The Cross-Section of Industry Investment Returns

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Abstract

Firm level characteristics explain the cross section of investment returns of industry portfolios that include listed and unlisted firms. Moreover, common asset pricing models explain the cross-sectional variation of characteristic-based investment returns which include listed and unlisted firms. Assuming that managers of unlisted firms are less likely to be affected by investor misvaluation and are less likely to overinvest, our results are consistent with a rational interpretation of the role of characteristics. Given a portfolio characteristic, there are no systematic differences in expected investment returns for listed and unlisted firms suggesting their cost of equity are unrelated to whether a firm is listed or unlisted.

JEL Classification: G0, G12, G31.

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1 Introduction

The role of firm characteristics in describing the cross section of stock returns has led to the claim that mispricing is prevalent in the economy. Daniel and Titman (1997) show that characteristics dominate covariances in explaining the cross section of returns.[1] These findings are part of the backbone of the evidence suggesting investors exhibit behavioral biases (see the discussion in Barberis and Thaler (2003)). However, Lin and Zhang (2012) show that in general equilibrium, just like covariances, firm characteristics are sufficient statistics for expected stock returns, and expected stock returns are determined endogenously jointly with covariances (as in the consumption approach of Lucas, 1978) and firm characteristics (as in the investment approach of Cochrane, 1991). Therefore, the search for mispricing through running horse races of covariances against characteristics is pointless. Moreover, characteristics will dominate covariances in return regressions since, as Lin and Zhang (2012) show, the former are measured more precisely. However, this says nothing about mispricing; finding evidence that characteristics dominate covariances provides evidence that is consistent with both rational and irrational pricing.

In this paper, we examine the determinants of the cross section of industry investment returns, derived from the q-theory of investment (Cochrane, 1991, Liu, Whited and Zhang, 2009) using the NBER industry productivity data that aggregates both listed and unlisted (private) firms and includes all 459 manufacturing industries in the US. Examining investment returns of all firms, including unlisted firms, allows us to address three important issues. First, it has been established that investment returns are equal to stock returns.[2] Therefore, if the role of characteristics in investment returns in a sample that includes unlisted firms is the same as their role in investment returns of only listed firms, this lends some support to ruling out mispricing as an explanation for the role of these characteristics. The reason for this is that unlisted firms have no stock prices. Instead,

[1] More recent examples are Daniel, Hirshleifer, and Teoh (2002), Barberis and Thaler (2003), Richardson, Tuna, and Wysocki (2010), Dechow, Khimich, and Sloan (2011) and Hirshkeifer, Hou, and Teoh (2011).

[2] Cochrane (1991) demonstrates this and provides evidence at the aggregate level. Liu, Whited, and Zhang (2009) show that investment returns are equal to stock returns for portfolios sorted on charcteristics that give a large spread in stock returns.

the role of characteristics is likely to stem from their presence in the first order investment conditions of firms' optimal investment decisions.

Second, this is the first paper to address the risk-return relation of all firms. If a factor is a true *aggregate* risk factor, and investors are diversified, it should price all stocks, whether they are listed or not. At the present, the literature has only examined the risk-return relation of listed firms and therefore it has not been possible to establish whether common risk factors are actually sources of aggregate uncertainty or are relevant only for firms that are listed on the stock exchange. While all previous assessments of risk and return have focussed on listed firms, the importance of unlisted firms in the economy should not be underestimated and is an economically important topic. For instance, Asker, Farre-Mensa and Ljungkvist (2011) estimate that in 2007 private U.S. firms accounted for 54.5% of aggregate non-residential fixed investment, 67.1% of private sector employment, 57.6% of sales, and 20.6% of aggregate pre-tax profits. Thus, unlisted firms are an important, but often neglected, part of the US economy.[3]

Third, the estimates of the cost of equity capital for unlisted firms are notoriously difficult to obtain because of the lack of stock prices. However, by using investment returns of both listed and unlisted firms, we can obtain the first estimates of the cost of equity of unlisted firms from asset pricing models. Because most firms in the economy are unlisted, being able to obtain a risk based measure of the cost of equity is crucial to optimal decision making. Our paper assesses the only means of achieving this.

The empirical results we present are a novel contribution because the extant literature has not focused on the role of characteristics and risk-adjusted returns for all firms including unlisted firms due to the lack of stock return data for unlisted firms. Our approach of using investment returns, derived from the q-theory of investment, circumvents the need for stock return data. Since Cochrane (1991), Restoy and Rockinger (1994), and Liu, Whited and Zhang (2009) show empirically that investment returns are equal to stock returns, the results we present are consistent with those that would have been obtained

[3]The vast majority of firms in the U.S. are closely-held corporations The latest Census indicates seven million corporate tax filers, of which only about 8,000 are public firms. Closely-held corporations produce 51 percent of the private sector output and employ 52 percent of the labor force, see Nagar, Petroni and Wolfenzon (2009).

had stock return data been available.

Our main findings can be summarized as follows. First, we show that characteristics that have been shown to explain the cross section of stock returns, namely the investment to capital ratio (I/K), the return on assets (ROA) (see Chen, Novy-Marx and Zhang, 2010) and lagged investment returns are determinants of the cross section of investment returns of both industry portfolios with a relatively large fraction of listed firms as well as of industry portfolios with a relatively small fraction of listed firms. Therefore, because characteristics share the same role in the determination of average investment returns for both listed and unlisted firms, their role in determining investment returns is unlikely to stem from stock mispricing simply because unlisted firms have no stock price. Rather the role of characteristics stems from their fundamental part in the first order conditions for investment decisions (Lin and Zhang (2012)). We also find that idiosyncratic volatility is an important determinant of the cross section of investment returns of both portfolios with a large fraction of unlisted firms as well as of portfolios with a large fraction of listed firms. Idiosyncratic volatility could have a role for one of two reasons. First, under-diversification which may be present in unlisted firms where firms are more likely to be closely held. Second, growth options where, for example, Bartram, Brown, and Stulz (2011) argue that the high idiosyncratic of U.S. stock returns is related to high levels of investor protection and research intensity at the country level and high levels of research and development at the firm level. They relate these characteristics to a greater level of growth options and the opportunities to exercise them in the U.S.. Given that idiosyncratic volatility is important cross-sectionally in both listed and unlisted firms, it is unlikely to arise from under-diversification, but rather growth options.

Second, a three factor model derived from the q-theory of investment, as in Chen, Novy-Marx and Zhang (2010), composed of the "market" investment return, an I/K factor and an ROA factor performs well in explaining the cross-section of investment returns of twenty industry portfolio test assets composed of five I/K portfolios, five ROA portfolios, five portfolios sorted by lagged investment returns and five portfolios sorted by idiosyncratic volatility. The model also performs well in terms of small pricing errors and a large cross-sectional $\overline{R}^2$. This is the case irrespective of the amount of listed firms in each portfolio. We also find that the macroeconomic risk factor model of Chen, Roll, and Ross (1986) also performs very well in terms of describing the cross-section of listed and unlisted firms' investment returns. Therefore, because these two separate risk factor models affect both listed and unlisted firms they are likely to be true aggregate risk factors in that they are aggregate sources of uncertainty in the economy. Overall, whether looking at the role of characteristics or risk factors, we find that they are crucial in explaining the cross section of all portfolios and portfolios that vary according to the amount of unlisted firms that are included.

Third, based on the estimates from the three factor model, we calculate the cost of equity capital (expected return) for all industries and industries with varying degrees of listed firms in them. The differences in these estimates across listed and unlisted firms are generally small compared to the level of expected returns suggesting that listed and unlisted firms have similar costs of equity. There is certainly no systematic difference in the cost of equity in the sense that unlisted firms always have a higher cost of equity than listed firms. In fact, we find that the differences in the cost of equity capital are largest in the portfolios with high or low characteristics. This indicates that the characteristics, and not the fact that the portfolio contains more of less unlisted firms, are driving any differences in the cost of equity. To the extent that the cost of equity capital from the investment return approach is similar for listed and unlisted firms, given a portfolio formation characteristic, and given that investment returns are equal to stock returns (Liu, Whited and Zhang (2009)) then unlisted firms can use listed firms stock returns to proxy their cost of equity capital, particularly when the unlisted firms do not have an extreme value of one of the characteristics we examine.

The results that unlisted and listed firms have similar costs of equity capital, and in particular that there is no systematic difference across the two types of firms, might seem surprising given the lack of liquidity of unlisted firms and the potential under-diversification of their owners. However, these findings are consistent with Moskowitz and Vissing-Jørgensen (2002) who use estimates of private firm value and profits at the aggregate level and study the returns to entrepreneurial investment. They find that in spite of the poor diversification of the owners of unlisted firms, the returns to private equity are not higher than the returns to public equity. We differ from Moskowitz and Vissing-Jørgensen along several dimensions. First, we examine the determinants of the cross section of a large number of industries rather than the time-series of the aggregate market. Second, we estimate the returns on investment using production and capital stock data and not on equity value estimates.

