THE IDIOSYNCRATIC VOLATILITY ANOMALY: CORPORATE INVESTMENT OR INVESTOR MISPRICING?

This version: August 2015

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ABSTRACT

Most of the literature on the idiosyncratic volatility anomaly has focused on plausible explanations for it based on investor preferences, investor irrationality or market characteristics. Surprisingly, the role of asset-pricing models and firm characteristics in the estimation of idiosyncratic risk measures has been largely neglected. Our results suggest that investment and profitability, presumably driven by managers and therefore linked to idiosyncratic risk, are able to account for the anomaly in a cross-section of stock returns. Moreover, we show that this effect is independent and complementary to the effects related to investor preference for skewness.

JEL-classification: G12

Keywords: idiosyncratic risk, corporate investment, investor mispricing, Valuation Theory, accruals, anomaly, profitability

1. Introduction

The finding that portfolios with the highest idiosyncratic risk levels yield significantly lower returns than do those with the lowest levels came as a puzzling surprise in the asset-pricing literature (Ang *et al.*, 2006 and 2009). At first sight, this empirical fact controverted the concept of diversification, supposed to be a force sufficiently strong to eliminate any predictive power of idiosyncratic risk over expected returns. However, contradicting the anomaly, under-diversification models such as that described by Merton (1987) anticipate a positive relationship between idiosyncratic risk and expected returns. Therefore, it appears that there is more to the anomaly than a simple lack of diversification. Although this observation was initially contested in papers such as Bali and Caciki (2008) and Fu (2009), several studies on the idiosyncratic volatility anomaly written since the seminal work of Ang *et al.* (2006) revealed that the information content of idiosyncratic risk has become a relevant issue in asset pricing.

This is not surprising, because understanding the nature of the relationship between risk and return is a core necessity in the field of finance; that relationship has significant effects on both researchers and practitioners. In the case of the idiosyncratic risk, the discussion has been divided into the two strands of literature that we discuss below. The first strand is formed by papers that dispute the construction of the underlying risk measure. These papers are dedicated to showing that the estimation of the idiosyncratic risk varies largely with the methodologies and data used for the analysis and conclude that the puzzling empirical observation is not robust. In addition to those discussed at the beginning of this paper, relevant examples include Huang *et al.* (2010), who link the anomaly to microstructure issues such as return reversals or trading non-synchronicity. Moreover, Han and Lesmond (2011) and Malagon et *al.* (2015) suggest that the relationship between risk and return seems to become positive as the investor's time horizon increases.

The second strand comprises papers that assume the construction of the measures involved in the controversial empirical observation is sound. Therefore, the papers focus on explaining that the negative relationship between idiosyncratic volatility and returns is driven by familiar factors, for instance investor preferences or market microstructure, that justify observing lower returns for the stocks with higher idiosyncratic risk. In this strand, Kapadia (2006) argues that idiosyncratic risk and cross-sectional skewness are highly correlated, thus linking the anomaly to investors' preference for skewness. In a similar vein, Boyer *et al.* (2010) conclude that the anomaly can be explained by investors' preference for high idiosyncratic skewness. Yet another explanation related to preferences is provided by Bali *et al.* (2011) based on the idea that investors tilt towards stocks with lottery-like payouts. Their paper shows that a sort based on this characteristic accounts for the negative relationship between returns and idiosyncratic risk. In contrast with these explanations based on investors' rationality, Gao *et al.* (2012) provide evidence showing that the relationship between idiosyncratic volatility and expected returns depends on investor sentiment.

Given the recent nature of the anomaly, the debate is active and still developing in both strands as demonstrated by papers such as Jiang *et al.* (2009), who refute the hypothesis that investors' irrationality explains the idiosyncratic volatility anomaly, and Chen *et al.* (2012), who refute the market microstructure arguments.[1] Independently of the challenges each approach has recently faced, the underlying theoretic ideas behind both strands can co-exist. In other words, investors' preference for skewness and lottery-like payout stocks does not necessarily rule out that the idiosyncratic risk measure might be poorly estimated, and vice versa.

[1] An interesting related issue is why the anomaly is not arbitraged away. This issue is addressed in papers such as Boehme *et al.* 2009, Au *et al.* 2009, Cao 2010 and Duan *et al.* 2010 that argue that idiosyncratic risk determines arbitrage cost, making the anomaly costly to arbitrage.

Surprisingly, the literature arguing the puzzle is not robust has ignored the possibility that the asset-pricing model used to estimate the idiosyncratic risk might provide a poor approximation to the concept of firm-specific risk. Indeed, idiosyncratic risk is always estimated as a residual from a particular asset-pricing model such that, if the model is inaccurate, the measure of idiosyncratic risk could be capturing more information than it should. Moreover, the asset-pricing literature is a prolific source of models that have strong theoretical grounds and that have been proven to outperform the Fama and French three-factor model in explaining the cross-section of stock returns. Examples include models based on risk factors such as momentum (Carhart, 1997), co-skewness (Harvey and Siddique, 2000), liquidity (Pastor and Stambaugh, 2003), and more recently profitability and investment (Fama and French, 2014). Therefore, leaving aside the possibility of an inaccurate asset-pricing model in favour of more-complex rationales, the literature has neglected what a major field in research on asset pricing has to say about the relationship between idiosyncratic risk and expected returns.[2] In this context, asset-pricing models based on firm characteristics are of special relevance because idiosyncratic risk should be linked to managerial decisions that, in turn, are related to firm characteristics.

In this paper, we advance the hypothesis that the idiosyncratic risk measure typically used when discussing the risk-return relationship captures information about a firm's profitability and investment that is relevant in explaining the expected returns. These two characteristics depend on managerial decision making and could intuitively be linked to idiosyncratic risk. Our approach is based on Valuation Theory, which states that a given level of profitability, investment and expected returns are negatively related under both rational and irrational investor expectations. If our hypothesis is true, this theory implies that the idiosyncratic volatility anomaly should disappear after joint controls for

[2] A notable exception to this trend is a recent paper by Hou, Xue and Zhang (2015), who account for several anomalies, including the idiosyncratic risk one, based on an empirical q-factor model. We explain later in this paper how our results diverge from theirs.

profitability and investment are considered. The main contribution of this paper is that we offer a plausible and innovative explanation for the observation of the anomaly that is totally independent from investors and solely related to corporate decisions and, therefore, to firms' characteristics. In a recent paper, Hou, Xue and Zhang (2015) show an empirical q-factor model using investment and profitability factors to account for the idiosyncratic volatility anomaly. However, because we base our analysis on characteristics, we can go further. In particular, we study how the components of investment and profitability affect the idiosyncratic volatility. The results discussed in this paper suggest that the negative relationship between idiosyncratic risk and expected returns might be related to the management of inventories. We believe that showing that firms' characteristics might be powerful in explaining the cross-section of stock returns, and that these particular interactions and their consequences for the asset-pricing field could be overlooked when only considering pricing factors, is a relevant contribution. Additionally, to the best of our knowledge, no other papers treating the effects of inventories, turnover and other components of profitability and investment are available to date. A less relevant contribution is that because our hypothesis can be tested under periods of both investors' rationality and irrationality, our results allow us to reconcile the apparently contradictory findings of Jiang *et al.* (2009) and of Gao *et al.* (2012) mentioned above.

Our results strongly support our hypothesis; in the cross-section, profitability and investment are able to account for the idiosyncratic risk anomaly when they are considered together. Moreover, this result prevails both in times characterized by high investor sentiment and times characterized by low investor sentiment. In this sense, our results appear to indicate that the idiosyncratic volatility anomaly might not be related to investors' preferences or expectations but to managerial decision making, which affects both investment and firm profitability. Moreover, we show promising results when explicitly considering profitability and investment as risk factors in the estimation of the idiosyncratic risk through the Fama and French 5-factors model (2014) given that, in this case, the anomaly is halved in alphas.

The remainder of the paper is organized as follows. Section 2 discusses the methodologies and the data we consider together with some preliminary evidence to motivate our approach. In turn, section 3 describes our empirical findings based on cross-sectional regressions including controls related to corporate variables and on portfolio sorting once idiosyncratic risk is estimated through the Fama and French (2014) five-factor model. The section also includes a discussion of the relationship between our corporate variables and skewness, a variable that has been shown to account for the negative link between idiosyncratic risk and expected returns. Section 4 concludes the paper.

2. Methodology, data and preliminary evidence

2.1. Methodology

As previously stated, our discussion is framed in the context of asset-pricing models and the fact that the empirical patterns between investment, profitability and returns that have been identified in the past might influence the robustness of the idiosyncratic volatility anomaly. These patterns can be linked to Valuation Theory, which states that investment, profitability and returns are linked such that to study the relationship between any two of these variables, it is necessary to control for the third one. These links are demonstrated by Fama and French (2006) who, using the dividend discount model and clean surplus accounting, define equity market value as follows:

$$M_t = \sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau})/(1+r)^{\tau}, \tag{1}$$

where M_t is a share market price at time t, Y_t is equity earnings per share at time t, $dB_t = B_t - B_{t-1}$ is change in book equity per share, B_t, and r is the internal rate of return on expected dividends.[3]

Assuming the internal rate of return on expected dividends, r, is approximately equivalent to the long-term average expected stock return and fixing M_t/B_t and expected earnings to book equity, firms with higher expected equity investment, $dB_{t+\tau}$, have lower expected returns. Additionally, after controlling for M_t/B_t and expected growth in book equity, more-profitable firms have higher expected returns (Fama and French, 2006). In this framework, given profitability, there is a negative relationship between investment and expected returns and, given investment, the profitability-returns relationship is positive. Evidence of these patterns and a thorough discussion on how Valuation Theory theoretically supports them can be found in Fama and French (2006) and the references therein.[4]

In this paper, we explore the idea that the usual idiosyncratic risk estimate captures the effects of investment and profitability on stock returns. In other words, our hypothesis is that the negative relationship between idiosyncratic risk and returns reflects the known empirical pattern linking investment, profitability and stock returns. In addition to the arguments based on the Valuation Theory, we believe investment and profitability are interesting variables to consider because of their link with managerial decisions that should be reflected in the firm's risk. In particular, decisions made by managers should affect investment and profitability of the firm and its idiosyncratic risk. Moreover, under the

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[3] For a discussion of why results could hold although the clean surplus accounting assumption is violated, see Fama and French (2006).

[4] Investment and profitability are not the only firm characteristics that have been shown to have explanatory power over return. Since the 1980s, empirical evidence has shown that several firm characteristics explain the cross-section of stock returns. For instance, Basu (1983) shows that stocks of high E/P firms earn higher risk-adjusted returns than do stocks of low E/P firms; additionally, the book-to-market effect was first documented by Stattman (1980), and the size effect was demonstrated by Banz (1981).

characteristic-based model approach, decisions made by managers might presumably have an effect through certain firm-specific characteristics, both on systematic and idiosyncratic risk. To the best of our knowledge, papers on the idiosyncratic volatility-expected returns relationship have not previously considered this type of firm characteristic.

