the long-short regressions presented in Table 5. We report results for long-short regressions for firms without analyst coverage as reported by I/B/E/S. The first row presents results for the universe of firms without analyst coverage, followed by tests which sort the zero-analyst firms into below-median RSI and above median RSI groupings. In Panel A, we examine robustness across various alternative calendar time pricing models, while maintaining the equally-weighted portfolio, annual portfolio holding periods, and annual portfolio rebalancing procedure of Table 5. In Panel B, we only present the four-factor model, while varying the portfolio holding periods and frequency of portfolio rebalancing, and we also present results where the firms are weighted by the logarithm of market capitalization.

We report the long-term abnormal return of long-short (or zero-investment) calendar time portfolios, consisting of a long position in stocks with the highest SIGMA decile and a short position in stocks with the lowest SIGMA decile. The long-short portfolio abnormal returns are computed by forming calendar-time portfolios of either 12-month horizon (both in Panels A and B) or one-month horizon (Panel B only), and regressing the difference in portfolio returns ($R_{sigma\ 10,\ t}$ - $R_{sigma\ 1,\ t}$) on four-factor, five factor, Fama/French three-factor, CAPM, and Raw return models: The five factor model augments the four factor model with the LMH liquidity risk factor factor of Eckbo and Norli (2005), where LMH is the monthly difference in returns between low and high liquidity firms. In Panel A we utilize equally weighted portfolios, while in Panel B we utilize both equally and log-of-market-capitalization weighted portfolios. The abnormal return for each sub-sample is the intercept, (α_p) from the following regression (five factor model shown):

$$R_{sigma\ 10,\ t} - R_{sigma\ 1,\ t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + s_pSMB_t + h_pHML_t + u_pUMD_t + l_pLMH_t + e_{p,t}.$$

For Panel A, we repeat the Table 5 process where calendar-time portfolios are re-balanced once per year at the end of June, and the results are for the July 1988 to June 2003 period. In Panel B, in addition to the annual rebalancing and holding period method of Panel A, we also explore (1) one-month holding periods with monthly rebalancing and (2) twelve month holding periods with monthly rebalancing, where results of (1) and (2) are presented for the February 1988 to December 2002 periods. The estimation method is OLS. An abnormal return of 0.00613 below is to be interpreted as an abnormal return of 61.3 bps. per calendar month. The t-statistics (one-tail test) reporting positive statistical significance are shown in brackets beside the intercepts and are computed from the intertemporal variation in the monthly calendar-time portfolio returns. For expositional convenience, the first columns of both Panel A and Panel B (4-factor results) restate long-short-portfolio results from Table 5.

Panel A: Alternative Asset Pricing Models

Relative Short Interest (RSI) group	Asset Pricing Model									
	4-factor		5-factor		3-factor		CAPM		Raw Returns	
	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*
All RSI values	0.00613	*[0.97]*	0.01092	*[1.76]**	0.00452	*[0.75]*	0.00101	*[0.17]*	0.01324	*[1.48]**
Lower RSI half	0.01001	*[1.75]***	0.01283	*[2.32]***	0.01087	*[1.96]***	0.00832	*[1.45]**	0.01852	*[2.25]***
Upper RSI half	-0.00128	*[-0.18]*	0.00385	*[0.54]*	-0.00268	*[-0.39]*	-0.00689	*[-0.98]*	0.00576	*[0.59]*

*, **, *** denotes statistical significance at the 10, 5, and 1 percent levels, respectively

Panel B: Alternative rebalancing periods, investment horizons, and portfolio weighting

Relative Short Interest (RSI) group	Portfolio weighting method											
	Equally-weighted						Log-value-weighted					
	Rebalancing frequency											
	Annual		Monthly		Monthly		Annual		Monthly		Monthly	
	Investment Horizon											
	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*	Ab. Ret.	*t-statistic*
All RSI values	0.00613	*[0.97]*	0.00305	*[0.47]*	0.00377	*[0.52]*	0.01314	*[1.93]**	0.01027	*[1.46]*	0.01037	*[1.36]*
Lower RSI half	0.01001	*[1.75]***	0.01170	*[1.98]***	0.01248	*[1.77]***	0.01564	*[2.32]***	0.01794	*[2.70]****	0.01756	*[2.36]****
Upper RSI half	-0.00128	*[-0.18]*	-0.00572	*[-0.82]*	-0.01143	*[-1.40]*	0.00784	*[1.01]*	0.00292	*[0.39]*	-0.00254	*[-0.30]*

*, **, *** denotes statistical significance at the 10, 5, and 1 percent levels, respectively

Table 7: Fama-Macbeth regressions

We employ the Fama and Macbeth (1973) procedure in order to examine the cross-sectional relation between firm specific returns and idiosyncratic risk, while also controlling for visibility, relative short interest levels, size, book/market, prior momentum, and illiquidity.

