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Stock Return Anomalies, Industry Risk and Capital Structure

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by

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Abstract

My dissertation studies several topics related to the anomalous behavior of stock returns in the time series and cross section. It includes three parts.

The first part investigates the relation between leverage and stock returns. First, we provide the first empirical evidence that this relation is masked by maturity: stocks with higher short-maturity debt earn significantly higher returns, but stocks with higher long-maturity debt earn lower returns. The opposite directions separated by maturity help explain why the relation between leverage and returns has been mixed. We further show that the positive short-maturity return spread is significant, persistent, and not explained by well-known risk factors (such as size or book to market). Second, we also provide the first theoretical model to explain the relation between maturity-related leverage and stock returns by endogenizing debt maturity; Firms optimally choose the maturity of their debt by trading off the cost of long term maturity with its financial risk on equity. Firms with lower credit quality find it more expensive to borrow long term, so they optimally have debt with shorter maturity. In equilibrium, firms with higher short-term debt or lower long-term debt are riskier firms and earn higher expected returns. We show that the empirical evidence we uncover can be consistent with theoretical predictions.

In the second part; my co-authors, Long Chen, Ohad Kadan and I demonstrate an inconsistency of the momentum and reversal effects in explaining stock return dynamics. We argue that a two-way sorting based on long-term and recent performance can accommodate the two effects by distinguishing between fresh and stale winners and losers. Building on this idea, we propose a fresh momentum strategy which invests in fresh winners and fresh losers only. This strategy generates a fresh momentum profit of 5.1% per year even after controlling for the Carhart four-factor model (including momentum). To explain the phenomenon, we argue that investors mistakenly respond to shocks to firm fundamentals as if they are going to continue in the long run, and these mistakes are exacerbated for fresh momentum stocks, presumably generating the abnormally large returns over the short run. This hypothesis is strongly supported by evidence from earnings shocks, analyst forecast revisions, and post-earnings announcement returns.

In the third part, my co-author, Long Chen and I provide one of the first papers to document extensive stock return anomalies at the industry level. We find smaller industries, industries with lower investment and industries with lower inventory changes have bigger average industry returns. Value industries have lower industry returns in contrast to higher average returns of value firms. These anomalies are robust to even controlling for known (firm-level sorted) risk factors. We further explore the relation between these anomalies and business cycles. We find consistent business cycle dynamics with the return spreads associated with these anomalies.

Keywords : *Anomalies, leverage, debt maturity, financial risk, industry risk, market efficiency, business cycles*

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Part I

Dissecting the Leverage Effect on Stock Returns

1 Introduction

The theoretical relation between corporate leverage and stock returns is one of the most fundamental issues in finance, and, understandably, well taught in finance courses at all levels. It provides the basis for understanding important issues such as cost of equity and corporate bond pricing. By stark contrast, few people know the empirical relation between leverage and stock returns. The empirical findings are conflicting and at best inconclusive. Half a century after Modigliani and Miller (1958), financial economists are still searching for answers for the following first-order questions: what exactly is the empirical relation between leverage and stock returns, and why?

We provide the first comprehensive empirical study on the relation between leverage and stock returns. In particular, we examine whether stock returns are related to different leverage ratio measures including total leverage, short-term debt leverage, long-term debt leverage, short-term debt issuance, and long-term debt issuance. We find that higher stock returns are related to significantly higher short-term debt leverage, but to lower long-term debt leverage and significantly lower long-term debt issuance. In other words, the relation between stock returns and leverage goes in opposite directions depending on debt maturity. As a result, there is no relation between stock returns and total leverage.

The positive (negative) relation between stock returns and short-term leverage (long-term debt issuance) is significant. An annual sorting of ten portfolios based on short-term leverage (long-term debt issuance) generates a monthly spread of 0.75% (-0.34%). These spreads are large compared to the well-known value spread of around 0.5% per month and the size spread of around 0.2% per month. They are also robust to the well-known risk factors. For example, the return spread of short-term debt leverage remains significant at 0.66% after controlling for CAPM, 0.63% after controlling for the Fama-French three-factor model, and 0.56% after controlling for the four-factor Carhart model.

Why are stock returns related to leverage ratios? To understand this issue, we first conduct a double sorting of leverage measures and size. Interestingly, we find that the significant positive relation between stock returns and short-term leverage only exists among large firms. In contrast, the significant negative relation between stock returns and long-term debt issuance only exists among small and medium sized firms, but not among large firms. Therefore, even after controlling for size, stock returns are related to leverage (conditional on maturity) among a big chunk of firms.

Since having high leverage can make firms financially more constrained, we next explore whether financial constraints can explain the stock return-leverage relations. Following the current literature (e.g., Kaplan and Zingalas (1997) and Lamont et al. (2001)), we adopt various financial constraint measures; we find no clear relation between these measures and either short-term debt leverage or long-term debt issuance. Therefore, it seems that financial constraints might not explain the stock return-leverage relations.

Are there theories in the current literature that can explain the conditional relation between stock returns and leverage? We find that firms with higher short-term debt invest less, and firms with higher long-term debt issuance invest more. Investment-based models (e.g., Chen, Novy-Marx, and Zhang (2010)) predict that firms that invest a lot should have lower expected returns. Indeed, the Chen, Novy-Marx, and Zhang three-factor model can completely explain the conditional relation between stock returns and leverage across maturity. Therefore, the investment-based interpretation works. The limitation of this interpretation is that we still do not understand why certain firms invest more than others; nor do we know why investment decisions are related to debt maturity.

We thus proceed to develop a theoretical model to explain the relation between maturity-related leverage and stock returns by endogenizing debt maturity and investment. We show that the empirical evidence we uncover can be consistent with theoretical predictions. Our model is close to Gomes and Schmid's (2010) levered-return model. They conclude that the presence of growth options is crucial to understand the relation between leverage and stock returns.

The major difference between our model and theirs is that they do not consider debt maturity. To our best knowledge, this is the first model that studies the relation between stock returns and leverage by endogeonizing debt maturity decisions. We show that the theoretical leverage-return relation is indeed conditional on the debt maturity choice of firms. Firms optimally choose the maturity of their debt by trading off the cost of long term maturity with its financial risk on equity.[1] Firms with lower credit quality find it more expensive to borrow long term, so they optimally have debt with shorter maturity. In equilibrium, firms with higher short-term debt or lower long-term debt are riskier firms and earn higher expected returns.

Besides being consistent with the empirical evidence on the stock return-leverage relations, this interpretation is further supported by the evidence that higher business risk stocks (See Barclay and Smith (1995) and Guedes and Opler (1996)) – those belonging to the industries with higher volatility of changes in earnings – tend to have higher short-term debt or lower long-term debt.

The rest of part one proceeds as follows. Section 2 reviews the relevant literature. Section 3 explains the main empirical methodology and the primary relation between stock returns and maturity-related leverage measures. Section 4 studies various average firm fundamentals to understand the source of significant leverage-related anomalies and discusses the economic intuition behind our empirical results. Section 5 concludes the paper.

[1] Short term debt is usually cheaper. See Landier and Thesmar, (2009) and Greenwood, Hanson, and Stein (2009).

2 Literature Review

The empirical literature on the relation between leverage and stock returns is extensive, but inconclusive. A large number of studies try different definitions of expected returns to see if there is any empirical relation between leverage and equity risk. For example, Arditti (1967) finds a negative but statistically insignificant association between leverage and equity returns, which are taken as the geometric mean of returns. Hall et al (1967) uses another definition. Returns are taken to be profits after tax and the ratio of book value of equity to assets are used to measure leverage. He finds leverage has a negative relation with returns. Hamada (1972) defines returns as profits after taxes and interest which is the earnings the shareholders receive on their investments. He uses industry as a proxy for business risk. Bhandari (1988) gets inflation adjusted stock returns for all firms including financials. He uses the cross section of all firms without assuming different risk classes. He shows returns increase with leverage.

Different definitions for leverage are also implemented to understand the leverage-stock returns relation in the literature. Baker (1973) calculates financial leverage by taking the ratio of equity to total assets for the leading firms in an industry over one year. He shows that at the industry level, leverage raises industry profitability and higher leverage implies greater risks. Korteweg (2004) finds a negative association between stock returns and leverage based on pure capital structure changes such as exchange offers. Dimitrov and Jain (2005) report a negative relation between leverage and stock returns by studying changes in leverage and show that they are negatively related to current and future returns. They calculate returns as risk adjusted raw returns. They differentiate between borrowing for operations or for growth to examine the effect of leverage due to economic performance and not due to growth, mergers and acquisitions and other reasons. George et al (2006) find a negative relation between returns and leverage. They use book leverage in their tests. They argue that firms, which get affected more adversely in financial distress, have lower leverage. Penman et al (2007) investigate the book-to-price effect in expected stock returns and its relation to leverage. They divide the book to price value into an enterprise and a leverage component. These stand for the operational risk and financial risk. They show that the leverage component is negatively related to expected stock returns.

There is very little research that offers theoretical explanations to above empirical findings and proposes future empirical studies on the relation between leverage and equity risk. After the seminal work of Modigliani and Miller (1958), the most substantial theory on this subject is built by Gomes and Schmid (2010). In the former of these two studies, leverage is taken to be exogenous and the financial risk of leverage on firm's equity is noted under the assumption that there is no arbitrage in the market. In the latter study, it is recognized that leverage is endogenous and there can be a negative relation between expected stock returns and leverage since firms that have higher leverage also invest more. Through investment, these firms may exhaust their growth options, turning them into assets in place and making their total assets less risky. Hence, firms with higher leverage can have lower cost of equity.

Despite the extensive empirical literature on the relation between leverage and stock returns, there is no study examining the effect of short term or long term debt on returns. This is quite important since short term debt and long term debt are fundamentally different and they are used for different purposes, which have implications on cost of equity.