The findings we present regarding the role of characteristics and mispricing should be considered cautiously. The reason for this is that the lack of stock prices does not necessarily imply that investment returns are not affected by overvaluation or undervaluation of the firm. For example, if a certain characteristic indicates that a listed firm's stock is overpriced and subsequent stock returns are abnormally negative, then the same characteristic could be associated with abnormally high real investment due to managers' overvaluation of investment projects followed by negative abnormal investment returns for unlisted firms. However, to the extent that managers of firms, and especially of unlisted firms, are less affected by investors' misvaluation concerning the firm than investors in the stock market, our results are consistent with a rational-based explanation for the role of characteristics in explaining expected stock returns.

Our claim that the results are most consistent with a rational based explanation are based on a number of factors that lead us to believe that the investment returns of unlisted firms are less likely to be affected by investors' valuations. First, when managers possess private information on which they base their expectations and rational decisions they are likely to ignore investors' misvaluations. Given that private firms are likely to be characterized by a higher level of private information, the influence of investor sentiment is further diminished for these firms. This is collaborated in Hribar and Quinn (2010) who examine the trading patterns of managers and find evidence that they can see through market sentiment. Second, as noted by Polk and Sapienza (2009), if the market misprices firms according to their level of investment, managers may try to boost short-run share prices by catering to current sentiment. Managers with shorter shareholder horizons should cater more. This mechanism is unlikely to exist within unlisted firms. Stein (1996) argues that managers with short horizons should be aggressively investing when investors are overly optimistic. Asker, Farre-Mensa and Ljungkvist (2011) present evidence consistent with managers of listed firms being short-termist and managers of unlisted firms not being short-termist. Third, while managers of unlisted firms could still raise capital through private placement when their firms are overvalued, being non short-termist implies they will use the proceeds for investment in T-bills rather than undertake negative NPV projects (Stein, 1996). Fourth, Cooper and Priestley (2011) find that the investment-future stock return relation can be explained without recourse to arguments based on overinvestment or investor overreaction. In particular, they find that differences in systematic risk between high and low investment firms can explain the differences in average stock returns between high and low investment firms.

Overall, while we can not fully rule out that investment returns of unlisted firms are unaffected by sentiment or other behavioral biases, it is certainly the case that they are less likely to be. Therefore, our findings that the same characteristics and risk factors are relevant for both listed and unlisted firms points to the conclusion that the role of characteristics in both listed and unlisted firms investment returns and the previous reported role of them in stock returns, is unlikely to be related to mispricing.

The rest of the paper is organized as follows. In Section 2, we illustrate the equivalent role of characteristics and covariances in returns. Section 3 describes the data and variable construction. Section 4 presents the empirical findings. The paper concludes in Section 5.

2 The Equivalent Role of Characteristics and Covariances

In this section of the paper, we follow Lin and Zhang (2012) and show the equivalence between the role of characteristics and covariances. In the typical consumption economy with no production the agent's first order consumption problem results in the following well known expression for expected returns:

$$E_t \left[M_{t+1} r^s_{i,t+1} \right] = 1, \tag{1}$$

where M_{t+1} is the stochastic discount factor and $r^s_{i,t+1}$ is the gross return on stock i. Cochrane (2005) shows how to use the definition of covariance to write expression (1) in terms of a beta pricing model:

$$E_t \left[r^s_{i,t+1} \right] - r_f = \beta^M_i \lambda_M, \tag{2}$$

where $r_f = \frac{1}{E_t[M_{t+1}]}$ is the risk free rate, $\beta^M_i = -cov(r^s_{i,t+1}, M_{t+1})/var(M_{t+1})$ is the loading of $r^s_{i,t+1}$ on M_{t+1}, and λ_M is the price of risk defined as $var(M_{t+1})/E_t\left[M_{t+1}\right].$

Now turning to a production economy with adjustment costs, Cochrane (1991) shows that stock returns can be written in terms of characteristics:

$$r^s_{i,t+1} = \frac{\pi_{i,t+1}}{1 + a\left(\frac{I_{i,t}}{K_{i,t}}\right)}, \tag{3}$$

where $\pi_{i,t+1}$ is firm $i's$ productivity given a set of random aggregate shocks, $I_{i,t}$ is firm investment, $K_{i,t}$ is firm capital stock, and a is an adjustment cost parameter. Lin and Zhang (2012) focus on the equivalence between these two approaches:

$$r_f + \beta^M_i \lambda_M = E_t \left[r^S_{i,t+1} \right] = \frac{E_t\left[\pi_{i,t+1}\right]}{1 + a\left(\frac{I_{i,t}}{K_{i,t}}\right)}, \tag{4}$$

where the first term presents the expression for expected returns in terms of covariances and the final term in terms of characteristics. Rearranging makes the relationship between covariances and characteristics clearer:

$$\beta^M_i = \left(\frac{E_t\left[\pi_{i,t+1}\right]}{1 + a\left(\frac{I_{i,t}}{K_{i,t}}\right)} - r_f \right) / \lambda_M. \tag{5}$$

In a general equilibrium framework with positive adjustment costs, expected stock returns, covariances and characteristics all become endogenous. There is no causal relation among these variables. Specifically, no causality runs from covariances to expected returns, from characteristics to expected returns, or vice versa. Therefore, showing that risk factors (covariances) or characteristics are important in stock return regressions does not mean that they explain expected returns. We can say nothing about the rationality of prices from these approaches. However, we can say nothing about irrationality either. The point is that characteristics can show up in the cross section of returns because of their role in the firm's first order investment decision or because of mispricing.

Now consider Cochrane (1991) who shows that

$$r^s_{i,t+1} = \frac{\pi_{i,t+1}}{1 + a\left(\frac{I_{i,t}}{K_{i,t}}\right)} = r^I_{i,t+1}, \tag{6}$$

where $r^I_{i,t+1}$ is the firm's investment return. The equivalence between stock returns and investment returns allows us to use investment returns for unlisted firms. This allows us to address two central and important issues. First, if characteristics and loadings on risk factors are important in the determination of expected returns, and are similar for listed and unlisted firms' investment returns, then the role of characteristics in general is likely to be due to the first order production decisions of firms and not due to mispricing. Second, what is the cost of equity capital for unlisted firms and does it differ from that of listed firms? This issue has not been addressed before in a risk-return framework.

There is a further advantage with asset pricing tests that use unlisted firms as part of the sample. If a factor that is related to returns is a "true" risk factor then it is a necessary condition that it is a source of aggregate uncertainty which affects all firms in the economy. To our knowledge, the extant literature has focussed asset pricing tests entirely on returns of listed firms. Consequently, there is no possibility to assess whether these factors are an aggregate source of uncertainty. By including unlisted firms as well as listed firms we are able to assess whether risk factors are an aggregate source of uncertainty.

To the extent that managers of unlisted firms are less affected by investor sentiment or valuation mistakes regarding their firms than investors in the stock market and than managers of listed companies, finding that characteristics drive the cross section of returns would lend some support for the idea that it is the fundamental first order investment decision that explains the role of characteristics in the cross-section of returns.

3 Data and Variable Construction

We use the Bartelsman, Becker and Gray 2009 NBER-CES Manufacturing Industry Productivity Database (which we refer to as the NBER database), available on the NBER website, as well as the Compustat database. The NBER database contains annual 4-digit SIC industry-level data on output, investment, capital stock and other industry-related variables for all 4-digit manufacturing industries in the US for the period 1958-2005. The data covers 459 manufacturing industries and are collected from various government sources, with many of the variables taken directly from the Census Bureau's Annual Survey of Manufacturers (ASM) and Census of Manufacturers. The ASM is a survey of around 60,000 establishments, carried out by the Census Bureau. Bartelsman and Gray (1996) provide a detailed description of the database.

Our primary variable of interest is the rate of return on investment. Liu, Whited and Zhang (2009) assume a Cobb-Douglas production function and a quadratic adjustment cost function and derive the investment return as follows:

$$r^I_{i,t+1} = \frac{(1-\tau_{t+1})\left[\alpha\frac{Y_{i,t+1}}{K_{i,t+1}} + \frac{a}{2}\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2\right] + \tau_{t+1}\delta_{i,t+1} + (1-\delta_{i,t+1})\left[1+(1-\tau_{t+1})\,a\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)\right]}{\left[1+(1-\tau_{t+1})\,a\left(\frac{I_{i,t}}{K_{i,t}}\right)\right]} \tag{7}$$

where α is the share of capital in production, Y is sales, K is the stock of capital, I is investment, δ is capital depreciation and a is an adjustment cost parameter. A larger value of a implies that the industry is facing higher adjustment costs of investment.