An interesting discussion in methodological terms is whether the existing patters between firm characteristics and expected returns are consistent with an aggregate risk explanation, thereby leading to the development of multifactor asset-pricing models, or whether these patterns are incompatible with the correlation structure expected from a factor model explanation to hold. Some of the relevant studies illustrating this discussion include Fama and French (1992, 1996), who justify their three-factor model because size and book-to-market are proxies for financial distress; Lakonishok *et al.* (1994), who indicate that the correlation of these factors with macro factors is too low to allow the interpretation of the distress risk; and Daniel and Titman (1997), who conclude that it is characteristics and not risk factors that drive the explanatory power of these variables over the cross-section of stock returns.[5] Profiting from this discussion, we explore several methodological approaches to study the anomaly from various perspectives.

First, we show preliminary evidence mostly based on the portfolio sorting methodology used in several papers on the idiosyncratic risk-expected return relationship, including the seminal ones by Ang *et al.* (2006, 2009). Second, based on Daniel and Titman's (1997) idea that firm characteristics can explain the cross-section of stock returns, we perform Fama and MacBeth (1973) regressions including controls for investment and profitability and analyse their effect on the risk-return relationship. Additional evidence in favour of

[5] These major critiques have been largely ignored both by academia and by practitioners. However, the characteristic-based asset-pricing framework continues to be respected, as shown by a recent paper by Penman et al. (2012), who, in an attempt to reconcile the firm characteristic and risk approaches, explore the explanatory power of several accounting measures over the cross-section of expected returns under a risk-compatible framework.

this approach is provided by Novy-Marx (2013), who argues that current profitability predicts returns through its effect on important determinants of future stock prices such as earnings, cash flow and payouts. Conversely, we use the recent Fama and French (2014) five-factor model, in which additional factors are based on profitability and investment, to consider explicitly the effect of a change in the asset-pricing model used to estimate the measure of idiosyncratic risk. This approach is also supported by Chen *et al.* (2011), who develop an asset-pricing model with factors based on profitability and investment that performs well in explaining the cross-section of stock returns. In both cases, our hypothesis is that the inclusion of profitability and investment measures would account for the negative relationship observed between idiosyncratic risk and subsequent returns. In the rest of the section, we first describe our data and the variables we use in our empirical analyses. Then, in the last part of the section, we provide some preliminary evidence for our results.

2.2. Data and variable construction

The study is developed using daily returns information on all non-financial common stocks in the NYSE, AMEX and NASDAQ available in the merged Compustat – CRSP (Chicago Research Stock Prices) database. To allow time for accounting information to become public knowledge, we leave a window of six months after each fiscal year end. The resulting sample dates are from July 1982 to December 2009. However, for the Fama-MacBeth regressions in section 4, the sample is reduced to the period from January 1983 to December 2009 by excluding firms with only a year of information in Compustat and excluding months in which mergers and acquisitions result in a strong variation of our accounting measures. The final sample is formed by 865,483 firm-month observations, approximately 2,679 firms per month.

Both investment and profitability are multidimensional concepts and, as such, are not uniquely defined. For instance, a company might invest in physical assets that will be worn out slowly over years or in inventories that should be sold in the short term to realize profits. Therefore, we incorporate several commonly used measures of profitability and investment that are described below.

2.2.1. Profitability measures

We consider six alternative measures of profitability from different sources. The information used to construct these variables is available in the merged Compustat - CRSP database. First, we contemplate straightforward profitability measures based on financial ratios often used by researchers and practitioners. In particular, we include controls for ROA, ROE and ROI, defined as follows:

$$ROA = EBIT/TA, \tag{2}$$

$$ROE = NI/CEQ, \tag{3}$$

$$ROI = NI/ICAPT, \tag{4}$$

where EBIT is earnings before interest and taxes, TA is total assets, NI is net income, CEQ is total common equity and ICAPT is total invested capital.

We also include the gross profitability measure developed by Novy-Marx (2013) defined as follows:[6]

[6] Novy – Marx (2013) offer two additional measures of profitability, earnings and free cash-flow. We do not consider these measures because we lose a large amount of observations when constructing free cash-flow and because we consider an alternative measure of earnings described further in this section.

$$Gross\ profitability\ =\ (REVT - COGS)/\ TA, \tag{5}$$

where REVT is revenues and COGS is costs of goods sold. This measure can be decomposed in two alternatives ways that we consider in our analysis to provide additional insights about the driving forces behind our results. The first is given by the following:

$$Gross\ profitability\ = \frac{EBITDA}{TA} + \frac{XSGA}{TA}, \tag{6}$$

where EBITDA is earnings before interest, taxes, depreciation and amortizations, and XSGA is selling, general and administrative expenses.

The second is defined as follows:

$$Gross\ profitability\ = \frac{REVT}{TA} \times \frac{GP}{REVT}, \tag{7}$$

where $\frac{REVT}{TA}$ stands for asset turnover and $\frac{GP}{REVT}$ for gross margin.

It is also possible to define profitability as the capacity of the firm to generate gains to its investors. We therefore add Compustat items "earnings per share" and "dividends per share" to our list of profitability measures. Therefore, our measures of profit are ROA, ROE, ROI, Gross Profitability, Earnings and Dividends.

2.2.2. Investment measures

Our investment proxy is asset growth, defined as the growth rate of total assets in the previous two years (Cooper *et al.*, 2008). This measure is used in recent papers such as Fama and French (2014) and has the advantage of being comprehensive in contrast with other measures such as accruals or capital expenditures that only consider certain aspects of investment. Our proxy is defined as follows:

$$AG_t = \frac{TA_{t-1} - TA_{t-2}}{TA_{t-2}}, \quad (8)$$

where AG represents asset growth and TA is total assets.[7]

As in the case of the gross profitability measure, we further decompose asset growth into its components on the left-hand side of the balance sheet to better identify the forces underlying our results. Following Cooper *et al.* (2008), the decomposition is given by the following:[8]

$$AG_t = \Delta C_t + \Delta NCCA_t + \Delta PPE_t + \Delta OA_t, \quad (9)$$

where ΔC is cash growth, $\Delta NCCA$ is non-cash current asset growth, $\Delta PPE$is plant, property and equipment growth, and ΔOA is other assets growth.

To analyse further the effect of investment-related measures in our results, we also include a capital investment measure as in Titman et *al.* (2004), defined as follows:

$$CI_{t-1} = \frac{CE_{t-1}}{(CE_{t-2} + CE_{t-3} + CE_{t-4})/3} - 1, \quad (10)$$

where CI_{t-1} represents the abnormal Capital Investment and CE_{t-1} is capital expenditures scaled by sales in year t – 1.

[7] Being a comprehensive measure of investment, asset growth can be linked to accruals. In fact, Richardson *et al.* (2005) define accruals as the left-hand side of the following equation:

$$\Delta\mathrm{NOA} = \Delta\mathrm{NFO} + \Delta\mathrm{B},$$

where NOA stands for net operating assets and is derived as the difference between operating assets and operating liabilities; NFO stands for net financial obligations and is calculated as short-term debt plus long-term debt less financial assets; B stands for the book value of equity; and Δ denotes changes.

Conversely, asset growth can be written as follows:

$$\Delta\mathrm{TA} = \Delta\mathrm{NOA} + \Delta\mathrm{OL} + \Delta\mathrm{FA},$$

where ΔOL represents operating liabilities and ΔFA is change in financial assets.

The previous equations make clear that asset growth proxies for accruals, allowing us to compare our results with other studies on the idiosyncratic risk (such as the one by Jiang et al. (2009)) that consider investment-related measures such as accruals.

[8] Cooper et al. (2008) also provide a decomposition of asset growth based on the left-hand side of the balance sheet. However, we do not use it in this paper because we lose a large proportion of data points when constructing it.

In the rest of the section, we present some preliminary evidence on the negative relationship between idiosyncratic risk and expected returns in our sample. We also explore how the variables described here are related to idiosyncratic risk and how they perform individually in explaining the cross-section of stock returns.

2.3. Preliminary evidence

We first verify that the idiosyncratic volatility anomaly is observed in our sample. Each month of year t, we consider firms reporting information for the previous fiscal year in Compustat. Then, firms are sorted monthly from the lowest to the highest level of idiosyncratic risk as defined by the standard deviation of the residuals ($\sigma_{\varepsilon_t^i}$) of the Fama and French (1993) three-factor model,

$$R_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i, \tag{11}$$

where R_t^i is the stock return in excess of the risk-free rate and $\{MKT_t, SMB_t, HML_t\}$ represent the market, size and book-to-market factors.[9] Next, we form quintiles and calculate monthly value weighted returns for each. Once the vector of monthly returns is formed for each quintile, we calculate their alphas from Equation (11).

Table 1 summarizes the information on the idiosyncratic risk anomaly for our sample. Columns report average monthly returns and alphas (all in percentages) for each quintile of idiosyncratic risk. Because stocks are organized so that the first quintile has lower idiosyncratic risk than the fifth one, we expect the [5-1] difference to be significantly negative. As expected, the idiosyncratic volatility anomaly is observed both in raw and risk-adjusted returns; the [5-1] difference in monthly raw returns is equal to a

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[9] These data have been obtained from Kenneth French's website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

significant -0.77% and is even more pronounced in risk-adjusted terms. The difference in alphas is equal to -1.17%, with an associated t-statistic of -4.08. In addition, we observe a pattern common to previous studies of the idiosyncratic volatility anomaly: a sharp drop in the returns is observed for the fourth or fifth quintile (for example, Chen and Petrokva (2012) or Malagon *et al.*, (2015)).

[Insert Table 1 here]

Our basic argument is that the measure of idiosyncratic risk estimated through the Fama and French (1993) three-factor model captures the effects of both investment and profitability that have explanatory power over returns. Therefore, for our hypothesis to be plausible, we must observe significant correlations between our estimates of these three variables. Table 2 displays the correlation matrix based on our monthly measures of idiosyncratic risk, asset growth and profitability. The first column of the matrix shows that the idiosyncratic risk measure based on the Fama and French (1993) three-factor model is significantly positively correlated with investment, measured with asset growth, and significantly negatively correlated to every measure of profitability.[10] The correlation between risk and our broad proxy for investment is 0.10. In terms of the magnitude of these correlations between idiosyncratic risk and profitability, the measures can be divided into two groups. The first one includes dividends, earnings, ROA, ROE and ROI that display correlations between -0.15 and -0.34. The second one includes gross profitability that exhibits lower correlations in magnitude, -0.02.[11] Our measure of investment, asset growth, is also significantly negatively correlated to all the profitability measures, ranging from -0.09 to -0.14 and providing evidence in favour of our hypothesis.

[Insert Table 2 here]

[10] Similar results are observed for quarterly and yearly correlations. Results are available upon request.
[11] Unreported results show that components of gross profitability defined in equations (6) and (7) exhibit larger correlations with idiosyncratic risk.