Investment is known to be related to cost of equity (e.g., Chen, Novy-Marx, and Zhang (2010)). Firms that invest more have lower cost of equity, on average. Loan maturities vary with the types of assets that are being financed. As Hart and Moore(1998) observe, assets tend to be matched with liabilities. Long term debt is often used to finance fixed assets (property, machinery, land etc.), while short term debt tends to be used for working capital purposes (mitigating seasonal imbalances, payroll, inventories etc.). In this sense, firms that invest more usually do it with longer maturity of debt.

Maturity of debt is also important for the cost of debt and hence capital structure decision of the firm. Bankruptcy is directly related to current debt situation, in other words, to short term debt. This is relevant since interest rates on debt are lower if bankruptcy costs are higher (Leland, 1994). Long term debt is affected by the existence or lack of collateral assets but short term debt is not (Pindalo, Rodriguez and de la Torre, 2006). Short term debt is also useful to banks in terms of collecting their loans back quickly in the case of bad performance of borrowers. For the entrepreneur, short term debt is better because it is cheaper. Thus, both entrepreneur and bank prefers short-term debt (Landier and Thesmar, 2009).

3 Empirical Results

3.1 Data

We use the merged CRSP and COMPUSTAT datasets covering 1974-2009. The CRSP data provides monthly returns and market cap for each firm; and the COMPUSTAT data provides firm fundamental information at annual frequency. The starting year of 1974 is adopted to ensure that we have a reasonable number of firms with data on short term leverage. We exclude financial firms since their leverage ratios are high by nature. Thus, firms that fall in the four-digit SIC industries coded between 6000 and 6999 are excluded. To mitigate the backfilling bias, a firm must be listed in Compustat for two years to enter our sample. (Fama and French (1993)).

We use multiple leverage measures. Short-term leverage is calculated as the total current liabilities (compustat item lct) over book value of total assets (compustat item at); long term leverage is the ratio of total long term liabilities to the book value of total assets. Long term liabilities are calculated by subtracting total current liabilities from total liabilities (compustat item lt). Total leverage is the sum of long term and short term leverage. Debt maturity is the ratio of long term liabilities to total liabilities. Our measure of net long term debt issuance is calculated as the difference between long term debt issuance (compustat item dltis) and long term debt reduction (compustat item dltr) scaled by contemporaneous book value of total assets (compustat item at). Short term debt issuance is the annual change in debt in current liabilities (compustat item dlc) scaled by contemporaneous book value of assets.

We use book leverage instead of market leverage since we want to focus on leverage decisions rather than the market valuation impact. The latter has been widely studied and documented (e.g., Fama and French (1992) and Berk (1995)). Using book values encompasses the total of all liabilities and ownership claims (Schwartz, 1959). The use of book values in defining the capital structure ensures that the effects of past financing are best represented (Rajan and Zingales, 1995). Graham and Harvey (2001) report that managers focus on book values when setting financial structures. Additionally, Barclay et al. (2006) show how book leverage is preferable since using market values in the denominator might spuriously correlate with exogenous variables.

3.2 Portfolio Method

We use a portfolio-based approach to examine the empirical relation between different measures of leverage and stock returns. We construct stock portfolios based on the leverage measures discussed earlier.

Following Fama and French (1992), we match the accounting data for the fiscal year end in calendar year t-1 with the monthly returns for July of year t to June of year t+1 for each stock. This way, we leave a minimum of six-month time interval between fiscal year ends and the returns.

Stocks are sorted into ten equally populated portfolios based on each leverage measure. Portfolios are held for twelve months till next sorting occurs. In this sense, portfolios are re-balanced annually. In the entirety of the following analysis, the tenth portfolio based on each leverage measure contains one tenth of the stocks with the highest level of the sorting measure.

3.3 Average Excess Returns

Summary Statistics

Table 1 reports the summary statistics of value-weighted portfolio excess returns, in which case excess return is defined as stock return over the risk free rate. There is a significantly positive relation between short-term debt leverage and excess returns: the return spread is 0.75% with a t-statistic of 3.56. There is also a significantly negative relation between long-term debt issuance and excess returns: the return spread is -0.34% with a t-statistic of -2.36.

Therefore, the relation between leverage and stock returns seems to depend on debt maturity. The relation is positive for short-term debt, but negative for long-term debt issuance.

What is the unconditional relation between total leverage and returns then? This relation is positive with a return spread of 0.57% and a t-statistic of 2.11. However, we also find that the return spread is only an insignificantly 0.05% if we use equal-weighted returns. The relation between excess returns and total leverage thus seems unstable.[2]

Next, we evaluate the investment implications of these findings. We check the profitability of straightforward investment styles that use short term leverage and long term debt issuance information. Figure 1 shows monthly profits from holding highest short term leverage portfolio and shorting lowest short term leverage portfolio. Monthly profits from holding lowest long term debt issuance portfolio and shorting highest long term debt issuance portfolio are also depicted. Average spreads, or monthly profits of these strategies, up to twenty-four months ahead of portfolio sorting have been graphed. We see that investing on either short term leverage or long term debt issuance information is highly profitable.

For instance, the monthly short term leverage return premium stays above 0.3% for almost 18 months after portfolio sorting. We also see that short term leverage effect is

[2]In contrast, the relation between excess returns and short-term debt leverage and the relation between excess returns and long-term debt issuance are significant for both value- and equal-weighted portfolios.

more persistent than long term debt issuance effect on returns.

In figure 2, we plot the cumulative profits up to two years ahead of portfolio construction obtained by holding the same portfolios. We see that stock portfolio strategy based on short term leverage or long term debt issuance information is quite profitable in the economic sense with 6.35% and 4.00% annual cumulative excess returns for short term leverage and long term debt issuance investing up to one year. We note that profitability of these trading strategies are quite persistent. The uniform decline of monthly profits also suggests that either short term leverage or long term debt issuance effect is not coincidental with the specific sample we use.

The opposite impact of short-term and long-term debt on total leverage can be seen in Table 2. In Panel A, firms with higher short-term debt have significantly lower long-term debt or long-term debt issuance; even though they also have higher total debt, this trend is weaker because of the conflicting impact of short-term and long-term debt. Similarly, firms with higher long-term debt issuance tend to have a bit lower short-term debt, but higher long-term debt.

In summary, the relation between leverage and stock returns can go in opposite directions depending on maturity. This conditional relation is largely masked when one uses a total leverage measure that includes both short-term and long-term debts. As a result, the relation between total leverage and stock returns seems unstable, a result that is consistent with the current literature.

Our finding is thus important in the following sense: we not only provide new evidence on the conditional relation between leverage and returns, but also provide a new empirical interpretation on why the relation between total leverage and returns is confusing in the current literature.

Factor Regressions

So far, we have identified two significant return patterns related to leverage. Naturally, we then ask whether common risk factors can explain these patterns. In particular, we regress portfolio excess returns on the CAPM market factor, the Fama-French three-factor model, and the Carhart four-factor model respectively, and see whether there is still a pattern of alphas left. The results are reported in Table 3.

In Panel A for the short-term debt portfolios, the alpha spread is 0.66% (t-statistic 3.13) after controlling for CAPM, is 0.63% (t-statistic 2.94) after controlling for the Fama-French three-factor model, and is 0.56% (t-statistic 2.55) after controlling for the Carhart four-factor model.

In Panel B for the long-term debt issuance portfolios, the alpha spread is -0.46% (t-statistic -3.26) after controlling for CAPM, is -0.35% (t-statistic -2.50) after controlling for the Fama-French three-factor model, and is -0.23% (t-statistic -1.63) after controlling for the Carhart four-factor model.

Therefore, the two leverage-return relations remain significant after controlling for the common risk factor models. While our primary goal is to conduct a comprehensive study on the leverage-return relation, we have identified new profitable "anomalies" that are robust even after controlling for some well-known risk factors.

Are the results driven by small firms?

To answer this question, we conduct a two-way independent sorting of either short-term debt leverage or long-term debt issuance with size. We use three size categories, defined as small, medium, and large using the 30th and 70th NYSE breakpoints.

The results are reported in Table 4. In Panel A, the return spread based on short-term debt leverage is only significant for large firms: the spread is 0.83% with a t-statistic of 3.45. It is insignificant for the other two size categories.

In Panel B, the return spread based on long-term debt issuance is significant among small firms: the spread is -0.73% with a t-statistic of -6.65; the return spread is also significant for medium-sized firms with a spread of -0.32% and a t-statistic of -2.82; the spread is still negative for large firms at -0.19%, but insignificant at the 5% level (t-statistic -0.96).

We conclude that the conditional leverage-return relations are not primarily driven by small firms. In fact, the positive relation between short-term debt leverage and returns only exists for large firms.

Are the results driven by financial constraints?

Firms that are heavily levered might be financially constrained in the sense that they might find it difficult to borrow additional money. What are the roles of financial constraints in the empirical relations we have uncovered?

We have four measures of financial constraints. The first is the Kaplan and Zingales (1997) index; the second is the net cash outflows; the third is interest coverage ratio; and finally, the fourth is dividend pay-out ratio. We describe more detailed definitions in Appendix E2. Higher levels of KZ index, higher net cash outflow, lower interest coverage ratio, or lower dividend pay-out ratio means a higher level of financial constraint.

The results are reported in Table 5. In Panel A, using KZ index, net cash outflow, or dividend pay-out ratio, higher short-term debt leverage firms seem to be less financially constrained; and there is no relation using the interest coverage ratio. Therefore, financial constraints do not seem to explain why higher short-term debt firms have higher returns. In Panel B, firms with lower long-term debt issuance do not seem to be more financially constrained.

We conclude that financial constraints do not seem to be the primary reason for the conditional relations between leverage and returns.