As Liu, Whited and Zhang (2009) note, the investment return given in equation (7) is the ratio of the marginal benefit of an additional unit of installed capital (marginal q) to the marginal cost of installing an extra unit of capital. The term $(1-\tau_{t+1})\left[\alpha\frac{Y_{i,t+1}}{K_{i,t+1}}\right]$ is the marginal after-tax profit produced by an extra installed unit of capital. The term $(1-\tau_{t+1})\left[\frac{a}{2}\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2\right]$ is the marginal after-tax reduction in adjustment costs caused by having an extra unit of installed capital. The term $\tau_{t+1}\delta_{i,t+1}$ is the marginal depreciation tax shield, and the last term is the marginal continuation value of an extra unit of capital net of depreciation.[4]

To calculate industry investment returns at the aggregate industry level we need several data items and estimates. We use the value of shipment data item from the NBER database, deflated by a value of shipment deflator in order to obtain data on real industry output, Y. We use the real capital stock series from the NBER database for the capital stock K. Investment, I, is given by total capital expenditures, deflated by a deflator for that series in order to obtain investment in real terms, where both capital expenditure per industry and the investment deflator are from the NBER database. We follow Liu, Whited and Zhang and measure τ_t, the corporate tax rate, as the statutory corporate income tax rate. The source for the tax data is the Commerce Clearing House annual publications. We use Compustat data on depreciation and amortization (item DP) to compute industry-level rates of depreciation as follows. For each industry each year, we sum the depreciation of all firms in that industry and divide by the sum of capital stock of all firms in the industry.

For the industry-specific capital share parameter α and the adjustment cost parameter a we use the estimates in Belo, Xue and Zhang (2010). Belo Xue and Zhang use GMM on the investment Euler equation and on a valuation equation to estimate these parameters for the Fama French 48 industries (as well as characteristic-based portfolios). For each of the four-digit SIC code industries in our sample we assign the α and a parameters of the two-digit industry from the 48 Fama and French industries that industry belongs to.[5]

A potential problem when using the NBER database to calculate industry investment returns is the fact that the data are only for US-based variables. That is, there is no information in this database on the stock of capital of US industries held abroad, as opposed to the Compustat data which includes data on total firm capital held domestically

[4]Note that the price of an installed unit of capital is equal to its marginal value (marginal q), which under optimality equals the marginal cost of investment given by $a\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)$. Thus, the last term in (7) reflects the value of the undepreciated extra unit of capital.

[5]We remove from the sample industries which do not have data for all years from 1958 to 2005, which reduces our sample to 449 industries.

and abroad. Note, however, that the required return on investment in the stock of capital held in the US should not be affected by the exclusion of capital held in other countries for the following reason. If a firm undertakes an investment project in the US it will require a rate of return on that investment that either corresponds to the risk of the project, or is related to some behavioral biases the firms' managers have. Thus, it is possible to study the risk-return relation for such projects independently of capital held in foreign countries. This is similar to examining the cross section of average stock returns in a sub-sample of the CRSP database, for example in a sub-sample that contains NYSE stocks only. Any asset pricing model would contend that average returns of firms in that sub-sample of firms are related to their riskiness or to some characteristics.

Common measures of the return on real investment such as the return on investment (ROI), the return on assets (ROA) or the return on equity (ROE) might be imprecise for several reasons. First, these measures assume that the marginal return on investment equals the average return on investment. However, the return on investment is likely diminishing. Second, the denominators of ROA and ROE do not account for adjustment costs of investment. Third, the numerators account only for the cash flow part of investment but disregard the part that is due to the undepreciated capital and the reduction in future adjustment costs caused by installing capital in the present.

4 Empirical Results

This section of the paper presents results on the determinants of the cross section of investment returns at the four-digit manufacturing industry level. The industry portfolios consist of both listed and unlisted firms. We focus on the following characteristics. The investment to capital ratio and the return on assets (ROA), both of which explain the cross section of average stock returns (Chen, Novy-Marx and Zhang, 2010). We also examine whether lagged investment returns and a measure for idiosyncratic volatility explain the cross section of average returns. Subsequently, we examine the determinants of average investment returns separately for industries in which the ratio of the sales of listed firms to the sales of both listed and unlisted firms is lower than the median (and the 25% lowest) for all industries, and also when this ratio is above the median (and highest 25%). This test enables a closer inspection of the differences in the determinants of average investment returns between listed and unlisted firms.

We perform asset pricing tests by examining the cross sectional patterns of investment returns when using three investment return based risk factors. These factors are a "market" investment return factor, an I/K factor and an ROA factor. We also show that the Chen, Roll, and Ross (1986) factors, which have also been employed exclusively on stock return data, can also explain the cross section of investment returns. Finally, we investigate whether the cost of equity capital calculated from the asset pricing model varies between listed and unlisted firms within the manufacturing sector.

4.1 Characteristics and the cross section of industry investment returns

In Table 1, we run year-by-year cross sectional Fama MacBeth regressions of investment returns in excess of the risk free rate on industry characteristics. The second column reports the results for univariate cross sectional regressions of investment returns on the one year lagged investment to capital ratio. That is, we regress investment returns in year t on the ratio of investment in year $t-1$ to capital in year $t-2$. Consistent with the result for stock returns (see Xing, 2008), the coefficient on the investment to capital ratio is negative and it is statistically significant, with a t-statistic of 10.99. The size of the coefficient in Xing (2008, Table 3) is considerably larger (-4.75) relative to our estimate of -1.02. This can be explained by the fact that we use investment returns and industry portfolios whereas Xing uses individual stock returns. The $\overline{R}^2$ is 4% (versus 1% in Xing, 2008). This first result in Panel A of Table 1 indicates that the investment effect in investment returns is likely prevalent among all firms, including unlisted firms.

The third column of Table 1 reports the results for ROA. Chen, Novy-Marx and Zhang (2010) show that the q-theory of investment implies a positive relation between ROA and future stock returns. Given a certain level of investment, a firm's riskiness must increase with ROA to justify the level of investment. The intuition is as follows. Consider two firms with a given investment to capital ratio. As investment is determined by expected future cash flows and by risk, the firm with higher ROA, that is higher expected cash flows, must also have higher risk to explain that its investment to capital ratio is not higher. Indeed Chen, Novy-Marx and Zhang (2010) show that the risk premium on a stock return factor defined as the excess return of high ROA stocks over low ROA stocks is 0.76% per month and is statistically significant. Looking at the third column of Panel A, the coefficient on ROA is 0.09 and it is highly statistically significant, with a t-statistic of 11.66 and the $\overline{R}^2$ is 4.76%.

The fourth column of Table 1 presents the results for one-year lagged investment returns. The coefficient on last year's investment returns is 0.23 and is statistically significant and the $\overline{R}^2$ is 10.57%. Thus, like in stock returns, we find a momentum effect in investment returns. This result is consistent with Liu and Zhang (2011) who find a momentum effect in investment returns of listed firms.

The result for idiosyncratic volatility appears in the fifth row of Table 1. To measure idiosyncratic volatility we form a "market" portfolio by equal-weighting the investment returns of all 449 industries using the NBER database. We use this "market" portfolio to estimate idiosyncratic volatilities using the full sample period. We first regress the excess investment returns of each industry (using the risk free rate from Kenneth French's website) on the "market" portfolio's excess returns using the whole sample. The standard deviation of the residuals from this regression is our proxy for the industry idiosyncratic volatility. Idiosyncratic volatility is an important determinant of investment returns with a coefficient of 0.33 and a t-statistic of 4.25 and the $\overline{R}^2$ is 7.37%. This result is qualitatively similar to Mueller (2011).[6] Fu (2009) finds that idiosyncratic volatility is positively related to expected stock returns, while Ang, Hodrick, Xing, and Zhang's (2006) find a negative relation between idiosyncratic volatility and expected stock returns.

The last column of Table 1 shows multiple regression results, where the regressors are

[6] Mueller (2011) uses proxies for the value of equity of unlisted firms and finds similar results. Our approach is different than Mueller's as we use production data and examine investment, rather than equity, returns. Moreover, Mueller measures idiosyncratic risk as the degree of lack of diversification of a firm's owners whereas we derive idiosyncratic risk from market model regressions in which the market return is the investment return of a broad index of all of the US manufacturing industries investment returns.

the variables used in the univariate regressions in the previous columns. The signs of the coefficients remain unchanged and the $\overline{R}^2$ increases to 27%. There are two notable quantitative changes relative to the univariate regressions. First, the coefficient on the lagged investment to capital ratio doubles (in absolute value) from -1.02 to -2.09. Second, the coefficient on idiosyncratic volatility nearly halves, as it drops from 0.33 to 0.17. All the estimates remain statistically significant indicating the four characteristics have different roles.