Given that the significance of correlations between investment, profitability and idiosyncratic risk measures and between investment and profitability measures is aligned with our hypothesis, we further analyse whether profitability or investment measures on their own can account for the negative relationship between idiosyncratic risk and expected returns. To do so, we turn to Fama and MacBeth (1973) cross-sectional regressions in which we investigate the relationship between idiosyncratic volatility and expected returns by examining the sign and statistical significance of γ_1, the coefficient on the idiosyncratic volatility measure in the following regression:

$$r_{it} = \alpha_{it} + \gamma_1 \varepsilon_{it-1} + \gamma_2 \beta_{mkt,it} + \gamma_3 \beta_{smb,it} + \gamma_4 \beta_{hml,it} + \gamma_5 s_{it-6} + \gamma_6 lr_{it-6}, \quad (12)$$

where current month stock returns (r_{it}) are regressed on one-month lagged idiosyncratic risk (ε_{it-1}), current loadings on the market factor ($\beta_{mkt,it}$), the SMB factor ($\beta_{smb,it}$) and the HML factor ($\beta_{hml,it}$) of a Fama and French (1993) model, size (s_{it-6}) and lagged returns over the previous six months (lr_{it-6}). All accounting-based measures are built with data available to the market for the last 6 months, and all independent variables are winsorized at the 1% level to avoid the influence of outliers and to keep comparability with previous studies.

Table 3 presents, in the first column, the Fama-MacBeth (1973) estimates of equation (12) as a baseline case. To assess the independent effects of investment and profitability measures on the statistical significance of $\gamma_1$in Equation (12), we include in Panel A our broad measure of investment, asset growth (AG_{it-6}), and each of our six profitability measures independently in Panel B. Results in Table 3 clearly show that neither any of the profitability measures nor the investment measure is sufficient to change the significance of the coefficient attached to the idiosyncratic volatility measure.[12]

[12] Several studies on the idiosyncratic risk anomaly include Newey-West adjustments in their analysis. However, few of them motivate their choices for this adjustment. As established by Petersen (2006), Fama

Analysing Panel A, including the investment variable alone, is relevant for two reasons. First, in Valuation Theory, profitability plays a major role in estimating the relationship between expected returns and investment. Therefore, it would be difficult to justify an interpretation from this framework if investment alone was sufficient to account for the anomaly. Second, because accruals can be linked to our investment measure, this specification using only asset growth is consistent with Jiang *et al.* (2009), who show that accruals are not able to account for the negative relationship between idiosyncratic risk and expected returns. In the context of our hypothesis, neither should investment fully explain the negative sign in this relationship because profitability is left aside. Consistent with our hypothesis, when controlling only for investment, the relationship between idiosyncratic risk and expected returns remains significantly negative at the 10% level, with γ_1 being equal to -0.0725 with an associated t-statistic of -1.75.

In Panel B, we introduce each profitability measure individually. We find that in the cases in which the measure of profitability is significant, that is, gross profitability, dividends and earnings, the t-statistic attached to the γ_1 coefficient ranges from -1.99, when earnings is considered, to -1.71, when profitability is measured with dividends. Interestingly, this table also shows that ROA and ROE, measures that are very highly correlated with idiosyncratic risk, slightly decrease the significance of the negative risk-return relationship but are not significant themselves. This fact is discussed in more detail

and MacBeth (1973) regressions correctly estimate the standard errors in panel data when only a time effect is identified, but they must incorporate a Newey-West correction when a firm effect is also present in the sample. We follow Petersen's (2006) procedure to test for both time and firm effects in our panel data to establish technically whether the Fama and MacBeth (1973) regressions we run in this paper need a Newey-West adjustment. Greater than 3 times differences are only observed when comparing the results of OLS regressions clustered by time with the results of OLS regressions using White correction. This fact, together with the fact that there are no large differences in the standard errors of OLS regressions clustered individually by time or firm with the standard errors of OLS regressions clustered by both dimensions, shows that there is no need to incorporate Newey-West corrections. Therefore, all tables available in this paper are estimated using Fama and MacBeth (1973) regressions without Newey-West corrections. Results are available upon request.

in the next section in which we analyse the effect that controlling for profitability and investment together has over the idiosyncratic volatility-expected returns relationship.

[Insert Table 3 here]

Before testing our hypothesis, we use the decompositions of asset growth and gross profitability presented in section 2 to clarify what components are more relevant for our discussion. Results are presented in Table 4. The first column of results presents our baseline case without controlling for investment or profit. In Panel A, according to (10) and following Cooper et al. (2008), we decompose asset growth in cash growth (ΔC_t); non-cash current asset growth ($\Delta NCCA_t$); plant property and equipment growth (ΔPPE_t) and other asset growth (ΔOA_t). We also present the estimation using aggregate asset growth as a means of comparison in column 2. In Panel B, we split gross profitability in two different ways according to Novy-Marx (2013). First, we divide gross profitability into EBITDA and XSGA (selling, general and administrative expenses). Then, we divide it into gross margin and asset turnover. Both decompositions are considered separately, and we show the estimation using gross profitability in column 4 to compare results.

[Insert Table 4 here]

As we presented in Table 3, the t-statistic attached to the idiosyncratic volatility measure in our baseline case is -1.99 and is significant at the 5% level. When we incorporated asset growth, the significance decreased to the level of 10% with a t-statistic of approximately 1.75. We observe similar results after considering the investment decomposition proposed by Cooper et al. (2008), which reduces the t-statistic attached to the γ_1 coefficient to -1.69, still significant at the 10% level. In terms of investment, the only controls that appear significantly different from zero are non-cash current asset growth ($\Delta NCCA_t$) and other asset growth (ΔOA_t). Concerning profitability, all components are significant; therefore, we can find no evidence for a main driving force. As with investment, in all cases the significance of the γ_1 coefficient remains at 10%, just as it did when we incorporated aggregated gross profitability.

3. The idiosyncratic risk-investment relationship conditional to profitability

In this section, we approach the study of the effects of investment and profitability on the idiosyncratic risk-expected return relationship using two different methodologies. On the one hand, we explore the results of Fama and MacBeth (1973) cross-sectional regressions including investment and profitability measures together. On the other hand, we pursue a portfolio sorting methodology based on idiosyncratic risk estimates using the recent Fama and French (2014) five-factor model that adds a profitability-based and an investment-based factor to their usual three-factor model.

Therefore, in the initial part of our analysis, we focus our interest on the statistical significance of γ_1, the coefficient on the idiosyncratic volatility measure in the following regression:

$$\begin{aligned} r_{it} = \alpha_{it} + \gamma_1 \varepsilon_{it-1} + \gamma_2 \beta_{mkt,it} + \gamma_3 \beta_{smb,it} + \gamma_4 \beta_{hml,it} + \gamma_5 s_{it-6} + \gamma_6 lr_{it-6} \\ + \gamma_7 AG_{it-6} + \gamma_8 prof_{it-6}, \end{aligned} \tag{13}$$

where current month stock returns (r_{it}) are regressed on one-month lagged idiosyncratic risk (ε_{it-1}), current loadings on the market factor ($\beta_{mkt,it}$), the SMB factor ($\beta_{smb,it}$) and the HML factor ($\beta_{hml,it}$) of a Fama and French (1993) model, size (s_{it-6}), lag returns over the previous six months (lr_{it-6}), asset growth (AG_{it-6}), and a profitability measure. We estimate alternative models changing the measure of profitability to ROA, to ROE, to ROI, to earnings, to dividends and to gross profitability and its decompositions, with all variables as defined in the previous section. As in the previous regression, both asset growth and the profitability measures are built with data available to the market for the last 6 months. To avoid the influence of outliers and to keep comparability with previous studies, all independent variables are winsorized at the 1% level.

The first column in Table 5 represents our baseline case and reports the results of the Fama and MacBeth (1973) regressions for Equation (12). In this model, stock returns are only regressed on one-month previous idiosyncratic risk (ε_{it-1}), current loadings on the Fama and French (1993) model ($\beta_{mkt,it}$, $\beta_{smb,it}$ and $\beta_{hml,it}$), size (s_{it-6}) and lag returns over the previous six months (lr_{it-6}). This specification is standard in the literature and is intended to show the risk-adjusted relationship between firm-specific risk and expected returns when no controls on investment and profitability are included. As expected, the idiosyncratic risk anomaly is observed; the coefficient related to idiosyncratic volatility is equal to -0.085 and is largely significant, with a t-statistic of approximately –1.99.

[Insert Table 5 here]

The models that actually test our hypothesis are the last 8 columns in Table 5, in which each model corresponds to alternative specifications of Equation (13) using one of our proxies for profitability. Each of these models should fully account for the idiosyncratic volatility anomaly. Columns 2 to 4 consider ROA, ROE and ROI as measures of profitability. These financial ratios seem not to be effective in accounting for the negative risk-return relationship; none of them is significant in the cross-section analysis, and, with the exception of the specification that includes ROA, the coefficient of idiosyncratic volatility is significant at 10%. The coefficient γ_1 is also significant in the model using earnings in which, although earnings per share are significant, the measure is not sufficient to account for the anomaly. However, both dividends and gross profitability measures strongly support our hypothesis; these measures show as strongly significant and, when considered together with investment, make γ_1 non-significant.

Additionally, both decompositions of gross profitability exhibited in the last columns of Table 5 largely support our hypothesis; γ_1 becomes non-significant, and its magnitude decreases by 29% in the first case and by 22% in the second. These results seem to indicate that gross profitability plausibly plays a relevant role in the negative relationship between idiosyncratic risk and returns. Finally, as expected in the framework of the Valuation Theory, in all the regressions, investment is negatively related to returns, and all the measures of profitability we consider are positively related to them.

To analyse further which components of gross profitability could be responsible for the non-significance of γ_1, in unreported results, we run regressions including each of the components of gross profitability individually. Interestingly, together with asset growth, both EBITDA and asset turnover are able to account fully for the anomaly without the other part of the respective decomposition. Indeed, these two models exhibit some of the lowest t-statistics for γ_1 (-1.55 and -1.78, respectively) and some of the larger R^2 for the overall regression. When XSGA or gross margin is included individually, the variables are not significant and the idiosyncratic risk anomaly does not disappear. Therefore, it seems that the most relevant components of profitability could be related to EBITDA and asset turnover instead of other components.

We have used asset growth as proxy for investment. The main motivation for this measure is that it is a comprehensive measure of investment that has been used in several empirical studies on the cross-section of returns, such as Novy-Marx (2013), and in recent studies based on risk factors, such as Fama and French (2014). With the objective of providing additional insights, we decompose assets growth in Table 6 into its components on the right side of the balance sheet in equation (10) as defined in the previous section.

[Insert Table 6 here]

The results in terms of the negative relationship between idiosyncratic risk and subsequent returns are very similar to the ones in the previous table. That is, investment measures on their own are not sufficient to account for the significance of the coefficient attached to idiosyncratic risk (the baseline case in Table 6). Additionally, only when profitability measures are included does the risk-return relationship become non-significant. Comparing the results reported in Table 6 with those of Table 5, we observe that all models, except the ones in which ROI and earnings per share are used to proxy profitability, support our hypothesis.