4 Theoretical Interpretations

We have identified two leverage-related anomalies that are conditional on debt maturity. Jointly, they help explain why the current literature has found conflicting evidence on the relation between total leverage and returns. These anomalies are robust after controlling for common risk factors, and do not seem to be primarily driven by firm size or financial constraint considerations.

Given the evidence, can we find theoretical interpretations for why the leverage-return relation is conditional on debt maturity? We explore this issue in this section.

4.1 Investment-based Interpretation

Investment-based models predict that firms, which invest more, tend to have lower expected returns since a lower cost of equity is an important driver of investment. Does investment explain our empirical findings?

To investigate this issue, we first examine whether the return patterns across the leverage portfolios are related to investment or profitability, the major factors in Chen, Novy-Marx, and Zhang's (2010, hereafter CNZ) investment-based three-factor model. The results are reported in Table 6.

In Panel A, firms with higher short-term debt have significantly lower capital expenditure; they also have higher profitability (ROA, return on capital), though this relation is hump-shaped rather than being monotonic. We then regress the excess returns of the portfolios on the CNZ three-factor model. The alpha spread is 0.12% (t-statistic 0.59) with the regression.

In Panel B, firms with higher long-term debt issuance have significantly higher capital expenditure; there is no relation between long-term debt issuance and profitability. We then regress the excess returns of the portfolios on the CNZ three-factor model. The alpha spread is -0.03% (t-statistic -0.24) with the regression.

Therefore, the CNZ model can completely explain the conditional leverage-return relations. The reason is that firms with higher short-term debt invest less, suggesting that they face higher expected returns (i.e., higher cost of equity). Similarly, firms with higher long-term debt issuance invest more, suggesting that they face lower expected returns (i.e., lower cost of equity).

Two points are noteworthy here. First, even though the CNZ model can explain the conditional leverage-return relations, it does not diminish the contribution of this paper. Our primary goal is to provide a comprehensive study to understand what the leverage-return relations are and why they are so. These are important and yet unsettled questions in the current literature.

Second, the CNZ model is a partial equilibrium model. It is insightful to conjecture that firms facing higher expected returns are likely to invest less. But, the model does not explain why certain firms face higher expected returns. More importantly, it does not explain why firms with different debt maturity should have different cost of equity.

4.2 A Model Based on Industry Risk

In the following, we develop a model that is motivated by the empirical evidence on business risk. Business risk is defined as industry-level earnings variability measured as the standard deviation of annual changes in earnings before interest and taxes over book value of assets for each 3-digit standard Industrial Classification(SIC) industry. High business/industry risk implies low credit quality.[3]

Table 7 reports the summary statistics on business risk for firms sorted by their leverage measures. Firms with higher short-term leverage and lower long-term debt issuance have significantly higher business risk. Therefore, one potential interpretation is that firms with high leverage and lower credit quality (due to higher business risk) face higher long-term debt costs. So, they optimally choose to have more short-term debt. The higher returns

[3]See Barclay and Smith (1995), Guedes and Opler (1996).

on these firms are thus reflections of their higher business risk. Similarly, firms with lower business risk face lower long-term cost of debt. They thus optimally choose to have more long-term debt. The lower returns of these firms are reflections of their lower business risk.

We develop a formal model below that bears the above intuition. In particular, we build a real options valuation model that is based on continuous time over infinite horizon, where investment in current assets, fixed investment and maturity of debt are endogenously determined. To our best knowledge, the relation between equity risk and different maturities of leverage has not been studied either in theoretical or in empirical literature. Incorporating different maturity options of debt to explain equity risk, linking investment and borrowing choices both to systematic and idiosyncratic demand shocks are some of the important contributions of our model.

4.3 Model

Economy

There is a multitude of firms that are maximizing value in a perfectly competitive market. Corporate tax rate is assumed to be zero. Operating profits at time t is given with the following expression for each firm in industry i as follows:

$$CF_{ti} = Y_{ti}(K - A) \tag{1}$$

K is the total assets that are financed with debt. In this sense, higher K implies higher leverage. Initial value of firm's assets before debt financing is normalized to zero. In the following sections, we will see how leverage imposes financial risk. Leverage is exogenous in the model. So, we do not dispute the risk increasing effect of leverage. Instead, we propose there is another endogenous variable related to leverage that also has risk implications, which is debt maturity. Firm keeps some of the assets as cash, which is denoted as A. The rest of the assets are used in production and hence they are fixed assets such as plant and equipment. In this sense, K-A captures investment in the model. Y is the total demand shock in the economy and has two components.

$$Y_{ti} = X_t + Z_{ti}$$

Assumption 1. *X is the systematic component of the total demand shock and follows geometric Brownian motion.*

$$\frac{dX_t}{X_t} = \mu dt + \sigma dM_t \tag{2}$$

where M is standard Brownian motion under risk neutral measure. Existence of M is assumed in the economy.

Z is idiosyncratic industry-wide random demand shock as defined below;

$$Z_{ti} \sim N(0, \sigma_i^2) \quad ; \quad Z_{ti} \perp X_t \tag{3}$$

Z has a normal distribution with mean zero and industry specific variance σ_i^2. It is independent of X by definition and identically and independently distributed over t. We model idiosyncratic risk with industry risk instead of firm specific risk. Firms that are in the same industry compete in the same product market. Strategic interactions between them are important in their operating decisions. Their actions are similar in product and technology innovations. They behave closely in the face of changes in supply and demand conditions and regulatory environment. Moreover, their growth opportunities, investment and financing decisions are highly correlated. Since, X is a stochastic process with a drift, high level of X_t suggests high levels of future aggregate demand.

Cross sectional heterogeneity of investment behavior originates from the differences of industry risk in the economy. K is financed by an amortized bond portfolio with market value of $B(X_t, Z_{ti})$. The portfolio consists of a set of bonds with different maturities. There is no final period debt payment. Depending on the average maturity, m of the portfolio, there is an amount of debt that is being rolled over continuously. If the average maturity is low, a bigger proportion of total debt will be rolled over continuously. Debt pays coupon, c at each point in time, t. Coupon is made of a fixed payment and roll-over cost. Roll-over cost is the amount that is being transfered from borrowers to lenders by rolling over debt. Higher the amount being rolled over, higher the roll-over cost. If leverage is high than total coupon payment is also high.[4]

At time of debt issuance, there is a one time issuance cost, q. In the case of bank borrowing, issuance cost can be thought as a type of screening cost. For market borrowing, it is simply cost of debt. Issuance cost is increasing with leverage; firms that borrow more, pay more to do so. Also, this cost is increasing with debt maturity. We assume that long term borrowing is costlier. Lenders spend more resources to screen borrowers before they get into longer debt contracts. Overall, firms that want to borrow long term, need to pay a premium. Collateral value of firm's assets is also relevant for issuance cost. If collateral value is higher, then firm's debt is safer which implies that issuance cost is lower. Cash is liquid and fixed assets are not. In other words, we assume that investment in fixed assets, capital expenditures which are denoted as $K - A$ is partially irreversible. Higher cash ratio increases the liquidity of total assets, which in turn increases their collateral value. So, issuance cost decreases in cash holdings level, A.

Industry risk is captured by the volatility of industry specific demand shock, σ_i. We take industry risk as a measure of business risk, which lenders take into account to determine the issuance cost. Firms that operate in riskier industries need to pay more to be able to borrow long term. This implies that issuance cost is even higher for long term borrowing when industry risk is high.[5]

[4] $c = g(m)f(K) \qquad g_m < 0, \quad f_K > 0$

[5] $q = Q(m, K, \sigma_i, A), \quad Q_m > 0, \quad Q_K > 0, \quad (Q_m)_{\sigma_i} > 0, \qquad Q_A < 0$

Valuation

Given the above setup and assumptions, the market value of equity at time t can be written with the following Bellman equation for a given level of A and m;

$$V(y) = y(K - A) - c + \frac{E[V(Y + dY; .)]}{1 + rdt} \tag{4}$$

The expected value of next period equity value is discounted by an instantaneous risk free rate since standard Brownian motion, M is taken to be under risk neutral measure. Similarly, value of bond portfolio can be defined as follows;

$$B(y) = c + \frac{E[B(Y + dY; .)]}{1 + rdt} \tag{5}$$

boundary conditions are obtained at the default threshold. If X falls under a threshold X_D, then firm chooses to default. The default option mitigates the downside risk for the equity holders. Value matching and smooth pasting conditions give the following set of equations for equity and bond value at the default threshold.

$$\begin{aligned} V(X_D, Z_{ti}, c) &= 0 \\ V'(X_D, Z_{ti}, c) &= 0 \\ B(X_D, Z_{ti}, c) &= 0 \end{aligned} \tag{6}$$

the final equality comes from the assumption of zero recovery value of the bond at the default threshold. This assumption is made for simplicity and positive recovery value can be incorporated into the model in a straightforward way.

Using Ito's rule and boundary conditions, we derive closed formed solutions for the market value of bond and equity of the firm;

Theorem 1. *Under the given assumptions, the value of the bond portfolio is given as;*

$$B = \frac{c}{r} \times (1 - (\frac{X_D}{X})^{-\nu}) \tag{7}$$

the theorem shows that value of the bond portfolio is increasing in the coupon payment, decreasing in discount rate, r and decreasing in the default threshold. This implies that value of the bond is lower if the default threshold is higher. Since default threshold is a lower bound, higher value indicates higher probability of default. All these implications are certainly sensible and valid in standard fixed income asset pricing framework.