Overall the results in Table 1 show that characteristics that are important for explaining the cross section of stock returns are also important for explaining the cross section of investment returns even when the portfolios are composed of all firms, including unlisted firms. Given the large size of the unlisted company sector in the economy, our results are important and are not likely driven only by listed firms and lend support to the risk-based explanations for the role of characteristics in explaining average stock returns based on the investment first-order condition.

4.1.1 Listed versus Unlisted Firms

Table 1 illustrates that characteristics explain the cross section of investment returns for industry portfolios composed of both listed and unlisted companies. We now separate industries into two groups, based on two measures that aim to separate listed from unlisted firms. The first is the fraction of the sales of listed firms to total industry sales and the second is the fraction of the number of employees of the listed firms in the industry to the total number of employees in the industry. Our rationale is that industries for which the fraction of sales (employees) of listed firms to total industry sales is low include predominately unlisted companies. Thus examining the cross section of returns for such industries enables a closer inspection of whether characteristics play a role in determining the cross section of investment returns among unlisted firms.

We examine data for 308 industries for which data is available both in Compustat as well as in the NBER database. For each year, we split industries into four groups as follows. The first group consists of industries which are below the median fraction of sales of listed firms to total industry sales, the second group includes the industries in the lowest 25% fraction of listed firms' sales to total industry sales. The third group is the group of industries above the median fraction of sales and the fourth group is the top 25% industries. We conjecture that when the fraction of sales of listed firms to total industry sales is low, a large fraction of firms in that industry are unlisted firms. Thus, finding that the cross sectional results hold for the group of industries with the lower fraction of listed firm sales to total industry sales would constitute further evidence that characteristics are important determinants of the cross section of investment returns among unlisted firms, and would lend support to the rational explanation for the role of characteristics in determining the cross section of returns.

We use sales data from Compustat, aggregated over all firms in each industry for the sales of listed firms in each industry and we use the non-deflated value of shipment series from the NBER database for total industry sales. We note that the data on sales from Compustat includes data for the sales of all listed firms within an industry, including the sales from operations abroad of these firms. The data on the value of shipment at the NBER includes sales (including sales abroad) of only US-based establishments. Hence the ratio of the sales of listed firms to the sales of the aggregate industry might be biased upward in general and quite likely the bias varies across industries. However, unless for some reason the ratio of publicly listed sales to total industry sales of the above the median group is systematically less upward biased than that of the below the median industries, our results reflect the variation in the determinants of the cross section of investment returns across industries with different weights of public and private firms.

Panel A of Table 2 presents the results for the investment to capital ratio. The coefficient on I/K is nearly twice as large (in absolute value) for the group of industries with below the median fraction of sales of listed firms as in the group of industries with a high fraction of sales of listed firms (-1.21 vs. -0.72). The coefficient for the low 25% group of industries is even larger and is more than twice as large as the coefficient for the group in which the weight of listed firms is the highest 25% industries (-1.47 vs. -0.62). One of the behavioral explanations for the investment effect in stock return is a slow reaction of the market to overinvestment by empire building managers (Titman, Xie and Wei, 2004). This explanation is less likely to hold for private firms, for which agency conflicts between managers and shareholders are less likely to be prevalent. The other behavioral explanation for the investment effect in stock returns is market overreaction to firm growth (Cooper, Gulen and Schill, 2008). As there is no market price for private firms this explanation is also less likely to hold for the investment effect within private firms. Our results, and in particular those that show the size of the coefficient is greater for the sample with a higher fraction of unlisted firms, where mispricing might be thought to be less prevalent, lend support to the rational-based explanation of the investment effect. This is consistent with recent findings by Cooper and Priestley (2011) that the spread in stock returns between low investment firms and high investment firms can be largely explained by loadings on macroeconomic risk factors.

The coefficient on ROA is roughly similar across the four groups as seen in Panel B (0.09 for the low fraction of sales groups, and 0.08 for the high fraction of sales groups). The results in Panel C show that momentum in investment returns is substantially more important for industries with a high share of sales of listed industries to total industry sales, but the effect still holds for the low fraction of listed firms industries. Panel D presents the results for idiosyncratic volatility. Idiosyncratic volatility seems to be a somewhat more important determinant of investment returns among listed firms with a coefficient estimates of 0.45 and 0.47 for the above the median and high 25% groups, respectively, versus 0.34 and 0.33 for the below the median and low 25% groups, respectively. This result is somewhat surprising given the low diversification of the owners of private firms (see Moskowitz and Vissning–Jørgensen (2002)) but could be consistent with real growth option explanation in Bartram, Brown, and Stulz (2011) where high U.S. stock return volatility is explained by high levels of investor protection, aggregate research intensity and high levels of firm research and development, all of which lead to the more valuable and easily exercisable growth options.

The multivariate results presented in Panel E are consistent with the univariate results, except that the coefficient on I/K is considerably larger now for the above the median group than in the univariate regression and the effect of idiosyncratic volatility is smaller for all of the groups in the multivariate regression.

As a robustness check on the splitting of the sample by the amount of listed and unlisted firms, Table 3 reports results when we use the number of employees as a means of distinguishing listed from unlisted firms. We form four groups by the ratio of employees of listed firms to total industry employees. The results for each of the characteristics are very similar to those in Table 2, providing reassurance that our results are not induced by some measurement error.

The results in Tables 2 and 3 show that characteristics that are important determinants of stock returns play a central role in explaining the investment returns of both listed firms as well as of unlisted firms. These findings lend support to the conjecture that the role of characteristics in explaining cross sectional patterns in returns is due to rational behavior.

4.2 Asset Pricing Tests

In this section of the paper, we assess whether the CAPM, the three factor model of Chen, Novy-Marx, and Zhang (2010) and the macroeconomic factor model of Chen, Roll, and Ross (1986) can explain the cross-section of average investment returns of the twenty portfolios formed according to I/K, ROA, momentum and idiosyncratic volatility using the cross-sectional regression approach of Fama and MacBeth (1973). The three factors are the market portfolio, formed by equal-weighting the returns of all industries. The market portfolio in our sample earns on average 11.29% with a t-ratio of 11.80. The I/K factor return in year t is defined as the excess investment return in year t of the low 33% investment-to-capital industries in year $t-1$ over the return on the top 33% investment-to-capital industries in year $t-1$. The I/K earns a substantial premium of 10.14% and is highly statistically significant with a t-ratio of 11.77. The return on the ROA factor in year t is defined as the year t excess return of the top 33% ROA industries in year $t-1$ over the bottom 33% ROA industries in year $t-1$. The average investment return on the ROA factor is 11.80% with a t-ratio of 14.48.

The Fama and MacBeth (1973) procedure involves a first step in which a time series regression is employed to estimate the factor loadings (betas) of the portfolio returns. The second step runs cross-sectional regressions of investment returns on the estimated betas in order to estimate the prices of risk. The use of annual data rules out using the typical rolling regression approach to estimate betas for each period. Instead, we use full sample estimates to obtain factor loadings (betas) and in the second step we estimate a cross-sectional regression of average investment returns in each year on the factor loadings estimated over the full sample. This is the method recommended and employed by Lettau and Ludvigson (2001) for quarterly data over a relatively short time series sample such as ours, and discussed in Cochrane (2005).

In the first instance, we want to know if the CAPM can explain the cross-section of investment returns. To this end, we estimate

$$r_i = \lambda^0 + \lambda^m \widehat{\beta}_{i,m} + \epsilon_i. \tag{8}$$

where r_i is the actual investment return on the ith portfolio, $\widehat{\beta}_{i,m}$ is the estimate of portfolio $i's$ market beta, λ^0 is the intercept which should equal the risk free rate of return or zero beta rate, λ^m is the estimate of the market price of risk, and ϵ_i is a residual. We also report the cross-sectional $\overline{R}^2$ which, following Jagannathan and Wang (1996) and Lettau and Ludvigson (2001), is calculated as $\overline{R}^2 = [Var_c(\overline{r}_i) - Var_c(\overline{e}_i)] / Var_c(\overline{r}_i)$, where Var_c is the cross-sectional variance, $\overline{r}_i$ is the average investment return and $\overline{e}_i$ is the average residual. We also assess the performance of the model by calculating the square root of the squared pricing error across all twenty portfolios and across each group of five portfolios separately. Finally, we report a statistic that tests whether the pricing errors are jointly zero. This is a Chi-sq test given as $\widehat{\alpha}' cov(\widehat{\alpha})^{-1}\widehat{\alpha}$, where $\widehat{\alpha}$ is the vector of average pricing errors across the twenty portfolios and cov is the covariance matrix of the pricing errors.