The value of these models, however, is on the side of the investment in the sense that its decomposition should help us identify the forces underlying its explanatory power over expected returns. We therefore turn to the interpretation of the results based on the investment decomposition. As in the previous section, the decomposition reveals that both the growth of non-cash current assets and the growth of other assets are related to the idiosyncratic risk-expected returns relationship. The components related to cash and to property, plant and equipment are not significant in any of the models, and the other assets component shows mixed results. In particular, the growth of the non-cash current assets variable is highly significant in all of the models included in Table 6. Therefore, it appears that adding profitability measures does not substantially change the relationship between the non-cash current assets or the other asset growths and idiosyncratic risk. Presumably, inventories and accounts receivable form a large portion of non-cash current assets;

therefore, it appears that how firms manage their inventories and their collection policy might be related to their idiosyncratic risk.

The interpretation is somewhat more difficult when addressing the changes in other assets, given its residual nature. Therefore, to study whether the growth of the non-cash current assets variable is sufficiently relevant to infer conclusions, we estimate the models in Panel B using only this variable as investment proxy simultaneously with each of the profitability measures. Unreported results show that, in general, the relationship between idiosyncratic risk and expected returns is not significant in these cases, allowing us to conclude that changes in non-cash current assets actually constitute the most relevant component of investment in our analysis.

To add to the robustness of this result, we analyse whether Titman et *al.'s* (2004) measure of abnormal capital investment (CI) proves useful for accounting for the idiosyncratic volatility anomaly. In line with the fact that changes in property, plant and equipment are not significant, Table 7 reports that capital investment proves in general unable to account for the anomaly even after controlling for profitability. In this case, the second column of the table shows that capital expenditures are not significantly related to the cross-section of stock returns on a standalone basis. Once profitability measures are included (cf. columns 3 to 10), capital investment shows mixed results, occasionally being significant at 10% and occasionally being not significant at all. However, none of the cases, controlling for profitability and investment measured as capital investment, results in the negative risk-return relationship turning non-significant. Results in Tables 6 and 7 could be considered aligned with studies on the informational power of inventories such as Thomas and Zhang (2002), which show that inventory changes are negatively related to stock returns because investors are unable to anticipate demand shifts masked by earnings management. However, given that the negative risk-return relationship does not become non-significant without also controlling for profitability, it is not possible to explain the idiosyncratic volatility anomaly purely with investors' inability to disentangle earnings information. In fact, given that Valuation Theory also holds within an irrational expectation framework, the results seem to favour our hypothesis rather than an investor-related one.

[Insert Table 7 here]

Overall, the evidence thus far suggests that investment and profitability are firm characteristics that have explanatory power over the cross-section of stock returns and that they turn the idiosyncratic risk-expected returns relationship non-significant. In this sense, the evidence supports our hypothesis that the so-called idiosyncratic volatility anomaly might not be related to investor preferences but only to elements omitted when estimating the idiosyncratic risk measure. A natural extension is therefore to check whether estimates of idiosyncratic risk based on additional risk factors decrease the significance of the negative idiosyncratic risk-expected returns relationship. To that end, we will use the recently proposed five-factor asset-pricing model of Fama and French (2014), which includes two additional factors involving investment and profitability to the Fama and French (1993) three-factor model. In this exercise, we extend our sample to match the original one in Ang *et al.* (2006) to include every stock in the CRSP with more than 17 observations in a month for the NYSE, AMEX and NASDAQ markets from July 1963 to December 2009. For each month, we sort stocks according to their idiosyncratic volatility, defined as the standard deviation of the residuals ($\sigma_{\varepsilon_t^i}$), in the five-factor model of Fama and French (2014) (hereinafter 5FF):

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{RMW}^i RMW_t + \beta_{CMA}^i CMA_t + \varepsilon_t^i, \quad (14)$$

where r_t^i is the stock return in excess of the risk-free rate, $\{MKT_t, SMB_t, HML_t\}$ represent the market, size and book-to-market factors, RMW is the factor based on operating profitability, and CMA is the investment factor based on change in total assets.[13] Details about construction of these factors are in Fama and French (2014). The profitability and investment factors, RMW and CMA, are constructed similarly to HML, except the second sort is on either operating profitability (robust minus weak) or investment (conservative minus aggressive). As in HML, RMW and CMA can be interpreted as averages of profitability and investment factors for small and large stocks, respectively.

A major issue to be considered here is that daily RMW and CMA factors are currently not available, being available only in monthly bases. Therefore, to perform our analysis, we approximate them by computing an optimal disaggregation of the low frequency (monthly) time series for CMA and RMW factors into high frequency (daily) time series. The unobserved high frequency values can be computed by considering the high frequency sample information (in this case we use daily information of SMB, and HML Fama and French factors) and low frequency indicators (the monthly time series for CMA and RMW available). Here, we use daily information of SMB, and HML Fama and French factors as indicators to disaggregate the RMW and CMA, series from the (2x2x2x2) sorts.[14] Details about this method can be found in Anderson and Moore (1979), De Jong (1989) and Casals

[13] These data have been obtained from Kenneth French's website
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[14] Fama and French (2104) use three different sets of factors, depending on the different sorts of stocks used. For example, when they sort stocks into two Size groups and three B/M groups, they obtain independent 2x3 sorts. Factors are created from 2x3 or 2x2 or 2x2x2x2 sorts on variables Size, B/M, OP, or Inv. Because HML, RMW and CMA from the (2x3) or (2x2) sorts weight small and large stock portfolio returns equally, they are neutral with respect to size. However, because HML is constructed without controls for OP and Inv., it is not neutral with respect to profitability and investment; therefore, the average HML return is likely a mix of premiums related to B/M, profitability and investment. Analogous comments apply to RMW and CMA. The authors note that factors from the 2x2x2x2 sorts isolate better the premiums in average returns related to B/M, OP and Inv. However, factor exposures produced by the factors from the 2x3 or 2x2 could be different.

et al. (2000). Although this methodology has been used before, it is an approximation and could well be inaccurate; thus, the results obtained should be interpreted with caution.

[Insert Table 8 here]

Table 8 illustrates that the results are satisfactory for our hypothesis in the sense that the idiosyncratic volatility-expected returns relationship is equal to -0.66% in raw returns and only significant at 10%, whereas the 5FF alphas are halved to -0.46% (t-stat = -2.38), compared with the -1.17% (t-stat = -4.08) based on the three-factor model and exhibited in Table 1. However, the 5FF alphas remain highly significant, somewhat casting a shadow on our results. Many factors could explain this fact. For instance, our evidence in the cross-sectional regressions shows that, although measures of operating profitability such as ROA are highly and significantly correlated with idiosyncratic risk, they are not relevant in the idiosyncratic risk-expected return relationship. Given that the Fama and French (2014) profitability factor is constructed based on operating profitability, results might change if different measures of profitability were used. As previously stated, results might also be sensitive to our approximation of the daily profitability and investment factors used in the estimation of the idiosyncratic risk. Alternatively, it is plausible that it is characteristics and not risk factors that drive explanatory power over the cross-section of stock returns as shown in Daniel and Titman (1997) for the case of the Fama and French (1993) three-factor model.

4. Further issues and robustness

Thus far, our results suggest that the negative idiosyncratic risk-expected return relationship might arise from the information content of firm characteristics (in particular investment and profitability) that, although under the influence of managers, are not considered in the estimation of the idiosyncratic risk. Our hypothesis is that, at least in part, the negative risk-returns relationship might settle on an inaccurate measure of idiosyncratic risk. However, many studies argue that this negative relationship is based on investor preferences or irrationality. This section provides a basis to discuss further how our results behave under different rationality regimes and how they compare with the results obtained when considering investor preference for return skewness.

As previously stated, our hypothesis is not based on any mispricing on the part of investors, given that Valuation Theory provides a rationale for our results that holds under both rational and irrational expectations. We therefore turn to analyse how our controls behave over different ‘rationality regimes’. This will allow us to test our hypothesis further and to discard the idea that the anomaly is solely related to investor sentiment as argued by Gao *et al*. (2012). Investor sentiment is addressed in a vast and recent literature that highlights the fact that assumptions about financial markets based on a standard unemotional investor fail to explain stock price patterns at all times (Baker and Wurgler, 2006 and 2007). According to the sentiment literature, this could be explained by two facts. One is that investors are subject to sentiment; thus, their beliefs about fundamentals are not objectively justified (Delong *et al.,* 1990). The second is that arbitrageurs are not sufficiently powerful to win when betting against this type of investor (Shleifer and Vishny, 1997). Baker and Wurgler (2006 and 2007) develop a monthly sentiment index wherein higher levels of the index signal that the proportion of sentiment investors to arbitrageurs is greater and that irrational expectations are more likely to be latent.

We therefore include a multiplicative effect in our model, $\varepsilon_{it-1} * Sent_{t-1}$, measuring the interaction between the value of the Baker and Wurgler Index and the idiosyncratic volatility in the previous month. The interaction isolates the relationship between idiosyncratic risk and expected returns once the sentiment effect is considered. The resulting model can be written as follows:

$$r_{it} = \gamma_1 \varepsilon_{it-1} * Sent_{t-1} + \gamma_2 \varepsilon_{it-1} + \gamma_3 Sent_{t-1} + \gamma_4 \beta_{mkt,t} + \gamma_5 \beta_{smb,t} + \gamma_6 \beta_{hm} + \gamma_7 s_{it-6} + \gamma_8 lr_{it-6} + \gamma_9 prof_{it-6} + \gamma_{10} ag_{it-6}, \tag{15}$$

where $Sent$ is the value of the Baker and Wurgler Index in month t-1, and the rest of the variables are defined as in Equation (13).[15] Here again, we estimate alternative models by changing the definition of the profitability measures. As in former equations, the relationship between idiosyncratic risk and expected returns moderated by investor sentiment is isolated by γ_1. In this sense, a significant $\gamma_1$would show that there is more to the negative risk-expected return relationship than pure investor sentiment.

[Insert Table 9 here]

Results are shown in Table 9 in which the baseline case, which solely considers controls related to risk-adjustment, shows that investor sentiment has indeed a moderating effect on the relationship between idiosyncratic risk and expected returns. Indeed, the interaction term in the regression, equal to -0.0246, is significant only at 10%. Therefore, investor sentiment is able to decrease the significance of the γ_1 coefficient from 5% to 10% but cannot make it disappear. This result is inconsistent with the findings of Gao *et al.* (2012), who argue that the anomaly is solely related to investor sentiment. However, because the controls for investment and profitability account for the significance of $\gamma_1$in all specifications (even after the effect of investor sentiment on the idiosyncratic volatility anomaly is explicitly considered through the interaction term, $\varepsilon_{it-1} * Sent_{t-1}$, in Equation (15)), it is very consistent with our hypothesis.

[15] The constant in the model is dropped given the fact that the Fama and MacBeth (1973) methodology implies that the regression in Equation (15) is run period by period. Then, in the case of a period of high sentiment, the constant and the variable Sent would create collinearity problems because both would be a vector of ones.