Similarly, we get closed form expressions for time t equity value for the firm.[6]

Theorem 2. *Under the relevant assumptions, the value of the equity for the firm is given as follows;*

$$V = -\frac{c}{r} + \frac{x(K-A)}{r-\mu} + A_0 x^v \quad ; \quad \nu < 0 \tag{8}$$

A_0 is positive. We see that equity values are increasing with the systematic shock and decreasing with coupon payment. Also, the effect of risk free rate is negative and the effect of the drift μ of the systematic shock is positive for the equity value.[7]

Risk and Return

We use the relative sensitivities of the equity value and systematic demand shock to find the equity beta for the stock of the firm [8];

Theorem 3. *Using equity value and systematic demand shock, real equity beta for the firm is given as follows;*

$$Beta = \frac{c}{Vr} + 1 + \frac{(v-1)A_0 x^v}{V} \tag{9}$$

[6]Details for the derivation are in Appendix
[7]The constants A_0 and ν are given in the Appendix
[8]$\beta = \frac{d \ln V}{d \ln X}$

The first term in equity beta captures the financial risk associated with debt. Betas are increasing with the level of coupon payment. This shows that financial risk is increasing with leverage but decreasing with maturity.[9] The second term is basically the asset risk that is normalized to one.

The last term in the equity beta is the effect of default option. Since default option cuts downside risk, it lowers beta. Simply, default option makes the cash flows less correlated with the systematic demand shock by bounding the down side movement of equity value. It is also a function of leverage and maturity. The effects of leverage and maturity for default option risk mitigation and financial risk are at the opposite direction. Default option reduces some of the financial risk originating from coupon payment. Also, it makes maturity less effective in terms of decreasing beta. However, financial risk channel is stronger and high leverage and low maturity implies higher equity betas.

A straightforward one factor pricing model is obtained.[10]

Theorem 4. *Equity betas in the model have one-to-one correspondence with the factor betas of the following one factor conditional asset pricing model.*

$$E_t[R_{tj} + 1] = r + \beta_{tj}\sigma\lambda \tag{10}$$

λ is a positive constant and σ is the volatility of the systematic demand shock. By this theorem, we notice that higher equity betas imply higher expected returns.

Corporate Decisions

So far, we did all the valuation and risk analysis for a given level of debt maturity, m and cash level A. Other variables are exogenous, such as assets financed by debt, K or industry risk σ_i. Firm maximizes the sum of its equity and debt value minus the issuance cost at the time of borrowing and investing by choosing the average maturity of debt and level

[9] see definition of c

[10] see Appendix for details.

of cash. Firm also chooses level of capital expenditure or investment in fixed assets by choosing level of cash. Following is the firm's optimization problem;

$$max \quad V + B - Q \qquad w.r.t \quad (A, m)$$

We would like to note that we have a static model. Our model has cross sectional and time series implications. One aspect of the the model is that it takes leverage as exogenous and shows how it creates financial risk for equity holders. This feature is quite standard in literature. The major contribution of the model is that it identifies and explains the effect of debt maturity on expected equity returns by taking into account that debt maturity is an endogenous choice. Making leverage endogenous will make the model more sophisticated but at the same time more complicated without obvious benefits for the economic intuition that explains our results.

4.4 Optimal Capital Structure

Under general model setup and assumptions for coupon payment c and issuance cost q, we get interior closed formed solutions for optimal maturity and cash holdings.[11] We mentioned previously that the cross sectional differences in asset values and corporate choice come from industry specific demand shock volatility since systematic demand shock is same for all firms in a given point in time.

There are two trade-offs for the firm in optimizing its total value. Firm trades off the higher issuance cost and lower roll-over cost of high maturity. When maturity is high, the amount of debt being rolled over is low which makes the firm incur less roll-over cost. Also, firm trades off higher liquidity and lower productivity of cash holdings. Higher liquidity increases the collateral value of firms assets, making issuance cost lower. Cash can not be used in production so higher amount of cash decreases the size of productive assets. Higher cash ratio also makes cash flows to equity less correlated with the systematic shock,

[11] details are in the Appendix

X, since systematic shock affects cash flows through fixed assets.

We see that optimal maturity is decreasing with industry risk[12]. Firms that operate in risky environments, have low credit quality and this makes issuance cost of long term maturity higher. This will induce firms to decrease their optimal level of average debt maturity, m. If current level of systematic demand shock X is higher, this will imply lower possibility of default and decreases the financial risk of low maturity. In this case, firms will decrease their average debt maturities, benefiting from cheap issuance of short term debt.[13]

We have the following intuition for the optimal choice of cash holdings, $\tilde{A}$. If industry risk is high, then issuance cost is high so firms will increase the collateral value of their assets to mitigate higher cost of issuance. They do this by increasing liquidity, hence by increasing cash holdings. If systematic demand shock is high, then productive or fixed assets are more valuable, so firms will decrease their cash holdings, using more of the assets financed with debt as fixed assets, K-A. Also, if discount rate r is high, then present value of cash flows is lower, making production less attractive. This will induce firms to increase optimal level of collateral value by increasing their cash holdings level.[14]

4.5 Effect of Corporate Decisions on Stock Returns

Optimal choice of debt maturity and cash holdings will affect equity betas through financial risk and default option channel. We see that higher maturity decreases beta since it imposes less financial risk and higher cash holdings decreases beta since it makes equity value less correlated with the systematic demand shock, X.

The exogenous variables in the model that create the cross sectional differences in equity betas are leverage, which is captured with assets financed with debt, K and industry risk σ_i. Firms with higher industry risk are shown to have lower maturity and higher cash

[12] see Appendix C

[13] $\frac{d\tilde{m}}{d\sigma_i} < 0 \qquad \frac{d\tilde{m}}{dx} < 0$

[14] $\frac{d\tilde{A}}{d\sigma_i} > 0 \qquad \frac{d\tilde{A}}{dx} < 0 \qquad \frac{d\tilde{A}}{dr} > 0$

holdings. This will create two opposing effects on the equity beta since lower maturity will increase beta and higher cash holdings will decrease beta. Higher industry risk alone doesn't necessarily create higher beta.

When we condition on leverage, the effect of maturity and cash holding on beta differs in magnitude. If leverage is high, then effect of maturity on beta is very strong. The intuition is that maturity will effect equity risk through leverage and if leverage is high, maturity becomes more relevant.

$$\frac{dBeta}{d\tilde{m}} < 0 \qquad |\frac{dBeta}{d\tilde{m}}|_K > 0$$

Also, if leverage is high, financial risk component of beta has more weight so risk decreasing effect coming from the default option is weaker. Consequently, the effect of cash holdings on beta is weaker.

$$\frac{dBeta}{d\tilde{A}} < 0 \qquad |\frac{dBeta}{d\tilde{A}}|_K < 0$$

4.6 Summary

The model predicts that higher short term leverage is associated with higher industry risk, higher cash holdings, lower investment, lower long term leverage, lower net long term debt issuance and higher expected stock returns (higher equity betas). Higher long term leverage and higher net long term debt issuance are associated with lower industry risk, lower cash holdings, higher investment, lower short term leverage and lower expected stock returns. Also, effect of long term leverage on expected stock returns is weaker since maturity and leverage affect equity risk in opposite direction. We conclude that our model is very successful in explaining our empirical findings mentioned in previous sections.

There are further empirical predictions developed by the model. The relation between equity risk and either short term leverage or long term debt issuance is derived by two exogenous variables, which are leverage and industry risk. We expect firms with high leverage and high industry risk to have higher expected returns than firms with low leverage and low industry risk.

4.7 Industry Risk and Leverage

To understand the relation between leverage, industry risk and equity betas further, we give specific functions for coupon payment and issuance cost. So far, we made certain assumptions for them and showed that results follow for general coupon and issuance cost functional forms. We use simple functions with the expense of losing quantitative implications and get the benefit of seeing the qualitative patterns in the cross section of returns clearly.[15] Figure 3 contains four plots. Plot 1 shows the change in beta as K, asset financed by debt (leverage), changes for a fixed, medium level of industry risk. Plot 2 shows how beta changes as K increases with increasing industry risk, σ_i (both leverage and industry risk increases). Plot 3 shows how beta changes as industry risk changes when K is fixed and low. Plot 4 shows how beta changes as industry risk changes when K is fixed and high. Range for K is from 0.5 to 1.5. Range for industry risk is from 0.05 to 0.15. We interpret the plots as follows; the equity beta is quite insensitive to leverage if we don't condition on industry risk. As we increase both leverage and industry risk, equity beta increases dramatically. Leverage is also relevant. When leverage is low, equity beta does not increase with industry risk. When leverage is high, we get the strong monotonic positive relation between industry risk and equity beta. We conclude that risk implications of debt on equity is conditional on both leverage and industry risk as shown by the model.

[15] Details and parameters are given in the appendix.

5 Conclusion

The main reason why empirical literature failed to find a robust and clear relationship between leverage and expected returns is that leverage consists of two fundamentally different parts; short term and long term leverage, which affect expected stock returns in the opposite direction. Short term leverage is priced negatively and firms that have higher levels of short term leverage have higher expected returns. The association between expected stock returns and long term leverage, total leverage, debt maturity and short term debt issuance is insignificant. Finally, firms with higher net long term debt issuance have significantly lower expected stock returns.

We find that higher short term leverage is associated with higher industry risk, lower investment, lower long term leverage, lower net long term debt issuance and higher current assets. Higher long term leverage and higher net long term debt issuance are associated with lower industry risk, higher investment, lower short term leverage and lower current assets.

Main economic intuition behind our results is as follows; firms optimally choose the maturity of their debt by trading off the higher cost of long term maturity with its lower financial risk on equity. Firms with lower credit quality find it more expensive to borrow long term, so they optimally have debt with shorter maturity. This increases the financial risk of debt on their equity.

One future research idea related to this study is the effect of maturity on bond returns. Bonds with different maturities will have different cash flow streams to debt holders and different default risk. Understanding the relevance of maturity on cost of debt is valuable for investors, managers and financial researchers.