The second row of Table 4 reports the estimates and shows that the market price of risk is estimated to be 19.9% per annum and is statistically significant with a t-statistic of 14.55. The estimated intercept of -8.7% per annum, however, is a long way from the average risk free rate over the sample of 6%. Notwithstanding this, the CAPM does a much better job at explaining the cross section of investment returns than the cross section of stock returns as reflected in the positive estimate of the market price of risk and the cross-sectional $\overline{R}^2$ which is 0.45. The remainder of the second row presents information on the size of the pricing errors. The average pricing error is 3.4% per annum for the I/K portfolios and 1.7% per annum for the ROA portfolios. The average pricing errors are largest for the momentum portfolios at 3.5%. The pricing errors for the idiosyncratic volatility portfolios are 2.3 per cent per annum. Across all portfolios the average pricing error is 2.7% per annum and the Chi-sq test rejects the null that the twenty pricing errors are jointly zero. To summarize, the CAPM provides a positive estimate of the market price of risk, something which in itself is different from recent results that use stock market returns, and provides a cross sectional $\overline{R}^2$ and pricing errors that are reasonable.

The third row of Table 3 reports the estimates of the prices of risk from the three factor model:

$$r_i = \lambda^0 + \lambda^m \widehat{\beta}_{i,m} + \lambda^{I/K} \widehat{\beta}_{i,I/K} + \lambda^{ROA} \widehat{\beta}_{i,ROA} + e_i. \tag{9}$$

where $\lambda^{I/K}$ is the price of risk associated with the I/K factor, $\widehat{\beta}_{i,I/K}$ is the beta with respect to the I/K factor, λ^{ROA} is the price of risk associated with the ROA factor, $\widehat{\beta}_{i,ROA}$ is the beta associated with the ROA factor, and e_i is the residual. The results show that all three factors are important in describing the cross-section of average investment returns. The market price of risk drops substantially to a more realistic value of 6.8% per annum and is statistically significant. The price of risk associated with the I/K factor is 11% per annum with a t-statistic of 12.11 and the price of risk associated with the ROA factor is 12.5% per annum with a t-statistic of 13.69. The cross-sectional $\overline{R}^2$ is 0.69, a substantial improvement on the CAPM.

The pricing errors for the three factor model are substantially lower than for those reported from the CAPM. For example, across all twenty portfolios the average pricing error is 1.9% as opposed to 2.7% for the CAPM and this extent in the fall of the pricing errors is observed across all four sets of portfolios except the idiosyncratic volatility portfolios. However, the Chi-sq test rejects the null hypothesis that the twenty pricing errors are jointly zero. Finally, the intercept, while not equal to the risk free rate of return, is much closer at 4.4%.

The remainder of Table 3 reports estimates from cross-sectional regressions that drop one of the factors one at a time. The aim here is to try and establish if all of the factors are economically important. First, we drop the ROA factor and estimate the regression with the market factor and the I/K factor. Both of these factors are statistically significant and have estimates of 16.1% and 8.8% per annum, respectively. However, the $\overline{R}^2$ is lower than that of the three factor model at 0.53 and the intercept is large and negative at -4.7%. The pricing errors, while substantially smaller for the I/K portfolios, are on average smaller than when estimating the CAPM at 2.3% per annum and the Chi-sq test rejects the null of jointly zero pricing errors.

The next row reports the results when dropping the I/K factor. The price of risk associated with the market factor is estimated at 14.5% per annum with a t-statistic of 9.23 and the ROA price of risk is 13.5% per annum with a t-statistic of 14.83. This version of the model does better than the CAPM but worse than the model that includes the market factor and the I/K factor. The cross-sectional $\overline{R}^2$ is 0.50 and the average pricing error is 2.7% per annum, the same as the the CAPM, but larger than the three factor model and the two factor model that includes the market factor and the I/K factor. The Chi-sq test of jointly zero pricing errors rejects the null hypothesis.

In the final row, we report the results from the two factor model that drops the market factor. Both the I/K and ROA factors have positive and statistically significant prices of risk of 10.3 and 12.6 per cent respectively, and the $\overline{R}^2$ is 0.70. The average pricing errors across all portfolios are small at 2.0% per annum, slightly larger than the three factor model. However, the intercept is 1.5, is a long way from the risk free rate of return.

Considering the performance of the different versions of the model, the three factor model produces estimates of the prices of risk that are all statistically significant. However, they are economically important as well since dropping any one of the factors individually leads to either a lower $\overline{R}^2$, higher average pricing errors, or estimates of the intercept that is further away from the risk free rate. These findings from the three factor model confirm that these factors are a source of *aggregate* uncertainty in the sense that they are important for *all* firms, not just listed firms.

It is evident that the three factor model motivated from the q-theory of investment is able to successfully explain the cross-sectional differences in the twenty portfolios formed on four characteristics that include a substantial number of unlisted firms. This is an important finding since it rules out, at least to some extent, the possibility that characteristics are driven by mispricing of stock prices. A large part of the sample has no stock price and, therefore, investors cannot under or over value many of these assets based on their characteristics. Coupled with the likely scenario that managers of unlisted firms are less likely to be affected by investor sentiment, the results point to the conclusion that, first, the three fundamentals factors are related to the risk and return characteristics of firms and second, the risk and return characteristics of non-listed firms are similar to those of listed firms.

The results in Table 4 are based on the sample that includes all firms, both listed and unlisted. Table 5 examines the cross-sectional relation between investment returns and the risk factors for firms that differ in the extent of the proportion of non-listed firms in the sample. The point of this analysis is to understand the extent to which the three risk factors can explain the cross-section of listed and unlisted firms separately.

In order to separate the data by the extent of listed versus non-listed firms, following the previous section, we rank the industries by the fraction of sales of the listed firms in the industry to the total industry value of shipment. In Table 5, we report results where we take the industries that are below the median and in the bottom quartile in terms of the fraction of sales of the listed firms. We subsequently sort these firms into quintile portfolios according to one of the four characteristics used in Table 4. This sorting procedure provides twenty portfolios that are predominately based on firms who are unlisted. We then repeat this sorting procedure using those industries above the median and in the top quintile in terms of the level of sales of the listed firms. As opposed to Table 4, where we estimate five versions of the asset pricing model, varying the inclusion of different risk factors, in Table 5, we report results only for the three factor model given its generally better performance.

The first row of Table 5 reports the results when estimating the three factor model for the twenty portfolios including only industries that have below the median sales from listed firms, likely to be predominately unlisted firms. All three factors command a positive and statistically significant price of risk. The major difference between these results and those that use all firms is that the market price of risk is substantially larger at 12.3% per annum as opposed to 6.8% per annum. In terms of the ability to price the assets, the cross sectional $\overline{R}^2$ is 0.85 compared to 0.69 when all firms are used and the pricing errors across all the portfolios are somewhat smaller for the sample that includes more unlisted firms at 1.3% per annum compared to 1.9% per annum. We find a similar result when looking at the next row of the Table which considers portfolios formed from industries that have less than 25% of their sales from listed firms. Therefore, the model works equally as well when reducing the number of listed firms in the sample.

The next two sets of results in the Table focus on industries that have first, above the median and second are in the group with high 25% of sales by listed firms. The only major difference, relative to the full sample and the samples with low listed sales is that the market price of risk becomes negative. The finding of a negative price of risk on the market investment return factor is consistent with many studies that find a negative price of risk on the stock market aggregate return factor when using stock returns and listed firms.

The three factor model of Chen, Novy-Marx and Zhang (2010) does a good job in describing the cross section of investment returns. We now consider a different set of risk factors, namely the macroeconomic variables proposed by Chen, Roll and Ross (1986). We form investment return based factor mimicking portfolios of the five factors which are based on the growth rate in industrial production, unexpected inflation, the change in expected inflation, the term structure, and default risk. These five factors are able to explain the cross-section of listed stock returns, see, for example, Chen, Roll, and Ross (1986) and more recently Liu and Zhang (2008) and Cooper and Priestley (2011). Therefore, we would expect that they can also price the cross-section of investment returns for all firms, irrespective of whether they are listed or not.

Table 6 reports the estimates of the prices of risk on the five factors. The test assets are the twenty portfolios formed according to the four characteristics using all industries. We first begin by estimating the model using all firms. The price of risk estimated on the industrial production factor is large at 16.3% per annum and statistically significant. This is interesting since the industrial production factor plays an important role in the tests of Liu and Zhang (2008) who look at momentum in stock returns and Cooper and Priestley (2011) who look at the real investment return relation in stock returns. All the factors command a statistically significant price of risk and the model performs quite well when we consider both the cross-sectional $\overline{R}^2$, which is 0.64, and the pricing errors which are 2.0% per annum across all firms. This is only slightly higher than the average pricing errors across all firms for the three factor model (1.9% per annum) and is driven entirely by the relatively high pricing error for the I/K portfolios. The pricing errors of the portfolios formed on momentum and idiosyncratic volatility are actually smaller when employing the CRR model.