Another interesting discussion in the context of the paper is how our results relate to studies on the idiosyncratic risk anomaly based on investor preferences. A relevant example is Boyer *et al.* (2010), who link the anomaly with skewness and report that the [5-1] difference in raw returns becomes non-significant when performing a double sort based on idiosyncratic risk and skewness. However, their results suffer from the fact that in risk-adjusted terms, skewness performs poorly in explaining the negative relationship between idiosyncratic risk and expected returns. This fact is reflected in the very significant t-statistic (equal to 2.34) attached to the -0.55 difference in extreme quintiles obtained through the double sort. This result suggests that there is more to the anomaly than only skewness of return distributions.

We acknowledge investor preference for positive skew return distributions, but we believe our results suggest that, at least to some degree, the informational nature of the idiosyncratic risk on subsequent returns could be related to problems in its estimation. To support this view further, we include skewness as a control variable in the Fama and MacBeth (1973) regressions. The results of the first specification with Skewness in Table 10 highlight that the skewness variable is significant in explaining the stock returns but is not able to account fully for the anomaly. These results are in accordance with Boyer et al. (2010), who using a double sorting method can only eliminate the anomaly in raw returns. Therefore, our approach appears more effective in the cross section of stock returns while, as discussed in the previous section, both hypotheses pose similar issues when addressing portfolio-sorting methodologies.

Investors of course prefer skewness, and there is no doubt that this preference might in part explain the negative risk-return relationship. However, there is no reason to believe that this fact makes less relevant the role of investment and profitability on the issue. This is supported both by intuition and by the fact that, when considered together, skewness does not undermine investment and profitability explanatory power over returns and, at the same time, does reduce further the significance of the idiosyncratic risk component, as observed in the rest of the specifications. Our results suggest that neither profitability nor investment is conflicted with the explanatory power of skewness on stock returns. Moreover, the results also suggest that skewness is not captured in the profitability or investment measures that we use. Overall, it appears that the effect of skewness on the cross-section of stock returns is independent of the investment and profitability effects we report in this paper, and that the possibility that the latter have an effect in the negative risk-return relationship cannot be dismissed through skewness-based arguments. The most likely reality is that both effects co-exist.

[Insert Table 10 here]

5. Conclusions

A considerable portion of the literature addressing the idiosyncratic volatility anomaly suggests that the anomaly is related to investors. Several papers identify either investor preferences or pricing inability as sources of the negative risk-return relationship. Surprisingly, the role of asset-pricing models in the estimation of idiosyncratic risk measures has been largely neglected despite the fact that several asset-pricing models known to outperform the Fama and French (1993) three-factor model are available in the literature. Even more striking, some of these models are related to firm characteristics that are under direct influence of the managers and should therefore be related to idiosyncratic risk. Our analysis is based on the idea that idiosyncratic risk and expected returns can be negatively linked if the measure of idiosyncratic risk captures features related to firm characteristics. This linkage is particularly relevant in the sense that the characteristics we consider are subject to managerial decision making that intuitively should be linked to idiosyncratic risk, therefore highlighting the relevance of managers to the issue. To the best of our knowledge, this approach has not previously been taken.

In the universe of firm characteristics, investment and profitability are of particular interest because a series of recent studies identify them as relevant for the pricing of stocks. In this paper, we show that these characteristics turn the negative relationship between firm-specific risk and expected returns non-significant in the cross-section of stock returns. In particular, our results highlight the fact that variables under the influence of managers such as inventories and accounts receivable together with asset turnover play a very relevant role in the idiosyncratic-risk relationship. In terms of interpretation, these results are very significant because they contradict the idea that the idiosyncratic risk anomaly is solely related to irrational investor expectations driven either by a misunderstanding of the information content of cash-flows or by euphoria in times of high sentiment. Moreover, our framework conciliates these apparently contradictory results because the former implies controlling only for investment and the latter can be linked to irrational expectations in valuation. Finally, we also provide evidence that the effect of firm characteristics driven by managers is independent of and complementary to the effects related to investor preferences – to investor preferences for skewness in particular. The paper also highlights the large, unsolved discussion about whether stock returns are driven by firm characteristics themselves or by risk factors proxied by the characteristics (Daniel and Titman, 1997). In the context of the idiosyncratic risk-expected return relationship, this discussion is particularly relevant and offers many research opportunities ahead.

Acknowledgments

We would like to thank the seminar participants at the Finance Forum Meetings (2012) and Belen Nieto for her helpful comments.

References

Anderson, B. D. O. and J. B. Moore (1979). Optimal Filtering. Englewood Cliffs, N.J.: Prentice Hall.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 51, 259–299

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: International and further u.s. evidence. Journal of Financial Economics 91(1), 1 – 23.

Au, A. S., Doukas, J. A., Onayev, Z., 2009. Daily short interest, idiosyncratic risk, and stock returns. Journal of Financial Markets 12(2), 290 – 316.

Baker, M. , Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61(4), 1645 – 1680.

Baker, M. , Wurgler, J. , 2007. Investor sentiment in the stock market. Journal of Economic Perspectives 21(2), 129 – 152.

Bali, T., Cakici, N., 2008. Idiosyncratic risk and the cross-section of expected returns. Journal of Financial and Quantitative Analysis 43, 29–58.

Bali, T. G., Cakici, N., Whitelaw, R. F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427–446

Banz, R. W., 1981. The relationship between return and the market value of common stocks. Journal of Financial and Quantitative Analysis 14, 421-441.

Basu, S., 1983. The relationship between earnings yield, market value and return for NYSE common stocks. Journal of Financial Economics 12, 126-156.

Boehme, R. D., Danielsen, B. R., Kumar, P., Sorescu, S. M., 2009. Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets miller (1977). Journal of Financial Markets 12(3), 438 – 468.

Boyer, B., Mitton, T. , Vorkink, K., 2010. Expected idiosyncratic skewness. Review of Financial Studies 23(1), 169 – 202.

Cao, J. , Han, B., 2010. Idiosyncratic risk, costly arbitrage, and the cross-section of stock returns. SSRN eLibrary.

Carhart, M. M., 1997. On Persistence in Mutual Fund Performance. Journal of Finance 52, 57–82.

Casals, J. M. Jerez and S. Sotoca (2000). “Exact Smoothing for Stationary and Nonstationary Time Series”, International Journal of Forecasting, 16, 59-69.

Chen, L. H., Jiang, G., Xu, D. and Yao, T., 2012. Dissecting the idiosyncratic volatility anomaly. SSRN eLibrary.

Chen, Z., and R. Petkova, 2012. Does Idiosyncratic Volatility Proxy for Risk Exposure? Review of Financial Studies 25(9), 2745-2787.

Chen, L., Novy-Marx, R. , Zhang, L., 2011. An alternative Three-Factor Model. Available at SSRN.

Cooper, M. J., Gulen, H. , Schill, M. J., 2008. Asset growth and the cross-section of stock returns. Journal of Finance 63(4), 1609 – 1651.

Daniel, K. and Titman, S., 1997. Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. Journal of Finance 52, 1-33.

DeLong, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J., 1990. Noise Trader Risk in Financial Markets. Journal of Political Economy 98, 703–38.

De Jong, P. (1989), "Smoothing and Interpolation with the State-Space Model", Journal of the American Statistical Association, 84, 408, 1085-1088.

Duan, Y., Hu, G. , McLean, R. D., 2010. Costly arbitrage and idiosyncratic risk: Evidence from short sellers. Journal of Financial Intermediation 19(4), 564 – 579.

Fama, E. and French, K.R., 1992. The cross-section of expected stock returns. Journal of Finance 46, 427-466.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. and French, K.R., 1996. Multifactor explanation of asset pricing anomalies. Journal of Finance 51, 55-84.

Fama, E.F. and French, K.R., 2006. Profitability, Investment and Average Returns. Journal of Financial Economics 82(3), 491 – 518.

Fama, E.F. and French K.R., 2014. A five-factor asset pricing model. Journal of Financial Economics. Available at: http://dx.doi.org/10.1016/j.jfineco.2014.10.010.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 71, 607–636.

Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics 91(1), 24 – 37.

Gao, X., Yu, J., Yuan, Y., Investor Sentiment and Idiosyncratic Risk Puzzle, Unpublished Working Paper, Hong Kong University, 2012.

Han, Y. , Lesmond, D., 2011. Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. Review of Financial Studies 24(5), 1590 – 1629.

Harvey, C. R. and Siddique, A., 2000. Conditional Skewness in Asset Pricing Tests. The Journal of Finance, 55(3), 1263 – 1295.

Hou, K., Xue, C., Zhang, L., 2015. Digesting Anomalies: An Investment Approach. The Review of Financial Studies, 28(3), 650 – 705.

Huang, W., Liu, Q., Rhee, S. G., Zhang, L., 2010. Return reversals, idiosyncratic risk, and expected returns. Review of Financial Studies 23(1), 147 – 168.

Jiang, G. J., Xu, D. , Yao, T., 2009. The information content of idiosyncratic volatility. Journal of Financial and Quantitative Analysis 44(1), 1 – 28.

Kapadia, N., 2006. The next Microsoft? skewness, idiosyncratic volatility, and expected returns. SSRN eLibrary.

Lakonishok, J., Schleifer, R., Vishny, R., 1994. Contrarian Investment, Extrapolation, and Risk. Journal of Finance 49, (5), 1541-1578.

Malagon, J., Moreno, D., and Rodriguez, R., 2015. Time horizon trading and the idiosyncratic risk puzzle. Quantitative Finance 15(2), 327-343.

Merton, R. C., 1987. A simple model of capital market equilibrium with incomplete information. The Journal of Finance 42(3), 483 – 510.

Novy-Marx, R., 2013. The Other side of Value: The Gross Profitability Premium. Journal of Financial Economics 108, 1-28.

Pástor, L., and Stambaugh, R. F.,2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111(3), 642 – 685.

Penman, S., Reggiani, F., Richardson, S., Tuna, I., 2012. A Characteristic Model for Asset Pricing, Working Paper, Accounting Research Center Chicago Booth.

Petersen, M. A. , 2008. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. Review of Financial Studies, 22(1), 435–480.

Richardson, S., Sloan, R., Soliman , M. Tuna, I., 2005. Accrual reliability, earnings persistence and stock prices. Journal of Accounting and Economics 39, 437 – 485.

Richardson, S.A., Tuna, I. , Wysocki, P., 2010. Accounting anomalies and fundamental analysis: A review of recent research advances. Journal of Accounting and Economics 50, 410-454.

Shleifer, A. and Vishny, R., 1997. The Limits of Arbitrage. Journal of Finance 52, 35–55.

Sloan, R. G., 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? The Accounting Review 71(3), 289 – 315.

Stattman, D., 1980, Book values and stock returns, The Chicago MBA: A Journal of Selected Papers 4, 25 – 45.

Thomas, J.K. and Zhang, H., 2002. Inventory changes and future returns. Review of Accounting Studies 7(2), 163-187

Titman, S., Wei, K. C. J., Xie, F., 2004. Capital Investments and Stock Returns. The Journal of Financial and Quantitative Analysis 39, 677-700.