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Appendix

Valuation

We begin with the valuation Bellman equation for the equity of the firm;

$$V(X_t, Z_{ti}, c) = (X_t + Z_{ti})(K - A) - c + \frac{E[V(X + dX; .)]}{1 + rdt} \tag{11}$$

since X and Z are independent, for given value of c, we can separate the Bellman equation using the linearity of expectation function:

$$V(X, Z) = F(X) + G(Z) \tag{12}$$

where

$$F(X) = X_t(K - A) - c + \frac{E[F(X + dX)]}{1 + rdt} \tag{13}$$

$$G(Z) = Z_{ti}(K - A) + \frac{E[G(Z)]}{1 + rdt} \tag{14}$$

since X and Z are independent, Z is identically and independently distributed over time and the expected value of Z is zero, we have the following equality;

$$G(Z) = Z_{ti}(K - A) \tag{15}$$

since Z_{ti} is only a constant at time t and Z is not in the expectation anymore so ex-dividend stock value can be found using F;

$$F(X) = X_t(K - A) - c + \frac{E[F(X + dX)]}{1 + rdt} \tag{16}$$

again, we used the fact that Z has mean zero to change the expectation. Using Ito's lemma, F can be shown to be the solution of an ordinary differential equation through following steps;

$$\begin{aligned} F(x) &= a + bx + \frac{E[F(X + dX)]}{1 + rdt} && (17) \\ &= \pi(x) + \frac{E[F(X + dX)]}{1 + rdt} && (18) \end{aligned}$$

where $a = -c, \quad b = K - A$ and $\pi(x) = a + bx$

$$F(x_0) \approx \pi(x_0)\Delta t + \frac{E[F(X(0+\Delta t)|X(0) = x_0]}{1 + r\Delta t} \tag{19}$$

we multiply by $1 + r\Delta t$, subtract $F(x_0)$ and divide by Δt as follows;

$$\begin{aligned}
(1 + r\Delta t)F(x_0) &\approx \pi(x_0)\Delta t(1 + r\Delta t) + E[F(X(0 + \Delta t)|X(0) = x_0] && (20)\\
r\Delta t F(x_0) &\approx \pi(x_0)\Delta t(1 + r\Delta t) + E[\Delta F|X(0) = x_0] && (21)\\
rF(x_0) &\approx \pi(x_0)(1 + r\Delta t) + \frac{E[\Delta F|X(0) = x_0]}{\Delta t} && (22)
\end{aligned}$$

as $\Delta t \to 0$;

$$rF(x_0) = \pi(x_0) + \frac{E[dF|X(0) = x_0]}{dt} \tag{23}$$

by Ito's Lemma, we know that

$$E[dF] = \frac{1}{2}\sigma^2 x^2 \frac{d^2F}{dx^2}(x) + \mu x \frac{dF}{dx}(x) \tag{24}$$

using above information and writing $\pi(x)$ explicitly, we obtain the following ordinary differential equation;

$$\frac{1}{2}\sigma^2 x^2 \frac{d^2F}{dx^2}(x) + \mu x \frac{dF}{dx}(x) + a + bx = rF(x) \tag{25}$$

This is a type of Euler-Cauchy second order linear differential equation. The general solution is given as follows;

$$F(x) = C_0 x^{\nu_0} + C_1 x^{\nu_1} + \frac{a}{r} + \frac{bx}{r - \mu} \tag{26}$$

where

$$\nu_0 = \frac{-\mu + \frac{\sigma^2}{2}}{\sigma^2} + \sqrt{\frac{(\mu - \frac{\sigma^2}{2})^2 + 2\sigma^2 r}{\sigma^2}} > 1 \tag{27}$$

$$\nu_1 = \frac{-\mu + \frac{\sigma^2}{2}}{\sigma^2} - \sqrt{\frac{(\mu - \frac{\sigma^2}{2})^2 + 2\sigma^2 r}{\sigma^2}} < 0 \tag{28}$$

The value of the equity is bounded below due to default option. So, the value can not fall below zero. This gives us a boundary condition captured by the default threshold. This boundary condition will be studied later in the appendix. There is another boundary condition. As the demand goes up, the probability of default diminishes and this makes the effect of default option on the equity value smaller. The default option value approaches to zero so, the total equity value approaches to the present value of continuous cash flows. Formally,

$$as \quad X_t \to \infty, \qquad F \to \frac{a}{r} + \frac{bX}{r-\mu}$$

This limit condition implies that C_0 is equal to zero.

Using the expressions above and natural boundary conditions for the general solution; we find that the F value for the firm as follows;

$$F(X_t, Z_{ti}, c) = \frac{-c}{r} + \frac{X_t(K-A)}{r-\mu} + A_0 X^{\nu} \tag{29}$$

the constant A_0 and the default boundary, X_D can be found using value matching smooth pasting conditions at default;

$$X_D = \frac{c}{r} \times \frac{r-\mu}{(K-A)} \times \frac{\nu}{\nu-1} \tag{30}$$

$$A_0 = \frac{(K-A)}{(\mu-r)\nu} \times X_D^{1-\nu} \tag{31}$$

Risk and Return

To find real (theoretical) betas, we use the demand elasticity of equity value. We show that our equity betas correspond to a conditional one factor pricing model beta. We begin with the construction of the conditional model and eventually reach our equity betas;

$$1 = E_t[M_{t+1}(1 + R_{i,t+1})] \tag{32}$$

where M_{t+1} is the stochastic discount factor (SDF) and $R_{e,t+1}$ is the return on the unobservable mean variance efficient frontier. We assume the following relation between the SDF and R_e, which gives the essence of the linear factor pricing argument;

$$M_{t+1} = a_t + b_t R_{e,t+1} \tag{33}$$

Here, we also assumed the existence of the SDF and mean variance efficient return. It is straightforward to show that for an asset i;

$$E_t[R_{i,t+1}] = R_{0,t} - b_t \times R_{0,t} \times var_t[R_{e,t+1}] \times \beta_{it} \tag{34}$$

where $R_{0,t}$ is the return on a zero-beta portfolio and

$$b_t = \frac{E_t[R_{e,t+1}] - R_{0,t}}{R_{0,t} \times var_t[R_{e,t+1}]} \tag{35}$$

and the beta has the following explicit form;

$$\beta_{it} = \frac{cov_t[R_{e,t+1}, R_{i,t+1}]}{var_t[R_{e,t+1}]} \tag{36}$$

Now, we can apply this general setting to our model. We take $R_{e,t+1} = \frac{dX_t}{X_t}$ and $R_{i,t+1} = \frac{dV_t}{V_t}$. X_t is the only state variable in the economy. Since industry shocks are idiosyncratic and can be diversified away, we can assume SDF is a linear function of the return on X_t. So, $R_{e,t+1}$ is on the mean variance efficient frontier. Then, we have the following equalities;

$$E_t[R_{e,t+1}] = E_t[\frac{dX_t}{X_t}] = E_t[\mu dt + \sigma dM_t] = \mu dt$$

$$var_t[R_{e,t+1}] = E_t[(\frac{dX_t}{X_t} - E\frac{dX_t}{X_t})^2] = E_t[(\sigma dM_t)^2] = \sigma^2 E_t[(dM_t)^2] = \sigma^2 dt$$

Above, we use the properties of Brownian motion;

$$E_t[dM_t] = 0 \qquad and \qquad E_t[(dM_t)^2] = dt$$

we also take $R_{0,t} = r$ since there is a risk free rate in the economy. We further simplify the factor pricing model as follows;

$$\begin{aligned}
E_t[R_{i,t+1}] &= R_{0,t} - (\frac{E_t[R_{e,t+1}] - R_{0,t}}{R_{0,t} \times var_t[R_{e,t+1}]}) \times R_{0,t} \times var_t[R_{e,t+1}] \times \beta_{it} && (37)\\
&= r - \frac{\mu - r}{r \times \sigma^2} \times r \times \sigma^2 \times \beta_{it} && (38)\\
&= r + \beta_{it} \times (r - \mu) && (39)\\
&= r + \beta_{it} \times \sigma \times \frac{(r-\mu)}{\sigma} && (40)
\end{aligned}$$

we take $\lambda = \frac{(r-\mu)}{\sigma}$. Finally, we have the following conditional one factor pricing model;

$$E_t[R_{i,t+1}] = r + \beta_{it} \times \sigma \times \lambda \tag{41}$$

here

$$\beta_{it} = \frac{cov_t[R_{e,t+1}, R_{i,t+1}]}{var_t[R_{e,t+1}]}$$

so it is the OLS regression coefficient for the following regression model;

$$R_{i,t+1} = \tilde{\beta}_{it} \times R_{e,t+1} + \epsilon_{it}$$

which implies $E_t[R_{i,t+1}] = \beta_{it} \times E_t[R_{e,t+1}]$ so,

$$\beta_{it} = E_t[\frac{R_{i,t+1}}{R_{e,t+1}}] = \frac{\frac{dV_t}{V_t}}{\frac{dX_t}{X_t}} = \frac{dlog(V_t)}{dlog(X_t)}$$

Optimal Corporate Structure

First order conditions for the optimization problem are given as;

$$g(\tilde{m}) = \frac{r}{f(K)}(\frac{Q_m r}{(1-v)x^v C_m G})^{-1/v}, \qquad where \quad G = \frac{v}{1-v}(\frac{v(r-\mu)}{(v-1)(K-A)})^{-v}$$

$$Q_{\tilde{A}} = \frac{-x}{r-\mu}$$

g is assumed be decreasing with m. C_m and G are negative. Q_m is positive. These imply that optimal level of maturity decreases with industry risk σ_i. Also, we see that optimal level of cash holdings, $\tilde{A}$ increases with industry risk since we assume $(Q_A)_{\sigma_i}$ is negative and Q is convex in A.

Comparative Statistics

We give specific functions for the coupon and issuance cost to do cross sectional comparative statistics. Our aim is to see the relation between maturity and cash holdings and equity betas in the cross section.