The findings in Table 6 strengthen the argument that the listed and unlisted firms expected returns are driven by the same macroeconomic factors and that portfolios of investment returns formed on firm characteristics can be explained by the CRR factors. The results also show that the CRR factor, that have been studied exclusively with stock returns, are aggregate sources of risk because they relate to the returns on unlisted firms as well as listed firms.

4.3 The Cost of Capital for Listed and Unlisted Firms

We now examine whether the cost of capital, namely expected investment returns that are calculated from the three factor model, vary between industries with a high ratio of sales of listed firms to total sales and industries with a low ratio of sales of listed firms to total sales. As seen in the previous tables, average investment returns vary considerable with industry characteristics. This part of the paper aims to answers the question of whether expected investment returns vary between listed and unlisted firms. The results are presented in Table 7.

The second and third columns of Table 7 report average and expected investment returns when we use all industries and the rows report different portfolios. There are some clear patterns in both actual and expected investment returns. For all the four characteristics, the portfolios have average investment returns and expected investment returns that match up well, consistent with the small pricing errors reported in the cross sectional tests. What is interesting is when we compare the average and, particularly, expected returns between samples that have different proportions of listed firms. Comparing the low (below median) and high (above median) sorting columns, we find similar expected investment returns for all but a few of the extreme portfolios. Similar findings are observed when we compare the 25% lowest and highest sorting. This indicates that for most of the portfolios the expected investment returns between portfolios that include more listed firms are similar to those that include more unlisted firms. Interestingly, there is certainly no systematic differences in the expected returns across the portfolios with different amounts of listed firms that would indicate a unlisted firm effect in the cost of equity. Any differences that are observed are likely to be a results of a difference in the value of a particular characteristic, for example a higher (lower) I/K ratio rather than being due to the firms being listed or unlisted.

The pattern in expected investment returns is seen more clearly in Table 8 which reports the differences in the expected investment returns of portfolios sorted according to the amount of listed firms sales. We report the difference between below and above the median and lowest 25% and highest 25%. At the extreme portfolios, for losers and winners the differences are noticeable. However, other differences are generally small. On average the absolute differences are 2 and 2.8 percent per annum for the below the median minus above the median and the low 25% minus high 25%, respectively. What is particularly interesting is that there are no systematic differences in the costs of equity capital between the portfolios that include more or less listed and unlisted firms. This is an important finding and provides new evidence that the non-listed equity premium is similar to the listed equity premium. There are two interesting implications from this results. First, risk adjusted estimates of the cost of equity capital for unlisted firms, notoriously difficult to obtain, can be estimated from the investment returns of these firms. Second, since the cost of equity capital from the investment return approach is similar for listed and unlisted firms, given a characteristic, and given that investment returns are equal to stock returns (Liu, Whited and Zhang (2009)) then unlisted firms can use listed firms stock returns to proxy their cost of equity capital, especially if they do not have an extreme value of a particular characteristic.

The results that unlisted and listed firms have the same cost of capital might seem surprising given the lack of liquidity of unlisted firms and the potential under-diversification of their owners. However, the findings are consistent with Moskowitz and Vissing-Jørgensen (2002) who use estimates of private firms value and profits and study the returns to entrepreneurial investment. They find that in spite of poor diversification the returns to private equity are not systematically higher than the return to public equity.

5 Conclusion

This paper examines the determinants of the cross sectional variation in average investment returns for industry portfolios composed of both listed and unlisted firms. Investment returns are derived from the q-theory of investment (see Liu, Whited and Zhang, 2009). We use the NBER Productivity database to calculate investment returns at the aggregate industry level, which includes both listed and unlisted firms. The NBER Productivity database contains detailed data on real capital stock, real investment and sales for 459 manufacturing industries from 1958 to 2005.

We find that similar characteristics, namely the investment to capital ratio, the return on assets, lagged returns and idiosyncratic volatility explain the cross sectional variation of both listed and unlisted firms' investment returns. Given that unlisted firms have no stock price and if the managers of private firms are less susceptible to investor sentiment, our results lend some support for a rational based interpretation of the role of characteristics in the cross section of returns.

We also test the performance of the CAPM, the three factor model of Chen, Novy-Marx and Zhang (2010), and the macroeconomic factor model of Chen, Roll, and Ross

(1986). We test the model using twenty characteristic-based single sorted portfolios as test assets. The multifactor models perform well in describing the cross section of investment returns. This is a noteworthy finding since this is the first test of an asset pricing model over all assets, including unlisted firms. For a candidate risk factor to be a "true" risk factor, it must be an aggregate factor that effects all firms. We show that these three factors affect all firms and not only listed firms. This finding is reinforced by our results that show the factors work well when we vary the number of listed and unlisted firms in the test assets.

The asset pricing tests have economically important implications for cost of equity capital calculations for unlisted firms. The cost of equity capital for unlisted firms is difficult to measure using risk based measures. This is because of the lack of stock prices for these firms. We show that it is possible to use investment returns to calculate the cost of equity capital. Moreover, since stock returns are shown to be equal to investment returns in Liu, Whited, and Zhang (2009), an alternative way to calculate the cost of equity is to use proxy firms from the listed market and use their stock returns. Whilst this method has been used in the past, we show that it is a reliable benchmark to use.

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Table 1
Cross Sectional Regressions with Characteristics

This table reports coefficients from Fama MacBeth cross sectional regressions of industry investment returns on industry characteristics. Data is from the NBER Productivity database which contains data on all 459 US manufacturing industries with data on the of capital stock, investment, output and other variables aggregated over listed and unlisted companies. The frequency of the data is annual and the sample period is from 1960 to 2005. The table reports average intercepts and slopes from the cross sectional regressions. t-statistics are in parentheses. $\overline{R}^2$ is the average $\overline{R}^2$ of the cross sectional regressions.

$\hat{\gamma}_0$	0.14 (9.63)	−0.02 (−1.54)	0.04 (3.93)	−0.01 (−0.39)	0.08 (6.79)
$\hat{\gamma}_{I/K}$	−1.02 (−10.99)				−2.09 (−21.56)
$\hat{\gamma}_{ROA}$		0.09 (11.66)			0.10 (9.94)
$\hat{\gamma}_{MOM}$			0.23 (4.06)		0.25 (5.01)
$\hat{\gamma}_{idvol}$				0.33 (4.25)	0.17 (3.22)
$\overline{R}^2$ (%)	4.16	4.76	10.57	7.37	27.15

Table 2
Cross Sectional Regressions with Characteristics by Amount of Listed Firms' Sales

This table reports coefficients from Fama MacBeth cross sectional regressions for two groups. In each year the first group includes the industries in the NBER database for which the fraction of the sales of listed firms to total industry sales is below the median for that year, and the second group contains industries for which this ratio is above the median for that year. Data is from the NBER Productivity database. The frequency of the data is annual and the sample period is from 1960 to 2005. The table reports average intercepts and slopes from the cross sectional regressions. t-statistics are in parentheses. $\overline{R}^2$ is the average $\overline{R}^2$ of the cross sectional regressions.

Panel A - Investment to Capital

	$\hat{\gamma}_0$	$\hat{\gamma}_{I/K}$	$\overline{R}^2$ (%)
Below the Median	0.15 (8.11)	−1.21 (−11.98)	5.55
Low 25%	0.17 (8.03)	−1.47 (−7.72)	7.16
Above the Median	0.10 (7.58)	−0.72 (−5.60)	3.31
High 25%	0.11 (6.75)	−0.62 (−2.83)	3.89

Panel B - Return On Assets

	$\hat{\gamma}_0$	$\hat{\gamma}_{ROA}$	$\overline{R}^2$ (%)
Below the Median	−0.02 (−1.72)	0.09 (8.82)	5.68
Low 25%	−0.02 (−1.79)	0.09 (7.28)	6.67
Above the Median	−0.03 (−2.79)	0.08 (12.04)	4.22
High 25%	−0.02 (−1.41)	0.08 (9.19)	5.23

Panel C - Momentum

	$\hat{\gamma}_0$	$\hat{\gamma}_{MOM}$	$\overline{R}^2$ (%)
Below the Median	0.05 (3.29)	0.09 (3.35)	1.86
Low 25%	0.05 (3.76)	0.09 (3.01)	2.72
Above the Median	0.02 (1.46)	0.32 (4.67)	16.02
High 25%	0.01 (0.91)	0.38 (5.11)	19.30