Table 1: Portfolio returns sorted by idiosyncratic risk

		Returns	Alphas
Idiosyncratic risk quintiles	**Low 1**	1.26	0.30
			(3.76)
	2	1.17	0.08
			(0.88)
	3	1.26	0.07
			(0.61)
	4	1.09	-0.12
			(-0.75)
	High 5	0.49	-0.87
			(-3.64)
	[5-1]	-0.77	-1.17
		(-1.74)	(-4.08)

This table reports monthly average returns and risk-adjusted returns for quintiles formed after sorting stocks according to their level of idiosyncratic risk based on the Fama and French (1993) three-factor model. The sample includes all non-financial (SIC codes 6000 - 6999) common stocks available jointly on CRSP and Compustat from July 1982 to December 2009 (approximately 3,415 firms per month). Quintile 1 corresponds to the portfolio with the lowest idiosyncratic risk, and quintile 5 to the portfolio with the highest idiosyncratic risk. Returns and alphas are reported in monthly percentages. Row [5-1] is the difference between portfolio 5 and portfolio 1. Newey-West *t*-statistics are reported in parenthesis.

Table 2: Correlations between investment, profitability and idiosyncratic measures

	ε_t	AG_t	ROA_t	ROE_t	ROI_t	Gross $Prof_t$	$Dividends_t$	$Earnings_t$
ε_t	1							
AG_t	0.1022*	1						
ROA_t	-0.3438*	-0.1483*	1					
ROE_t	-0.2695*	-0.0983*	0.6790*	1				
ROI_t	-0.3003*	-0.1233*	0.8121*	0.8720*	1			
Gross $Prof_t$	-0.0241*	-0.0917*	0.3335*	0.1610*	0.1872*	1		
$Dividends_t$	-0.2254*	-0.0720*	0.1609*	0.1219*	0.1326*	0.0026*	1	
$Earnings_t$	-0.1545*	-0.1148*	0.3124*	0.3943*	0.4105*	0.0851*	0.1305*	1

This table reports the contemporaneous correlations between our measures of profitability, investment and the idiosyncratic risk measure based on the Fama and French (1993) three-factor model. * denotes significance at the 5% level.

Table 3: Profitability and investment individual effects

	Baseline Case	Panel A: Investment	Panel B: Profitability					
ε_{t-1}	-0.0848**	-0.0725*	-0.0719*	-0.0768*	-0.0772**	-0.0781*	-0.0706*	-0.0822**
	(-1.99)	(-1.75)	(-1.91)	(-1.95)	(-2.00)	(-1.85)	(-1.71)	(-1.99)
β_{MKT}	0.0042***	0.0043***	0.0043***	0.0043***	0.0043***	0.0043***	0.0046***	0.0043***
	(4.67)	(4.83)	(4.82)	(4.73)	(4.74)	(4.74)	(5.18)	(4.90)
β_{SMB}	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***
	(3.05)	(3.11)	(3.15)	(3.10)	(3.12)	(3.08)	(3.23)	(3.28)
β_{HML}	-0.0005	-0.0006	-0.0006	-0.0005	-0.0006	-0.0006	-0.0007	-0.0006
	(-1.000)	(-1.13)	(-1.08)	(-1.04)	(-1.03)	(-0.99)	(-1.35)	(-1.14)
Size$_{t-6}$	-0.0023***	-0.0023***	-0.0024***	-0.0024***	-0.0023***	-0.0023***	-0.0031***	-0.0027***
	(-5.00)	(-4.93)	(-5.56)	(-5.30)	(-5.34)	(-4.96)	(-6.13)	(-5.699)
Lag returns$_{t-6}$	0.0037	0.0035	0.0032	0.0034	0.0032	0.0032	0.0042*	0.0038
	(1.50)	(1.44)	(1.33)	(1.40)	(1.34)	(1.29)	(1.71)	(1.57)
AG$_{t-6}$		-0.0029***						
		(-5.13)						
ROA$_{t-6}$			0.0051					
			(1.18)					
ROE$_{t-6}$				0.0012				
				(1.03)				
ROI$_{t-6}$					0.0016			
					(0.747)			
Gross Prof$_{t-6}$						0.0093***		
						(5.24)		
Dividends$_{t-6}$							0.0073***	
							(4.67)	
Earnings$_{t-6}$								0.00035**
								(2.29)
Constant	0.0154***	0.0156***	0.0154***	0.0155***	0.0155***	0.0110***	0.0166***	0.0167***
	(4.92)	(5.01)	(4.92)	(5.00)	(5.01)	(3.34)	(5.36)	(5.44)
Observations	865,483	865,483	865,483	865,483	865,483	865,483	865,483	865,483
R^2 (%)	3.88	4.05	4.22	4.11	4.16	4.08	4.10	4.05

This table shows the Fama-MacBeth (1973) estimates of equation (12) as a baseline case, and the estimates of equation (13) for Panels A and B, in which investment and profitability measures are not included simultaneously.

$$r_{it} = \alpha_{it} + \gamma_1 \varepsilon_{it-1} + \gamma_2 \beta_{mkt,it} + \gamma_3 \beta_{smb,it} + \gamma_4 \beta_{hml,it} + \gamma_5 s_{it-6} + \gamma_6 lr_{it-6} + \gamma_7 ag_{it-6} + \gamma_8 prof_{it-6}$$

The sample contains all non-financial (sic codes 6000 – 6999) common stocks available jointly on CRSP and Compustat from January 1983 to December 2009. The dependent variable is monthly stock returns compounded from daily data. The explanatory variables are idiosyncratic volatility (ε), betas from the Fama and French (1993) three-factor model, size and lagged returns as a baseline case. In Panel A, a measure of investment (Asset Growth, **AG**) is also included, and in Panel B, six different measures of profitability are added. All independent variables are winsorized at the 1st and 99th percentiles. The t-statistics are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 4: Profitability and Investment Disaggregation

	Baseline Case	Panel A: Investment		Panel B: Profitability		
$d\varepsilon_{t-1}$	-0.0848**	-0.0725*	-0.0696*	-0.0781*	-0.0711*	-0.0757*
	(-1.99)	(-1.75)	(-1.69)	(-1.86)	(-1.89)	(-1.83)
β_{MKT}	0.0042***	0.0043***	0.0043***	0.0043***	0.0044***	0.0043***
	(4.68)	(4.83)	(4.90)	(4.74)	(4.92)	(4.83)
β_{SMB}	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***	0.0013***
	(3.05)	(3.11)	(3.15)	(3.08)	(3.18)	(3.10)
β_{HML}	-0.0005	-0.0006	-0.0006	-0.0006	-0.0005	-0.0006
	(-1.00)	(-1.13)	(-1.20)	(-0.99)	(-1.09)	(-1.04)
$Size_{t-6}$	-0.0023***	-0.0023***	-0.0023***	-0.0023***	-0.0023***	-0.0023***
	(-5.01)	(-4.93)	(-4.89)	(-4.96)	(-5.35)	(-5.02)
Lag $returns_{t-6}$	0.0037	0.0035	0.0033	0.0032	0.0025	0.003
	(1.50)	(1.44)	(1.39)	(1.30)	(1.05)	(1.22)
$\Delta\ Cash_{t-6}$			-0.001			
			(-0.85)			
$\Delta\ NCCA_{t-6}$			-0.006***			
			(-3.30)			
$\Delta\ PPE_{t-6}$			-0.0036			
			(-1.42)			
$\Delta\ OA_{t-6}$			-0.0042**			
			(-2.01)			
AG_{t-6}		-0.0029***				
		(-5.13)				
Gross $Prof_{t-6}$				0.0093***		
				(5.24)		
$EBITDA_{t-6}$					0.0108***	
					(2.62)	
$XSGA_{t-6}$					0.0083***	
					(3.98)	
Gross $Marg_{t-6}$						0.00897***
						(4.134)
Asset $Turnover_{t-6}$						0.0026***
						(4.21)
Constant	0.0154***	0.0156***	0.0158***	0.0110***	0.0113***	0.00828**
	(4.92)	(5.01)	(5.07)	(3.34)	(3.54)	(2.32)
Observations	865,483	865,483	865,483	865,483	865,483	865,483
R^2 (%)	3.88	4.05	4.27	4.08	4.40	4.18

This table shows the Fama-MacBeth (1973) estimates of equation (12) as a baseline case and the estimates of equation (13) for Panels A and B.

$$r_{it} = \alpha_{it} + \gamma_1 \varepsilon_{it-1} + \gamma_2 \beta_{mkt,it} + \gamma_3 \beta_{smb,it} + \gamma_4 \beta_{hml,it} + \gamma_5 s_{it-6} + \gamma_6 lr_{it-6} + \gamma_7 ag_{it-6} + \gamma_8 prof_{it-6}$$

The sample contains all non-financial (sic codes 6000 – 6999) common stocks available jointly on CRSP and Compustat from January 1983 to December 2009. The dependent variable is monthly stock returns compounded from daily data. The explanatory variables are idiosyncratic volatility (ε), betas from the Fama and French (1993) three-factor model, size and lagged returns. In Panel A, we also include investment measured by asset growth (**AG**) and a decomposition proposed by Cooper et al. (2008). In Panel B, we decompose the gross profitability measure (**Gross Prof**) following Novy-Max (2013). All independent variables are winsorized at the 1st and 99th percentiles. The t-statistics are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 5: Fama-MacBeth Regressions Controlling Simultaneously for Profitability and Investment Effects

	Baseline Case	Panel A: Simultaneous Controls by Investment and Profitability							
ε_{t-1}	-0.0848**	-0.0602	-0.0649*	-0.0653*	-0.0615	-0.0700*	-0.0659	-0.0603	-0.0661
	(-1.99)	(-1.63)	(-1.68)	(-1.73)	(-1.52)	(-1.74)	(-1.63)	(-1.64)	(-1.63)
β_{MKT}	0.0042***	0.0043***	0.0043***	0.0043***	0.0046***	0.0044***	0.0043***	0.0044***	0.0043***
	(4.67)	(4.96)	(4.88)	(4.89)	(5.29)	(5.04)	(4.88)	(5.05)	(4.97)
β_{SMB}	0.0012***	0.0012***	0.0012***	0.0012***	0.0013***	0.0013***	0.0012***	0.0012***	0.0012***
	(3.05)	(3.20)	(3.16)	(3.17)	(3.27)	(3.33)	(3.15)	(3.23)	(3.15)
β_{HML}	-0.0005	-0.0006	-0.0006	-0.0005	-0.0007	-0.0006	-0.0005	-0.0006	-0.0005
	(-1.00)	(-1.21)	(-1.17)	(-1.16)	(-1.44)	(-1.26)	(-1.11)	(-1.20)	(-1.15)
$Size_{t-6}$	-0.0023***	-0.0023***	-0.0023***	-0.0023***	-0.0030***	-0.0026***	-0.0022***	-0.0022***	-0.0023***
	(-5.00)	(-5.48)	(-5.21)	(-5.25)	(-5.96)	(-5.59)	(-4.89)	(-5.28)	(-4.97)
Lag $returns_{t-6}$	0.0036	0.0029	0.0032	0.0030	0.0039*	0.0036	0.0029	0.0023	0.0027
	(1.49)	(1.25)	(1.33)	(1.26)	(1.65)	(1.49)	(1.23)	(0.98)	(1.16)
AG_{t-6}		-0.0030***	-0.0029***	-0.0030***	-0.0024***	-0.0028***	-0.0026***	-0.0028***	-0.0027***
		(-5.67)	(-5.48)	(-5.65)	(-4.58)	(-5.21)	(-4.79)	(-5.38)	(-4.90)
ROA_{t-6}		0.0046							
		(1.11)							
ROE_{t-6}			0.0010						
			(0.93)						
ROI_{t-6}				0.0012					
				(0.62)					
$Dividends_{t-6}$					0.0067***				
					(4.49)				
$Earnings_{t-6}$						0.0003**			
						(2.19)			
Gross $Prof_{t-6}$							0.0090***		
							(5.12)		
$EBITDA_{t-6}$								0.0102***	0.0094***
								(2.61)	(4.33)
$XSGA_{t-6}$								0.0079***	0.0024***
								(3.76)	(4.07)
Gross $Marg_{t-6}$									
Asset $Turnover_{t-6}$									
Constant	0.0154***	0.0156***	0.0157***	0.0157***	0.0167***	0.0168***	0.0114***	0.0118***	0.0086**
	(4.92)	(5.01)	(5.09)	(5.10)	(5.39)	(5.51)	(3.47)	(3.68)	(2.42)
Observations	865,483	865,483	865,483	865,483	865,483	865,483	865,483	865,483	865,483
R^2(%)	3.88	4.36	4.26	4.31	4.25	4.20	4.24	4.53	4.34