Model Specifics

Following functions satisfy the assumptions made for coupon and issuance cost, previously. For the purpose of this section, functions are representative and constructed to capture qualitative patterns.

Coupon

$$c = (P - m) \times K \times z$$

Issuance Cost

$$Q = m \times \sigma_i \times K - \sigma_i \times log[A]$$

Optimal Maturity and Cash Holdings

σ_i also shows lack of credit worthiness. Cost of issuance is an increasing function of σ_i since high industry risk implies low credit quality and hence higher cost of borrowing and higher cost of long term maturity. Given the specific functions for the total coupon payment and issuance cost, we see that closed form explicit functions for optimal maturity and cash holdings can be calculated as follows;

Maturity;

$$\tilde{m} = P - \frac{r}{K \times z} \times (\frac{\sigma_i \times K \times r}{G \times z \times K \times x^v \times (v-1)})^{\frac{-1}{v}}$$

Constant in m;

$$G = \frac{v}{1-v} \times (\frac{v \times (r-\mu)}{(v-1) \times (K-A)})^{-v}$$

Cash Holdings;

$$\tilde{A} = \sigma_i \times \frac{r-\mu}{x}$$

Parameters

We use the following values for the parameters in the model. Drift of the systematic shock is taken to be zero for simplicity. The value of systematic shock, x is taken as constant since the comparative statistic is aimed to understand cross sectional patterns.

Risk free rate, $r = 0.05$
Drift of systematic shock, $\mu = 0$
Standard deviation of systematic shock, $\sigma = 0.2$
Upper bound of maturity, $P = 36$
Systematic demand shock, $x = 0.25$
Constant in coupon, $z = 0.01$

Empirical Measures

The variables used in the paper are given with corresponding Compustat and CRSP data item names.

Definitions for Raw Data Variables

lt: total liabilities.
at: total assets.
lct: current liabilities.
prc: stock price.
shrout: number of shares outstanding.
prcc-f: fiscal year closing price.
cshpri: common shares used to calculate earnings per share.
dlc: debt in current liabilities.
dltt: debt in long term liabilities.
pstkl: preferred stock.
txditc: deferred taxes and investment tax credit.
act: total current assets.
ni: net income.
pi: funds provided by operations.
ebit: earnings before interest and taxes.
ib: income before extraordinary items.
dp: depreciation and amortization.
ppent: net property, plant and equipment.
txdb: deferred taxes.
dvc: dividends common.
dvp: dividends preferred.
che: cash and short term investments.
capx: capital expenditures.
xint: total interest and related expenses.
prstkc: purchase of common and preferred stock.
csho: common shares outstanding.
adjex-c: cumulative adjustment factor.
dltis: long term debt issuance.
dltr: long term debt reduction.
invt: total inventories.

rect: total receivables.

Formulas for Constructed Variables

Short term leverage, (SLEV) = lt / at.

Long term leverage, (LLEV) = (lt - lct) / at.

Total leverage, (TLEV) = lt / at.

Debt maturity, (DEBTMAT) = (lt - lct) / lt.

Market value, (SIZE) = prc * shrout.

Total assets, (AT) = at.

Market-to-Book Asset, (MB) = (prcc-f * cshpri + dlc + dltt + pstkl - txditc) / at.

Business risk, (BUSRISK) = cross sectional standard deviation of annual changes in earnings over assets (ebit/at) by three-digit SIC industry.

Kaplan-Zingales Index, (KZ) = -1.002((ib + dp)/ ppent) + 0.0283((at + prrc-f * cshpri - ceq - txdb) / at) + 3.139((dltt + dlc) / (dltt + dlc + seq)) - 39.368((dvc + dvp) / ppent) - 1.314(che / ppent).

Net cash outflow, (NETCASHFLOW) = (capx - ib - dp) / ppent.

Interest coverage ratio, (INTCOV) = (ib + xint) / xint.

Dividend payout ratio, (DIVPAYOUT) = (dvc + prstkc) / ni.

Capital expenditure ratio, (CapEx) = capx / at.

Cash holdings, (CASH) = che / at.

Profitability, (ROA) = ib(t) /at(t-1).

Net long term debt issuance ratio, (LONGDEBT) = (dltis - dltr) / at.

Net short term debt issuance ratio, (SHORTDEBT) = [dlc(t) - dlc(t-1)] / at.

Table 1 Average Excess Returns

This table reports average excess returns for portfolios built on short term leverage (SLEV), long term leverage (LLEV), total leverage (TLEV), debt maturity (DEBTMAT), long term debt issuance (LONGDEBT) and short term debt issuance (SHORTDEBT). Sample period is from 1974 to 2009. Leverage portfolios are constructed using previous fiscal year's annual leverage data for stocks in July of the current year up to June of the following year. Portfolios are re-balanced every twelve months. Columns represent different leverage measures. All returns are in percentages.

Value Weighted Returns

	SLEV	LLEV	TLEV	DEBTMAT	LONGDEBT	SHORTDEBT
P1	0.22	0.72	0.26	0.69	0.68	0.70
P2	0.47	0.37	0.62	0.52	0.90	0.70
P3	0.58	0.54	0.49	0.77	0.75	0.63
P4	0.45	0.72	0.62	0.75	0.66	0.66
P5	0.52	0.60	0.55	0.55	0.73	0.85
P6	0.66	0.72	0.60	0.67	0.95	0.32
P7	0.65	0.65	0.63	0.69	0.29	0.36
P8	0.65	0.59	0.70	0.54	0.51	0.65
P9	0.80	0.61	0.64	0.48	0.56	0.62
P10	0.97	0.59	0.83	0.50	0.34	0.44
P10-P1	0.75	-0.12	0.57	-0.19	-0.34	-0.26
Annualized	9.02	-1.50	6.85	-2.23	-4.12	-3.06
t	3.56	-0.45	2.11	-0.67	-2.36	-1.83

Table 2 Measures of Leverage

This table reports average short term leverage (SLEV), long term leverage (LLEV), total leverage (TLEV), debt maturity (DEBTMAT), short term debt issuance (SHORTDEBT) and long term debt issuance (LONGDEBT) for short term leverage and long term debt issuance portfolios. Sample period is from 1974 to 2009. Please see the Appendix for detailed explanation of the fundamentals.

PANEL A : Short Term Leverage

	SLEV	LLEV	TLEV	DEBTMAT	SHORTDEBT	LONGDEBT
P1	7.32	39.24	46.58	75.59	-0.93	2.98
P2	11.37	37.65	49.04	69.89	-0.80	1.94
P3	14.83	35.07	49.92	63.60	-0.80	1.84
P4	17.91	30.21	48.08	55.46	-0.66	1.38
P5	20.95	25.33	46.16	47.92	-0.56	0.96
P6	24.16	25.87	50.02	47.21	-0.38	1.12
P7	27.82	23.72	51.53	42.16	-0.01	0.81
P8	32.54	22.90	55.40	38.48	0.43	0.81
P9	39.52	21.30	60.80	32.52	1.44	0.68
P10	53.93	18.26	72.01	23.28	4.21	0.56
Total	25.04	27.96	52.95	49.61	0.19	1.31
P10-P1	46.61	-20.98	25.43	-52.32	5.14	-2.42
t	361.86	-48.29	54.50	-130.00	62.83	-26.9

PANEL B : Long Term Debt Issuance

	SLEV	LLEV	TLEV	DEBTMAT	SHORTDEBT	LONGDEBT
P1	28.76	26.07	55.34	43.73	-1.84	-14.10
P2	27.20	25.19	52.74	44.76	-0.10	-3.89
P3	26.35	22.61	49.26	42.08	0.35	-1.72
P4	25.57	17.99	43.88	36.01	0.52	-0.66
P5	23.58	10.41	34.27	23.83	0.23	-0.12
P6	25.37	14.65	40.25	30.13	0.53	0.18
P7	25.67	25.00	51.24	45.36	0.88	1.03
P8	25.25	29.80	55.49	51.60	0.81	3.04
P9	24.72	32.43	57.63	55.31	0.66	7.54
P10	23.67	40.17	64.20	62.20	0.43	21.85
Total	25.63	24.93	50.95	44.17	0.22	1.38
P10-P1	-5.09	14.10	8.86	18.47	2.26	35.95
t	-52.90	70.85	48.93	94.94	13.32	138.59

Table 3 Factor Regressions

This table reports alphas from various factor regression models for short term leverage and long term debt issuance portfolios. Sample period is from 1974 to 2009. CAPM is capital asset pricing model. FF is Fama-French three factor model. CARHT is Carhart four factor model. Market, size, value and momentum factors are taken from French Kenneth's data library. Alphas and corresponding t statistics are reported. Values are in percentages.

PANEL A : Short Term Leverage

	CAPM	FF	CARHT
P1	-0.32	-0.31	-0.21
P2	-0.12	-0.11	-0.14
P3	-0.02	0.00	-0.03
P4	-0.15	-0.04	0.02
P5	-0.07	0.02	0.10
P6	0.11	0.15	0.11
P7	0.09	0.15	0.11
P8	0.08	0.13	0.13
P9	0.20	0.22	0.19
P10	0.34	0.32	0.35
P10-P1	0.66	0.63	0.56
Annualized	7.88	7.58	6.70
t	3.13	2.94	2.55

PANEL B : Long Term Debt Issuance

	CAPM	FF	CARHT
P1	0.07	-0.02	-0.09
P2	0.32	0.24	0.18
P3	0.19	0.23	0.20
P4	0.09	0.17	0.11
P5	0.01	0.25	0.27
P6	0.13	0.27	0.31
P7	-0.18	-0.13	-0.09
P8	-0.01	-0.03	-0.02
P9	-0.02	-0.07	-0.08
P10	-0.39	-0.37	-0.32
P10-P1	-0.46	-0.35	-0.23
Annualized	-5.49	-4.17	-2.71
t	-3.26	-2.50	-1.63

Table 4 Leverage and Size

Table reports average excess returns for portfolios that are two-way independently sorted respect to short term leverage, long term debt issuance and market size. Sample period is from 1974 to 2009. For portfolio months from July of year t up to June of year t+1, we take market size as the price per share times shares outstanding at the end of June of calendar year t. Portfolios are re-balanced every twelve months. Size portfolios are designated as small, medium and large, using NYSE break points at 30th. and 70th. percentiles. Monthly spreads are also annualized and t statistics for spreads are given. All returns are in percentages.