We estimate raw firm specific holding period returns for one month horizons for all firms. For the Fama/Macbeth procedure, the following four OLS regression models are estimated for each calendar month (n=180 months), where all returns are regressed onto ex ante independent variables:

Model 1: $ret_{i,t+1} = \alpha_0 + \alpha_1 IO_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY + \alpha_5 (MERTON\_DUMMY*SIGMA)_t + \varepsilon_t$

Model 2: $ret_{i,t+1} = \alpha_0 + \alpha_1 IO_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY + \alpha_5 (MERTON\_DUMMY*SIGMA)_t + \alpha_6 LOG\_SIZE_t + \alpha_7 B/M_t + \alpha_8 PRIOR\_RET_t + \alpha_9 ILLIQUIDITY_t + \varepsilon_t$

Model 3: $ret_{i,t+1} = \alpha_0 + \alpha_1 NO\_ANALYSTS_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY + \alpha_5 (MERTON\_DUMMY*SIGMA)_t + \varepsilon_t$

Model 4: $ret_{i,t+1} = \alpha_0 + \alpha_1 NO\_ANALYSTS_t + \alpha_2 RSI_t + \alpha_3 SIGMA_t + \alpha_4 MERTON\_DUMMY + \alpha_5 (MERTON\_DUMMY*SIGMA)_t + \alpha_6 LOG\_SIZE_t + \alpha_7 B/M_t + \alpha_8 PRIOR\_RET_t + \alpha_9 ILLIQUIDITY_t + \varepsilon_t$

Where, $ret_{i,t+1}$ is the holding period return of the firm, measured during the one-month following portfolio formation. The continuous variables used are as follows: IO (Institutional Ownership), the proportion of shares held by institutions, used as a visibility proxy in Models 1 and 2. NO_ANALYSTS, a dummy equal to 1 if the firm has zero analyst coverage on I/B/E/S and equal to zero otherwise, also used as a visibility proxy in Models 3 and 4. RSI is the Relative Short Interest for the firm, our proxy for dispersion of opinion. SIGMA is the idiosyncratic risk of the firm. LOG_SIZE is the logarithm of the firm's market capitalization, B/M is the book to market ratio of the firm, PRIOR_RET is the prior year raw holding period return (momentum), and ILLIQUIDITY is the Amihud (2002) illiquidity measure of the firm.

We expect the Merton effect to hold for the intersection of low visibility and low RSI — we thus construct the dummy variable MERTON_DUMMY. For Models 1 and 2 above, MERTON_DUMMY is equal to 1 if the firm is both in the lowest three quartiles of IO and the lower half of RSI, and equal to zero otherwise. In Models 3 and 4 above, MERTON_DUMMY is equal to 1 if the firm has both no analyst coverage and is in the lower half of RSI, and is equal to zero otherwise.

Reported below are the time series averages of the regression coefficients. The interacted variables are reported with one-tailed t-statistics testing for positive statistical significance. Statistical significance for all other variables is considered using two-tailed tests.

Variable	Model			
	(1)	(2)	(3)	(4)
Intercept	0.01321	0.05653	0.01545	0.06085
	*[4.73]****	*[6.34]****	*[4.79]****	*[7.17]****
IO	0.00350	0.01113		
	[0.88]	*[4.08]****		
NO_ANALYSTS			-0.00098	-0.00622
			[-0.46]	*[-3.62]****
RSI	-0.09133	-0.07797	-0.11627	-0.07979
	*[-5.17]****	*[-4.50]****	*[-5.71]****	*[-4.01]****
SIGMA	-0.04390	-0.13347	-0.03143	-0.12275
	[-0.79]	*[-2.81]****	*[-0.58]*	*[-2.64]****
MERTON_DUMMY	-0.00096	-0.00698	-0.00258	-0.00815
	[-0.49]	*[-3.62]****	*[-0.83]*	*[-2.85]****
MERTON_DUMMY * SIGMA	0.10731	0.10618	0.10683	0.11263
	*[3.87]****	*[4.13]****	*[2.73]****	*[3.27]****
LOG_SIZE		-0.00333		-0.00333
		*[-5.36]****		*[-5.24]****
B/M		0.00186		0.00197
		*[2.72]****		*[2.85]****
PRIOR_RET		0.00677		0.00704
		*[3.53]****		*[3.63]****
ILLIQUIDITY		-0.00020		-0.00012
		[-1.13]		*[-0.75]*
Avg. adj. RSQ	0.03429	0.04736	0.03381	0.04755

*, **, *** denotes statistical significance at the 10, 5, and 1 percent levels, respectively