This table shows the Fama-MacBeth (1973) estimates of equation (13), in which the baseline case represents equation (12).

$$r_{it} = \alpha_{it} + \gamma_1 \varepsilon_{it-1} + \gamma_2 \beta_{mkt,it} + \gamma_3 \beta_{smb,it} + \gamma_4 \beta_{hml,it} + \gamma_5 s_{it-6} + \gamma_6 lr_{it-6} + \gamma_7 ag_{it-6} + \gamma_8 prof_{it-6}$$

The sample contains all non-financial (sic codes 6000 – 6999) common stocks available jointly on CRSP and Compustat from January 1983 to December 2009. The dependent variable is monthly stock returns compounded from daily data. The explanatory variables are idiosyncratic volatility (ε), betas from the Fama and French (1993) three-factor model, size and lagged returns as a baseline case. In Panel A, we added controls of investment and profitability measures together. All independent variables are winsorized at the 1st and 99th percentiles. The t-statistics are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 6: Investment decomposition

	Baseline Case	Panel A: Simultaneous Controls by Investment and Profitability							
ε_{t-1}	-0.0696*	-0.0563	-0.0622	-0.0622*	-0.0592	-0.0672*	-0.0652	-0.0568	-0.0633
	(-1.69)	(-1.53)	(-1.624)	(-1.65)	(-1.47)	(-1.67)	(-1.59)	(-1.55)	(-1.57)
β_{MKT}	0.0043***	0.0043***	0.0043***	0.0043***	0.0046***	0.0044***	0.0043***	0.0044***	0.0044***
	(4.89)	(5.02)	(4.95)	(4.95)	(5.34)	(5.11)	(4.93)	(5.10)	(5.04)
β_{SMB}	0.0012***	0.0012***	0.0012***	0.0012***	0.0013***	0.0013***	0.0012***	0.0012***	0.0012***
	(3.14)	(3.23)	(3.19)	(3.20)	(3.30)	(3.36)	(3.17)	(3.26)	(3.18)
β_{HML}	-0.0006	-0.0006	-0.0006	-0.0006	-0.0007	-0.0006	-0.0006	-0.0006	-0.0006
	(-1.19)	(-1.28)	(-1.24)	(-1.23)	(-1.50)	(-1.33)	(-1.18)	(-1.27)	(-1.22)
Size$_{t-6}$	-0.0023***	-0.0023***	-0.0022***	-0.0022***	-0.0030***	-0.0025***	-0.0022***	-0.0023***	-0.0022***
	(-4.88)	(-5.47)	(-5.17)	(-5.21)	(-5.88)	(-5.54)	(-4.86)	(-5.29)	(-4.92)
Lag returns$_{t-6}$	0.0033	0.0028	0.0030	0.0029	0.0038	0.0034	0.0028	0.0022	0.0026
	(1.39)	(1.22)	(1.29)	(1.22)	(1.60)	(1.45)	(1.19)	(0.95)	(1.11)
Δ Cash$_{t-6}$	-0.0009	-0.0012	-0.0010	-0.0013	-0.0005	-0.0009	-0.0006	-0.0010	-0.0007
	(-0.84)	(-1.18)	(-0.98)	(-1.19)	(-0.50)	(-0.84)	(-0.59)	(-1.00)	(-0.65)
Δ NCCA$_{t-6}$	-0.0064***	-0.0069***	-0.0066***	-0.0067***	-0.0055***	-0.0064***	-0.0076***	-0.0077***	-0.0072***
	(-3.29)	(-3.42)	(-3.38)	(-3.42)	(-2.93)	(-3.25)	(-3.95)	(-3.93)	(-3.62)
Δ PPE$_{t-6}$	-0.0036	-0.0038	-0.0038	-0.0037	-0.0028	-0.0034	-0.0021	-0.0028	-0.0023
	(-1.41)	(-1.49)	(-1.49)	(-1.44)	(-1.08)	(-1.36)	(-0.89)	(-1.16)	(-0.96)
Δ OA$_{t-6}$	-0.0042**	-0.0037*	-0.0042**	-0.0042**	-0.0039*	-0.0042**	-0.0031	-0.0029	-0.0032
	(-2.00)	(-1.81)	(-2.02)	(-2.01)	(-1.85)	(-2.02)	(-1.47)	(-1.39)	(-1.51)
ROA$_{t-6}$		0.0054							
		(1.31)							
ROE$_{t-6}$			0.0009						
			(0.92)						
ROI$_{t-6}$				0.0013					
				(0.65)					
Dividends$_{t-6}$					0.0064***				
					(4.32)				
Earnings$_{t-6}$						0.0003**			
						(2.21)			
Gross Prof$_{t-6}$							0.0092***		
							(5.40)		
EBITDA$_{t-6}$								0.0111***	
								(2.82)	
XSGA$_{t-6}$								0.0079***	
								(3.94)	
Gross Marg$_{t-6}$									0.0094***
									(4.42)
Asset Turnover$_{t-6}$									0.0025***
									(4.24)
Constant	0.0158***	0.0158***	0.0159***	0.0159***	0.0168***	0.0170***	0.0115***	0.0119***	0.0086**
	(5.07)	(5.08)	(5.15)	(5.16)	(5.43)	(5.56)	(3.51)	(3.74)	(2.42)
Observations	865,483	865,483	865,483	865,483	865,483	865,483	865,483	865,483	865,483
R^2(%)	4.27	4.57	4.48	4.52	4.46	4.41	4.44	4.73	4.54

This table shows the Fama-MacBeth (1973) estimates of equation (13), in which asset growth (AG) is decomposed following Cooper et al. (2008), controlling simultaneously for investment and profitability measures.

$$r_{it} = \alpha_{it} + \gamma_1 \varepsilon_{it-1} + \gamma_2 \beta_{mkt,it} + \gamma_3 \beta_{smb,it} + \gamma_4 \beta_{hml,it} + \gamma_5 s_{it-6} + \gamma_6 lr_{it-6} + \gamma_7 ag_{it-6} + \gamma_8 prof_{it-6}$$

The sample contains all non-financial (sic codes 6000 – 6999) common stocks available jointly on CRSP and Compustat from January 1983 to December 2009. The dependent variable is monthly stock returns compounded from daily data. All independent variables are winsorized at the 1st and 99th percentiles. The t-statistics are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 7: An alternative measure of Investment: Capital Investment

	Baseline Case	Panel A: Investment	Panel B: Simultaneous Controls by Investment and Profitability							
ε_{t-1}	-0.0851**	-0.0860**	-0.0723*	-0.0804**	-0.0792**	-0.0723*	-0.0847**	-0.0826*	-0.0733*	-0.0804*
	(-1.97)	(-1.99)	(-1.84)	(-1.98)	(-1.99)	(-1.74)	(-2.01)	(-1.92)	(-1.87)	(-1.89)
β_{MKT}	0.0033***	0.0033***	0.0034***	0.0033***	0.0033***	0.0036***	0.0034***	0.0033***	0.0034***	0.0034***
	(3.77)	(3.79)	(3.94)	(3.87)	(3.87)	(4.24)	(4.00)	(3.81)	(3.99)	(3.91)
β_{SMB}	0.0008**	0.0008**	0.0008**	0.0008**	0.0008**	0.0008**	0.0008**	0.0008**	0.0008**	0.0008**
	(2.05)	(2.03)	(2.06)	(2.02)	(2.03)	(2.15)	(2.22)	(2.07)	(2.11)	(2.09)
β_{HML}	-0.0007	-0.0007	-0.0007	-0.0007	-0.0007	-0.0008*	-0.0008	-0.0007	-0.0007	-0.0007
	(-1.46)	(-1.46)	(-1.58)	(-1.53)	(-1.54)	(-1.80)	(-1.62)	(-1.44)	(-1.60)	(-1.46)
Size$_{t-6}$	-0.0015***	-0.0015***	-0.0017***	-0.0015***	-0.0016***	-0.0021***	-0.0019***	-0.0015***	-0.0016***	-0.0015***
	(-3.51)	(-3.54)	(-4.22)	(-3.79)	(-3.88)	(-4.52)	(-4.34)	(-3.49)	(-4.03)	(-3.51)
Lag returns$_{t-6}$	0.0060***	0.0060***	0.0056***	0.0058***	0.0056***	0.0064***	0.0062***	0.0055***	0.0051**	0.0052**
	(2.84)	(2.82)	(2.70)	(2.74)	(2.69)	(3.02)	(2.95)	(2.63)	(2.44)	(2.48)
CI$_{t-6}$		-0.0005	-0.0006*	-0.0006*	-0.0006*	-0.0005	-0.0005*	-0.0004	-0.0005	-0.0004
		(-1.58)	(-1.86)	(-1.82)	(-1.83)	(-1.52)	(-1.64)	(-1.30)	(-1.61)	(-1.46)
ROA$_{t-6}$			0.0089**							
			(1.96)							
ROE$_{t-6}$				0.0010						
				(0.86)						
ROI$_{t-6}$					0.0024					
					(1.02)					
Dividends$_{t-6}$						0.0047***				
						(3.68)				
Earnings$_{t-6}$							0.0003***			
							(2.69)			
Gross Prof$_{t-6}$								0.0084***		
								(4.71)		
EBITDA$_{t-6}$									0.0133***	
									(3.12)	
XSGA$_{t-6}$									0.0071***	
									(3.36)	
Gross Marg$_{t-6}$										0.0099***
										(4.06)
Asset Turnover$_{t-6}$										0.0026***
										(4.51)
Constant	0.0113***	0.0115***	0.0115***	0.0116***	0.0117***	0.0123***	0.0130***	0.0075**	0.0079**	0.0038
	(3.72)	(3.79)	(3.76)	(3.84)	(3.86)	(4.10)	(4.39)	(2.35)	(2.50)	(1.11)
Observations	598,926	598,926	598,926	598,926	598,926	598,926	598,926	598,926	598,926	598,926
R^2(%)	3.79	3.83	4.10	4.01	4.05	4.02	3.98	4.02	4.26	4.13