PANEL A : Short Term Leverage

Value Weighted Returns

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	Annualized	t
All FIRMS	0.22	0.47	0.58	0.45	0.52	0.66	0.65	0.65	0.80	0.97	0.75	9.02	3.56
SMALL	0.53	0.63	0.93	1.13	1.01	0.95	1.14	1.15	0.92	0.79	0.27	3.24	1.75
MEDIUM	0.51	0.71	0.78	0.76	0.87	0.84	0.91	0.89	1.00	0.60	0.09	1.06	0.49
LARGE	0.20	0.46	0.52	0.41	0.49	0.63	0.61	0.62	0.78	1.03	0.83	9.95	3.45

PANEL B : Long Term Debt Issuance

Value Weighted Returns

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	Annualized	t
All FIRMS	0.68	0.90	0.75	0.66	0.73	0.95	0.29	0.51	0.56	0.34	-0.34	-4.12	-2.36
SMALL	1.01	1.20	1.16	1.10	0.84	1.40	0.65	0.93	0.79	0.28	-0.73	-8.81	-6.65
MEDIUM	0.88	1.00	0.96	0.86	0.68	0.86	0.50	0.78	0.75	0.56	-0.32	-3.82	-2.82
LARGE	0.55	0.85	0.69	0.65	0.77	0.96	0.39	0.49	0.55	0.37	-0.19	-2.22	-0.96

Table 5 Financial Constraints

This table reports various financial constraint variables for short term leverage and long term debt issuance portfolios. Sample period is from 1974 to 2009. We calculate average Kaplan-Zingales index value (KZ), net cash outflows (NETCASHFLOW), interest coverage ratio (INTCOV) and dividend pay-out ratio (DIVPAYOUT). Please see the Appendix for detailed explanation of the variables.

PANEL A : Short Term Leverage

	KZ	NETCASHFLOW	INTCOV	DIVPAYOUT
P1	-2.73	0.20	11.02	45.40
P2	-1.58	-0.03	17.90	46.33
P3	-1.92	0.11	17.98	47.92
P4	-2.49	-0.17	24.41	52.11
P5	-3.71	-0.35	19.14	54.58
P6	-2.98	-0.23	12.27	58.83
P7	-3.51	-0.28	13.74	62.50
P8	-4.05	-0.23	12.89	54.01
P9	-3.61	-0.27	14.12	66.48
P10	-4.49	-0.27	13.80	56.66
Total	-3.11	-0.17	15.73	54.48
P10-P1	-1.76	-0.47	2.78	11.26
t	-13.22	-17.02	1.26	7.21

PANEL B : Long Term Debt Issuance

	KZ	NETCASHFLOW	INTCOV	DIVPAYOUT
P1	-2.35	0.40	0.14	0.20
P2	-1.97	0.22	0.93	0.26
P3	-2.76	0.33	-1.79	0.30
P4	-4.83	0.47	-0.42	0.30
P5	-10.68	0.90	15.31	0.29
P6	-7.88	0.50	13.59	0.30
P7	-2.47	0.27	0.43	0.34
P8	-1.45	0.25	0.29	0.37
P9	-0.95	0.23	1.26	0.37
P10	-1.56	0.77	-0.81	0.34
Total	-3.49	0.43	2.40	0.31
P10-P1	0.78	0.37	-0.95	0.14
t	9.04	16.96	-6.15	23.90

Table 6 Investment

This table reports various average firm fundamentals and Chen, Novy-Marx and Zhang three factor model alphas for short term leverage and long term debt issuance portfolios. Sample period is from 1974 to 2009. CapEx is total capital expenditures. ROA is return on assets. CASH is cash holdings. Investment and profitability factors are obtained from Chen, Novy-Marx, Zhang (2010). Please see the Appendix for detailed explanation of the fundamentals.

PANEL A : Short Term Leverage

	CapEx	CASH	ROA	ALPHA
P1	8.86	11.90	1.05	0.14
P2	9.21	9.85	5.42	0.12
P3	9.14	9.93	6.87	0.13
P4	8.85	11.07	8.14	0.07
P5	8.64	12.38	9.99	0.09
P6	8.43	10.55	9.53	0.09
P7	7.89	11.49	9.53	0.07
P8	7.74	10.00	9.36	-0.01
P9	6.82	11.00	8.62	0.12
P10	5.66	14.45	6.49	0.26
P10-P1	-3.21	2.55	5.44	0.12
t	-34.54	6.87	9.85	0.59

PANEL B : Long Term Debt Issuance

	CapEx	CASH	ROA	ALPHA
P1	6.40	-1.83	11.55	-0.08
P2	6.04	-0.35	11.71	0.23
P3	6.05	-0.82	14.21	0.20
P4	6.14	-0.66	18.18	0.19
P5	6.29	-2.20	26.14	0.19
P6	6.76	1.53	19.28	0.20
P7	7.74	0.25	11.77	-0.15
P8	8.48	0.66	9.37	-0.07
P9	10.16	0.39	8.26	-0.05
P10	12.85	-5.72	11.19	-0.11
P10-P1	6.46	-3.89	-0.35	-0.03
t	47.37	-16.17	-3.30	-0.24

Table 7 Business Risk

This table reports average business/industry risk (BUSRISK) for short term leverage, long term leverage, total leverage, debt maturity, long term debt issuance and short term debt issuance portfolios. Sample period is from 1974 to 2009. Please see the Appendix for detailed explanation of the variables. Values are in percentages.

	SLEV	LLEV	TLEV	DEBTMAT	LONGDEBT	SHORTDEBT
P1	8.83	21.76	20.91	21.60	15.83	16.09
P2	8.59	16.92	16.56	17.20	12.37	12.77
P3	9.94	16.43	15.05	15.69	13.13	12.90
P4	11.63	14.38	14.68	14.23	13.29	14.51
P5	13.50	12.93	12.76	13.04	16.09	11.50
P6	10.99	12.35	12.27	12.37	13.33	11.37
P7	10.17	11.60	11.46	11.06	12.32	12.94
P8	16.93	10.83	16.35	10.78	11.66	12.05
P9	36.13	8.44	9.60	10.32	11.76	12.50
P10	42.10	9.03	15.16	9.96	11.19	16.06
P10-P1	33.28	-12.73	-5.75	-11.65	-4.64	-0.03
t	8.72	-40.29	-14.54	-44.55	-9.38	-0.15

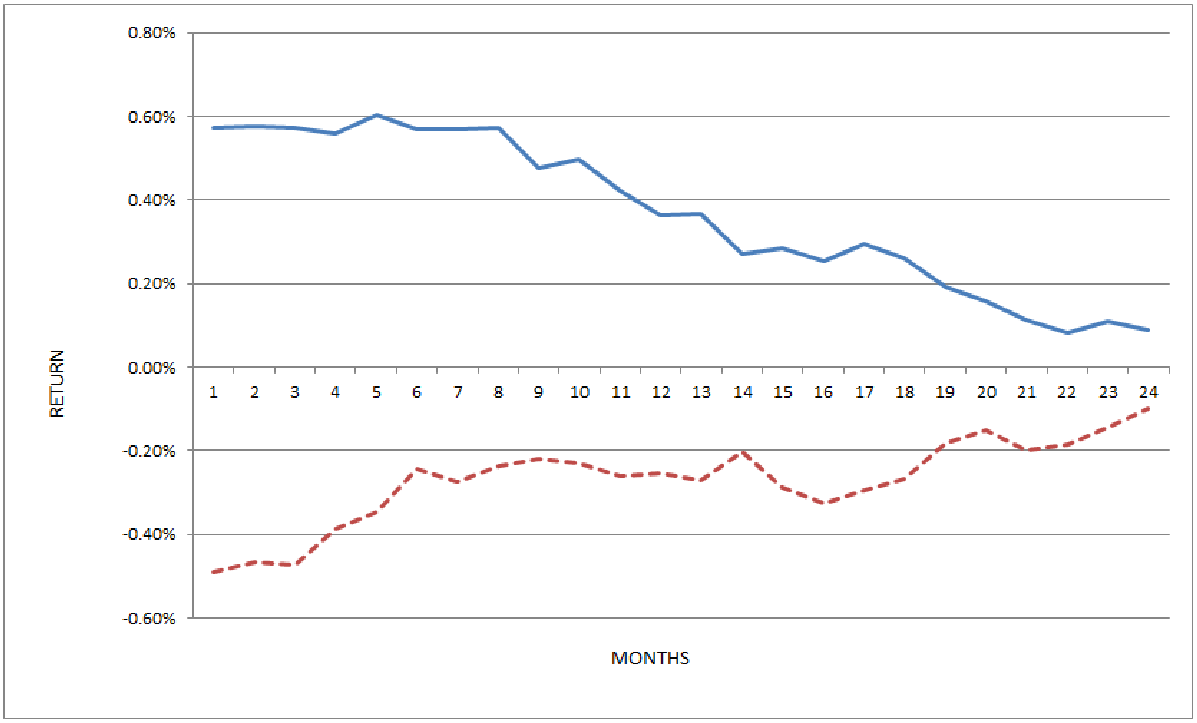

Figure 1 Spread

This figure shows monthly short term leverage premium (solid line) and long term debt issuance discount (dashed line). Sample period is from 1974 to 2009. Average monthly spreads between extreme portfolio average excess returns up to twenty-four months after portfolio sorting are graphed.