Panel D - Idiosyncratic Volatility

	$\hat{\gamma}_0$	$\hat{\gamma}_{idvol}$	$\bar{R}^2$ (%)
Below the Median	-0.01 (-0.68)	0.34 (3.63)	5.05
Low 25%	-0.01 (-0.48)	0.33 (2.92)	5.53
Above the Median	-0.05 (-1.60)	0.45 (3.16)	15.37
High 25%	-0.06 (-1.73)	0.47 (3.13)	17.59

Panel E - Multiple Regressions

	$\hat{\gamma}_0$	$\hat{\gamma}_{I/K}$	$\hat{\gamma}_{ROA}$	$\hat{\gamma}_{MOM}$	$\hat{\gamma}_{idvol}$	$\bar{R}^2$ (%)
Below the Median	0.08 (4.27)	-2.04 (-19.85)	0.11 (9.95)	0.13 (5.15)	0.20 (2.10)	21.37
Low 25%	0.10 (5.38)	-2.35 (-11.77)	0.11 (7.59)	0.13 (4.34)		25.05
Above the Median	0.05 (3.83)	-1.96 (-17.00)	0.09 (8.79)	0.28 (5.81)	0.21 (3.17)	32.01
High 25%	0.05 (3.55)	-2.03 (-14.65)	0.08 (6.04)	0.30 (5.70)	0.22 (3.04)	36.16

Table 3
Cross Sectional Regressions with Characteristics by Amount of Listed Firms' employees

This table reports coefficients from Fama MacBeth cross sectional regressions for two groups. In each year the first group includes the industries in the NBER database for which the fraction of the number of employees of listed firms to total industry employees is below the median for that year, and the second group contains industries for which this ratio is above the median for that year. Data is from the NBER Productivity database. The frequency of the data is annual and the sample period is from 1960 to 2005. The table reports average intercepts and slopes from the cross sectional regressions. t-statistics are in parentheses. $\overline{R}^2$ is the average $\overline{R}^2$ of the cross sectional regressions.

Panel A - Investment to Capital

	$\hat{\gamma}_0$	$\hat{\gamma}_{I/K}$	$\overline{R}^2$ (%)
Below the Median	0.14 (8.25)	−1.26 (−10.10)	5.74
Low 25%	0.18 (8.24)	−1.50 (−7.69)	7.32
Above the Median	0.10 (7.03)	−0.71 (−5.35)	3.40
High 25%	0.11 (6.56)	−0.56 (2.35)	3.70

Panel B - Return On Assets

	$\hat{\gamma}_0$	$\hat{\gamma}_{ROA}$	$\overline{R}^2$ (%)
Below the Median	−0.03 (−2.61)	0.08 (9.53)	5.34
Low 25%	−0.02 (−1.57)	0.09 (7.50)	6.71
Above the Median	−0.03 (−3.79)	0.08 (11.97)	4.89
High 25%	−0.01 (−1.06)	0.08 (10.98)	5.64

Panel C - Momentum

	$\hat{\gamma}_0$	$\hat{\gamma}_{MOM}$	$\overline{R}^2$ (%)
Below the Median	0.03 (2.42)	0.09 (3.14)	1.90
Low 25%	0.05 (4.00)	0.08 (2.95)	2.56
Above the Median	0.01 (1.28)	0.29 (5.06)	14.79
High 25%	0.02 (1.49)	0.39 (5.43)	19.25

Panel D - Idiosyncratic Volatility

	$\hat{\gamma}_0$	$\hat{\gamma}_{idvol}$	$\bar{R}^2$ (%)
Below the Median	-0.02 (-1.22)	0.31 (3.47)	4.50
Low 25%	-0.01 (-0.39)	0.33 (2.94)	5.51
Above the Median	-0.03 (-1.32)	0.36 (3.22)	13.88
High 25%	-0.04 (-1.41)	0.47 (3.10)	17.48

Panel E - Multiple Regressions

	$\hat{\gamma}_0$	$\hat{\gamma}_{I/K}$	$\hat{\gamma}_{ROA}$	$\hat{\gamma}_{MOM}$	$\hat{\gamma}_{idvol}$	$\bar{R}^2$ (%)
Below the Median	0.07 (4.74)	-2.13 (-14.26)	0.10 (9.60)	0.14 (5.07)	0.18 (1.92)	21.10
Low 25%	0.10 (5.03)	-2.36 (-12.07)	0.11 (7.76)	0.13 (4.29)	0.18 (1.61)	25.00
Above the Median	0.04 (3.10)	-1.83 (-15.37)	0.08 (7.87)	0.28 (5.74)	0.20 (3.02)	32.12
High 25%	0.06 (4.61)	-2.05 (-12.64)	0.08 (6.51)	0.31 (6.04)	0.21 (3.04)	36.59

Table 4
Cross Sectional Regressions with Risk Factors

We perform a set of cross sectional regressions of investment returns on factor loadings. The three factor model is

$$r_i = \gamma_0 + \gamma_{MKT}\widehat{\beta}_{i,MKT} + \gamma_{I/K}\widehat{\beta}_{i,I/K} + \gamma_{ROA}\widehat{\beta}_{i,ROA} + \epsilon_i,$$

where r_i is the investment return, $\widehat{\beta}_{i,MKT}$ is the factor loading on the market investment return portfolio, $\widehat{\beta}_{i,I/K}$ is the factor loading on the I/K investment return portfolio, $\widehat{\beta}_{i,ROA}$ is the factor loading on the ROA investment return portfolio, and ϵ_i is the residual. The factor loadings are estimated over the full sample period. The table reports the constant and the estimated prices of risk from various cross-section regressions that include different combinations of the factors (t-values in parenthesis). $R^2 = [Var_c(\overline{r}_i) - Var_c(\overline{e}_i)] / Var_c(\overline{r}_i)$, where Var_c is the cross-sectional variance, $\overline{r}_i$ is the average investment return and $\overline{e}_i$ is the average residual. $\bar{R}^2$ is the adjusted R^2. We define the pricing error for a given portfolio i as the difference between the actual investment return and the expected investment return according to the cross-sectional test; $p.e.$ represents the square root of the aggregate squared pricing errors across all portfolios in each division (p-value in brackets). The sample period is 1960 to 2005. The test assets are twenty portfolios, five each according to the I/K ratio, ROA, lagged investment, and idiosyncratic volatility.

Panel A: All Firms

γ_0	γ_{MKT}	$\gamma_{\frac{I}{K}}$	γ_{ROA}	$\overline{R}^2$	$pe_{\frac{I}{K}}$	pe_{ROA}	pe_{MOM}	pe_{VOL}	pe_{ALL}	χ^2_{ALL}
-0.087	0.199			0.445	0.034	0.017	0.035	0.023	0.027	41.923
(9.01)	(14.55)									[0.00]
0.044	0.068	0.109	0.125	0.687	0.009	0.015	0.029	0.024	0.019	55.790
(4.00)	(4.63)	(12.11)	(13.69)							[0.00]
-0.047	0.160	0.088		0.534	0.016	0.016	0.036	0.022	0.023	11.937
(5.07)	(11.84)	(9.53)								[0.88]
-0.033	0.145		0.135	0.500	0.035	0.015	0.032	0.025	0.027	131.749
(2.65)	(9.23)		(14.83)							[0.00]
0.015		0.103	0.126	0.697	0.011	0.014	0.030	0.023	0.020	14.258
(1.84)		(11.03)	(13.72)							[0.77]

Table 5
Cross Sectional Regressions with Risk Factors by Amount of Listed Firms' Sales

We perform a set of cross sectional regressions of investment returns on factor loadings. The three factor model is

$$r_i = \gamma_0 + \gamma_{MKT}\widehat{\beta}_{i,MKT} + \gamma_{I/K}\widehat{\beta}_{i,I/K} + \gamma_{ROA}\widehat{\beta}_{i,ROA} + \epsilon_i,$$

where r_i is the investment return, $\widehat{\beta}_{i,MKT}$ is the factor loading on the market investment return portfolio, $\widehat{\beta}_{i,I/K}$ is the factor loading on the I/K investment return portfolio, $\widehat{\beta}_{i,ROA}$ is the factor loading on the ROA investment return portfolio, and ϵ_i is the residual. The factor loadings are estimated over the full sample period. The table reports the constant and the estimated prices of risk (t-values in parenthesis). Below (Above) median refers to firms that have sales from the listed firms that are below (above) the median total sales. Low (High) 25% refers to firms that have below (above) 25% (75%) of their total sales from listed firms. Panel B reports results from estimating the cross sectional regressions using all industries and the Chen, Roll, and Ross (1986) factors. MP is the change in industrial production, UI is unexpected inflation, DEI is the change in expected inflation, TS is the term spread, and DS is the default spread. $R^2 = [Var_c(\overline{r}_i) - Var_c(\overline{e}_i)] / Var_c(\overline{r}_i)$, where Var_c is the cross-sectional variance, $\overline{r}_i$ is the average investment return and $\overline{e}_i$ is the average residual. $\bar{R}^2$ is the adjusted R^2. We define the pricing error for a given portfolio i as the difference between the actual investment return and the expected investment return according to the cross-sectional test; $p.e.$ represents the square root of the aggregate squared pricing errors across all portfolios in each division (p-value in brackets). The sample period is 1960 to 2005.