This table shows the Fama-MacBeth (1973) estimates of equation (13), in which the baseline case represents equation (12), in which investment and profitability controls are not included.

$$r_{it} = \alpha_{it} + \gamma_1 \varepsilon_{it-1} + \gamma_2 \beta_{mkt,it} + \gamma_3 \beta_{smb,it} + \gamma_4 \beta_{hml,it} + \gamma_5 s_{it-6} + \gamma_6 lr_{it-6} + \gamma_7 CI_{it-6} + \gamma_8 prof_{it-6}$$

The sample contains all non-financial (sic codes 6000 – 6999) common stocks available jointly on CRSP and Compustat from January 1983 to December 2009. The dependent variable is monthly stock returns compounded from daily data. The explanatory variables are idiosyncratic volatility (ε), betas from the Fama and French (1993) three-factor model, size and lagged returns as a baseline case. In Panel A, we add only the investment measure **CI$_{t-6}$** (Abnormal Capital Investment), and in Panel B, we include jointly controls of investment and profitability. All independent variables are winsorized at the 1st and 99th percentiles. The t-statistics are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 8: Portfolio returns sorted by idiosyncratic risk based on the Fama and French (2014) five-factor model

		Returns	Alphas
Idiosyncratic risk quintiles	**Low 1**	0.90	-0.06
			(-1.01)
	2	1.00	0.03
			(0.51)
	3	1.11	0.19
			(2.50)
	4	0.92	0.07
			(0.71)
	High 5	0.25	-0.52
			(-3.44)
	[5-1]	-0.66	-0.46
		(-1.83)	(-2.38)

This table reports monthly average returns and risk-adjusted returns for quintiles formed after sorting stocks according to their level of idiosyncratic risk based on the Fama and French (2014) five-factor model. The sample includes all non-financial (SIC codes 6000 - 6999) common stocks available on CRSP from July 1963 to December 2009. Quintile 1 corresponds to the portfolio with the lowest idiosyncratic risk, and quintile 5 to the portfolio with the highest idiosyncratic risk. Returns and alphas are reported in monthly percentages. Row [5-1] is the difference between portfolio 5 and portfolio 1. Newey-West *t*-statistics are reported in parenthesis.

Table 9: Effect of investor sentiment

	Baseline Case	Simultaneous Controls by Investment and Profitability and Sentiment							
ε_{t-1}*sent	-0.0246*	-0.0184	-0.0202	-0.0198	-0.0190	-0.0204	-0.0213	-0.0184	-0.0206
	(-1.64)	(-1.36)	(-1.46)	(-1.45)	(-1.39)	(-1.44)	(-1.51)	(-1.36)	(-1.47)
ε_{t-1}	-0.0467	-0.0307	-0.0334	-0.0341	-0.0313	-0.0378	-0.0347	-0.0307	-0.0340
	(-1.25)	(-0.95)	(-0.99)	(-1.03)	(-0.87)	(-1.06)	(-0.96)	(-0.95)	(-0.95)
sent	3.059	2.870	2.808	2.802	2.565	2.693	2.411	2.065	1.482
	(1.02)	(1.03)	(1.02)	(1.03)	(1.03)	(1.02)	(1.03)	(1.05)	(1.01)
b_{MKT}	0.0042***	0.0043***	0.0043***	0.0043***	0.0046***	0.0044***	0.0043***	0.0044***	0.0043***
	(4.67)	(4.96)	(4.88)	(4.89)	(5.29)	(5.04)	(4.88)	(5.05)	(4.97)
b_{SMB}	0.0012***	0.0012***	0.0012***	0.0012***	0.0013***	0.0013***	0.0012***	0.0012***	0.0012***
	(3.05)	(3.20)	(3.16)	(3.17)	(3.27)	(3.33)	(3.15)	(3.23)	(3.15)
b_{HML}	-0.0005	-0.0006	-0.0006	-0.0005	-0.0007	-0.0006	-0.0005	-0.0006	-0.0005
	(-1.00)	(-1.21)	(-1.17)	(-1.16)	(-1.44)	(-1.26)	(-1.11)	(-1.20)	(-1.15)
$size_{t-6}$	-0.0023***	-0.0023***	-0.0023***	-0.0023***	-0.0030***	-0.0026***	-0.0022***	-0.0022***	-0.0023***
	(-5.00)	(-5.48)	(-5.21)	(-5.25)	(-5.96)	(-5.59)	(-4.89)	(-5.28)	(-4.97)
lag $returns_{t-6}$	0.0036	0.0029	0.0032	0.0030	0.0039*	0.0036	0.0029	0.0023	0.0027
	(1.49)	(1.25)	(1.33)	(1.26)	(1.65)	(1.49)	(1.23)	(0.98)	(1.16)
ag_{t-6}		-0.0030***	-0.0029***	-0.0030***	-0.0024***	-0.0028***	-0.0026***	-0.0028***	-0.0027***
		(-5.67)	(-5.48)	(-5.65)	(-4.58)	(-5.21)	(-4.79)	(-5.38)	(-4.90)
ROA_{t-6}		0.0046							
		(1.11)							
ROE_{t-6}			0.0010						
			(0.93)						
ROI_{t-6}				0.0012					
				(0.62)					
$Dividends_{t-6}$					0.0067***				
					(4.49)				
$Earnings_{t-6}$						0.0003**			
						(2.19)			
Gross $Prof_{t-6}$							0.0090***		
							(5.12)		
$EBITDA_{t-6}$								0.010***	
								(2.61)	
$XSGA_{t-6}$								0.0079***	
								(3.76)	
Gross $Marg_{t-6}$									0.0094***
									(4.33)
Asset $Turnover_{t-6}$									0.0024***
									(4.07)
Observations	865,483	865,483	865,483	865,483	865,483	865,483	865,483	865,483	865,483
R^2(%)	11.5	12.0	11.9	11.9	11.8	11.8	11.8	12.1	11.9

This table shows the Fama-MacBeth (1973) estimates of equation (15):

$$r_{it} = \gamma_1 \varepsilon_{it-1} * Sent_{t-1} + \gamma_2 \varepsilon_{it-1} + \gamma_3 Sent_{t-1} + \gamma_4 \beta_{mkt,t} + \gamma_5 \beta_{smb,t} + \gamma_6 \beta_{hml,t} + \gamma_7 s_{it-6} + \gamma_8 lr_{it-6} + \gamma_9 prof_{it-6} + \gamma_{10} ag_{it-6}$$

The sample contains all non-financial (sic codes 6000 – 6999) common stocks available jointly on CRSP and Compustat from January 1983 to December 2009. The dependent variable is monthly stock returns compounded from daily data. The explanatory variables are idiosyncratic volatility (ε), the value of the Baker and Wurgler Index (Sent), interaction term, betas from the Fama and French (1993) three-factor model and different measures of profitability and investment. All independent variables are winsorized at the 1st and 99th percentiles. The t-statistics are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 10: Skewness vs. profitability and investment

	Base Case	Panel A: Skewness	Panel B: Investment, Profitability and Skewness Simultaneously				
ε_{t-1}	-0.0969**	-0.0838*	-0.0631	-0.0604	-0.0620	-0.0568	-0.0638
	(-1.96)	(-1.65)	(-1.30)	(-1.37)	(-1.30)	(-1.19)	(-1.33)
β_{MKT}	0.0048***	0.0048***	0.0048***	0.0050***	0.0049***	0.0052***	0.0049***
	(-5.37)	(5.41)	(5.59)	(5.80)	(5.63)	(6.22)	(5.77)
β_{SMB}	0.0008*	0.0008*	0.0009**	0.0008**	0.0008**	0.0009**	0.0009**
	(1.91)	(1.92)	(2.01)	(2.04)	(1.99)	(2.11)	(2.14)
β_{HML}	-0.0015***	-0.0015***	-0.0016***	-0.0016***	-0.0016***	-0.0018***	-0.0016***
	(-2.61)	(-2.63)	(-2.77)	(-2.97)	(-2.82)	(-3.27)	(-2.98)
Size$_{t-6}$	-0.0020***	-0.0020***	-0.0019***	-0.0019***	-0.0020***	-0.0029***	-0.0023***
	(-3.51)	(-3.46)	(-3.36)	(-3.62)	(-3.43)	(-4.51)	(-4.01)
Lag returns$_{t-6}$	0.0075***	0.0073***	0.0066***	0.0060***	0.0063***	0.0077***	0.0073***
	(3.43)	(3.37)	(3.09)	(2.88)	(3.00)	(3.61)	(3.39)
AG$_{t-6}$			-0.0032***	-0.0033***	-0.0032***	-0.0029***	-0.0034***
			(-4.56)	(-4.81)	(-4.59)	(-4.39)	(-4.90)
Gross Prof$_{t-6}$			0.0102***				
			(5.18)				
EBITDA$_{t-6}$				0.0111**			
				(2.41)			
XSGA$_{t-6}$				0.0094***			
				(3.68)			
Gross Marg$_{t-6}$					0.010***		
					(3.96)		
Asset Turnover$_{t-6}$					0.0026***		
					(3.89)		
Dividends$_{t-6}$						0.0068***	
						(3.65)	
Earnings$_{t-6}$							0.0004**
							(2.34)
Skewness		-0.0018***	-0.0019***	-0.0019***	-0.0019***	-0.0019***	-0.0019***
		(-4.15)	(-4.35)	(-4.49)	(-4.40)	(-4.37)	(-4.30)
Constant	0.0136***	0.0133***	0.0087**	0.0089**	0.0059	0.0150***	0.0148***
	(3.76)	(3.68)	(2.40)	(2.52)	(1.49)	(4.21)	(4.19)
Observations	604,655	604,655	604,655	604,655	604,655	604,655	604,655
R^2	2.65	2.70	2.94	3.14	3.02	2.99	2.92

This table shows the Fama-MacBeth (1973) estimates of the following equation:

$$r_{it} = \alpha_{it} + \gamma_1 \varepsilon_{it-1} + \gamma_2 \beta_{mkt,it} + \gamma_3 \beta_{smb,it} + \gamma_4 \beta_{hml,it} + \gamma_5 s_{it-6} + \gamma_6 lr_{it-6} + \gamma_7 ag_{it-6} + \gamma_8 prof_{it-6} + \gamma_7 Skewness_{it-1}$$

The sample contains all non-financial (sic codes 6000 – 6999) common stocks available jointly on CRSP and Compustat from January 1983 to December 2009. The dependent variable is monthly stock returns compounded from daily data. The explanatory variables are idiosyncratic volatility (ε), betas from the Fama and French (1993) three-factor model, a measure of investment (AG, asset growth), several measures of profitability and skewness. In Panel A, only Skewness is added, and in Panel B, we control simultaneously by skewness, investment and profitability measures. All independent variables are winsorized at the 1st and 99th percentiles. The t-statistics are reported in parentheses. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.