γ_0	γ_{MKT}	$\gamma_{\frac{I}{K}}$	γ_{ROA}	$\overline{R}^2$	$pe_{\frac{I}{K}}$	pe_{ROA}	pe_{MOM}	pe_{VOL}	pe_{ALL}	χ^2_{ALL}
Below median										
−0.031	0.122	0.073	0.145	0.850	0.013	0.012	0.021	0.005	0.013	37.482
(2.78)	(8.27)	(5.59)	(10.17)							[0.01]
Low 25%										
−0.025	0.121	0.079	0.102	0.785	0.018	0.024	0.015	0.015	0.019	36.875
(2.67)	(8.70)	(5.35)	(6.71)							[0.01]
Above median										
0.158	−0.076	0.049	0.128	0.849	0.020	0.011	0.014	0.014	0.015	127.376
(10.83)	(3.93)	(3.85)	(9.04)							[0.00]
High 25%										
0.177	−0.094	0.048	0.095	0.885	0.019	0.006	0.017	0.022	0.016	21.124
(9.50)	(4.05)	(3.14)	(4.99)							[0.34]

Table 6
Cross Sectional Regressions with CRR Risk Factors by Amount of Listed Firms' Sales

We perform a set of cross sectional regressions of investment returns on factor loadings. The three factor model is

$$r_i = \gamma_0 + \gamma_{MP}\widehat{\beta}_{i,MP} + \gamma_{UI}\widehat{\beta}_{i,UI} + \gamma_{DEI}\widehat{\beta}_{i,DEI} + \gamma_{TS}\widehat{\beta}_{i,TS} + \gamma_{DS}\widehat{\beta}_{i,DS} + \epsilon_i,$$

where r_i is the investment return, $\widehat{\beta}_{i,MP}$ is the factor loading on the industrial production investment return portfolio, $\widehat{\beta}_{i,UI}$ is the factor loading on the unexpected inflation investment return portfolio, $\widehat{\beta}_{i,DEI}$ is the factor loading on the change in expected inflation investment return portfolio, $\widehat{\beta}_{i,TS}$ is the factor loading on the term structure investment return portfolio, $\widehat{\beta}_{i,DS}$ is the factor loading on the default spread investment return portfolio, and ϵ_i is the residual. The factor loadings are estimated over the full sample period. The table reports the constant and the estimated prices of risk (t-values in parenthesis). Below (Above) Medium refers to firms that have sales from the listed firms that are below (above) the medium total sales. Low (High) 25% refers to firms that have below (above) 25% (75%) of their total sales from listed firms. $R^2 = \left[Var_c(\overline{r}_i) - Var_c(\overline{e}_i)\right]/Var_c(\overline{r}_i)$, where Var_c is the cross-sectional variance, $\overline{r}_i$ is the average investment return and $\overline{e}_i$ is the average residual. $\bar{R}^2$ is the adjusted R^2. We define the pricing error for a given portfolio i as the difference between the actual investment return and the expected investment return according to the cross-sectional test; $p.e.$ represents the square root of the aggregate squared pricing errors across all portfolios in each division (p-value in brackets). The sample period is 1960 to 2005.

γ_0	γ_{MP}	γ_{UI}	γ_{DEI}	γ_{TS}	γ_{DS}	$\overline{R}^2$	$pe_{\frac{I}{K}}$	pe_{ROA}	pe_{MOM}	pe_{VOL}	pe_{ALL}	χ^2_{ALL}
						All Firms						
−0.033 (3.93)	0.163 (17.13)	0.006 (2.71)	0.007 (7.57)	−0.012 (2.85)	−0.018 (14.23)	0.637	0.041	0.016	0.013	0.009	0.020	7742.711 [0.00]
						Below Medium						
0.070 (6.86)	0.096 (8.58)	−0.010 (4.24)	0.002 (3.35)	−0.048 (9.85)	−0.003 (2.79)	0.735	0.026	0.018	0.017	0.008	0.017	50.398 [0.00]
						Low 25%						
−0.017 (1.90)	0.049 (4.78)	−0.025 (7.57)	−0.003 (3.29)	−0.035 (7.78)	0.003 (2.62)	0.751	0.031	0.022	0.007	0.017	0.019	11181.431 [0.00]
						Above Medium						
−0.017 (1.41)	0.087 (7.55)	0.011 (4.31)	0.002 (1.98)	−0.004 (1.03)	−0.018 (8.89)	0.601	0.035	0.019	0.009	0.021	0.021	12.564 [0.86]
						High 25%						
0.009 (0.69)	0.114 (7.76)	0.008 (3.64)	0.004 (3.42)	0.013 (2.33)	−0.012 (6.28)	0.664	0.049	0.027	0.014	0.011	0.025	50.482 [0.00]

Table 7
Expected and Actual Investment Returns

This Table reports the average investment returns (AR) and the expected investment returns (ER) from the three factor model. The columns report the average and expected investment returns for All industries, industries that have below the median sales from listed firms (Low), industries that have above the median sales from listed firms (high), industries that have less than 25% sales from listed firms (Low 25%), industries that have more than 75% sales from listed firms (High 25%).

	All		Low		High		Low 25%		High 25%	
Port	AR	ER	AR	ER	AR	ER	AR	ER	AR	ER
Low I/K	0.162	0.154	0.186	0.187	0.131	0.101	0.214	0.194	0.137	0.118
2	0.143	0.138	0.139	0.105	0.147	0.165	0.153	0.126	0.175	0.179
3	0.117	0.120	0.112	0.125	0.117	0.110	0.120	0.130	0.121	0.090
4	0.093	0.065	0.087	0.100	0.107	0.086	0.099	0.119	0.108	0.109
High I/K	0.039	0.074	0.020	0.027	0.057	0.096	0.010	0.029	0.056	0.102
Low ROA	0.041	0.011	0.041	0.040	0.037	0.054	0.044	0.039	0.049	0.054
2	0.079	0.069	0.080	0.100	0.081	0.055	0.090	0.098	0.076	0.068
3	0.094	0.133	0.093	0.114	0.094	0.119	0.088	0.135	0.097	0.085
4	0.136	0.144	0.122	0.121	0.152	0.135	0.134	0.112	0.148	0.169
High ROA	0.202	0.195	0.208	0.170	0.194	0.196	0.243	0.215	0.229	0.223
Losers	0.078	0.068	0.095	0.125	0.061	0.039	0.113	0.125	0.051	0.019
2	0.080	0.096	0.087	0.088	0.072	0.092	0.085	0.092	0.081	0.109
3	0.092	0.100	0.100	0.094	0.087	0.090	0.102	0.102	0.087	0.079
4	0.120	0.120	0.121	0.107	0.115	0.115	0.139	0.159	0.107	0.115
Winners	0.183	0.170	0.142	0.131	0.224	0.223	0.159	0.122	0.272	0.274
Low IVOL	0.068	0.087	0.069	0.056	0.062	0.100	0.070	0.061	0.059	0.085
2	0.078	0.077	0.081	0.075	0.078	0.086	0.081	0.080	0.073	0.086
3	0.094	0.105	0.094	0.108	0.091	0.084	0.106	0.114	0.074	0.092
4	0.100	0.114	0.103	0.096	0.104	0.092	0.130	0.102	0.104	0.078
High IVOL	0.212	0.170	0.196	0.209	0.225	0.196	0.212	0.239	0.288	0.258

Table 8
Expected Investment Return Differences

This Table reports the difference in expected investment returns (ER) from the three factor model. The columns report the differences in expected investment returns between below and above the median sales by listed firms (low-high) and between the industries with less than 25% of sales from listed firms and above 75% of sales from listed firms (low25-high25).

Port	low-high	low25-high25
Low I/K	0.037	0.045
2	-0.017	-0.022
3	0.03	-0.013
4	-0.01	0.006
High I/K	-0.038	-0.031
Low ROA	-0.021	-0.039
2	0.011	0.017
3	0.004	0.037
4	0.015	-0.014
High ROA	-0.008	-0.018
Losers	0.046	0.065
2	0.01	0.015
3	0.004	-0.012
4	0.005	0.036
Winners	-0.064	-0.117
Low IVOL	-0.023	-0.006
2	0.022	0.014
3	0.025	-0.02
4	-0.014	0.018
High IVOL	-0.009	-0.02
Average	0.021	0.028