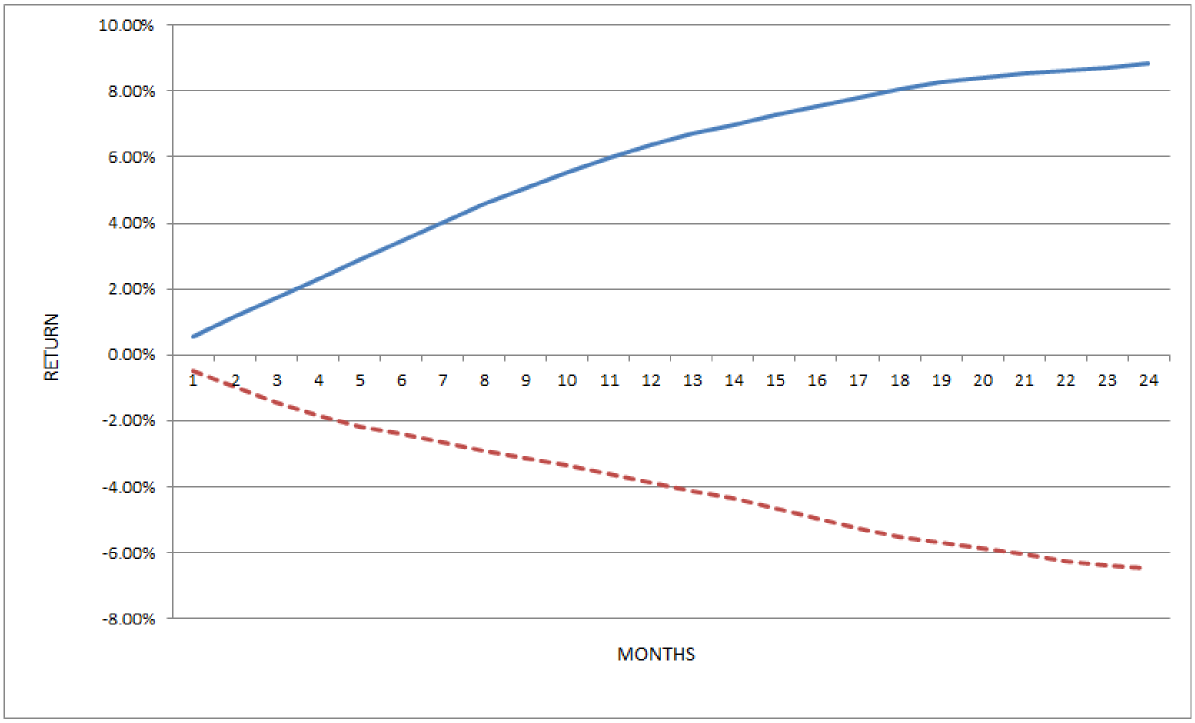

Figure 2 Cumulative Spread

This figure shows cumulative monthly short term leverage return premium (solid line) and long term debt issuance return discount (dashed line). Sample period is from 1974 to 2009. Cumulative average monthly spreads between extreme portfolio average excess returns up to twenty-four months after portfolio sorting are graphed.

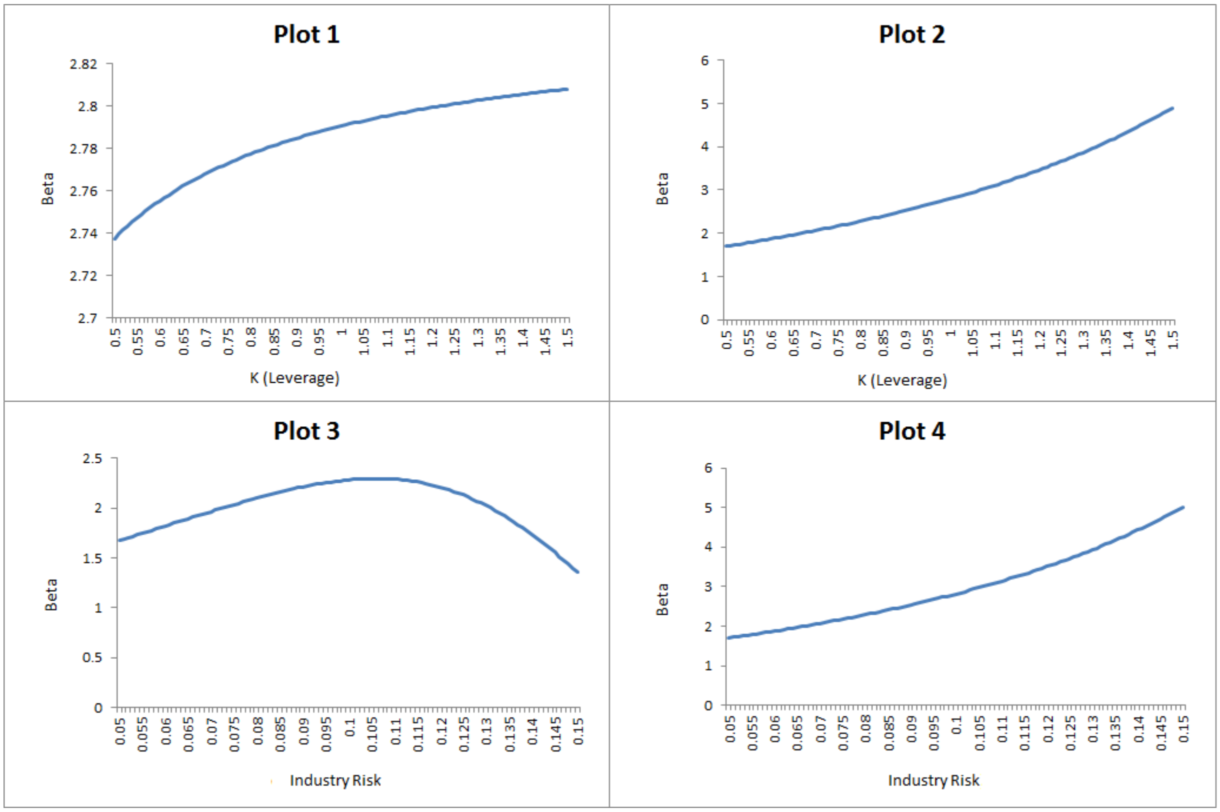

Figure 3 Comparative Statistics

Plot 1 shows the change in equity beta as K, assets financed by debt (leverage), changes for a fixed, medium level of industry risk. Plot 2 shows how beta changes as K increases with increasing industry risk, σ_i (both leverage and industry risk increases). Plot 3 shows how beta changes as industry risk changes when K is fixed and low. Plot 4 shows how beta changes as industry risk changes when K is fixed and high. Range for K is from 0.5 to 1.5. Range for industry risk is from 0.05 to 0.15.

Part II

Fresh Momentum

1 Introduction

In the second part, we demonstrate an inconsistency of the momentum and reversal effects in explaining stock return dynamics. Momentum implies continuation and reversal implies reversion of stock return performance. More specifically, this year's winners, namely stocks with high returns, are next year's winners due to momentum. They are also following year's winners due to second momentum at the end of next year. However, this year's winners must be losers in the year following next year due to reversal. So, it can't be the case that all momentum winners become winners and all momentum losers become losers in the future. In this regard, we want to distinguish between different types of momentum winners or losers.

To get a better picture about stock return dynamics associated with momentum and reversal, we examine stock migration patterns between past return performance ranks and future return performance ranks. In this way, we can sort stocks into long term past and short term past cumulative return performance ranks that will overlap with reversal and momentum portfolios. Observing which stocks end up being winners or losers in the short term future means going deeper in understanding momentum and reversal.

Short term past winners are most likely to be winners in the short term future according to their migration frequency. However, significant proportion of them actually become losers in the short term portfolio holding period. Same wedge shaped transition likelihood pattern is also observed for momentum losers; stocks that have the worst returns in the momentum portfolio sorting period are most likely to migrate into the worst holding period return generating group of stocks. However, these losers are second most likely to migrate into group of stocks with the highest short term holding period return. We get similar results for reversal migration patterns. This shows that one way sorting depending on either short or long term past stock return performance alone is quite a crude way of distinguishing among stocks in terms of their future return performance likelihood.

The solution to this puzzle is found to be considering short term and long term past return performance simultaneously to infer the likely pattern of stock migration. In other words, migration dynamics are path dependent in the sense that both long term and short term past performance matters to determine the likely migration of stocks among return performance ranks. This implies that momentum investing can be substantially improved by separating winners that keep winning and winners that reverse to become losers, as well as separating losers that will keep losing from losers that are about to reverse to become winners. This will definitely make momentum investing substantially improved by cleaning the reversal effect.

Motivated by the observation that momentum is not a very efficient way of investing, we sort stocks into portfolios according to their short term and long term past return performance. We separate momentum winners as stale and fresh winners. Stale winners are both reversal and momentum winners. These stocks have been top performers both for the short term and the long term past. Fresh winners were losers in the long term past, but happened to be winners in the short term past. In other words, they are momentum winners but reversal losers. In this sense, they are recently started their superior return performance.

Intuitively, we expect fresh winners to get the highest portfolio holding period return, since momentum and reversal effect work together, supporting each other. Similarly, we expect fresh losers to have the lowest short term holding period return. We find that fresh winners indeed exceed fresh losers by 1.35% monthly average excess return between 1925 and 2011. Momentum investing gives 1.00% monthly average return and reversal investing gives 0.31% monthly average return in the same sample period. Fresh momentum is stronger than both momentum and reversal economically and statistically.

Then, we regress fresh momentum portfolio returns on CAPM, Fama-French and Carhart factor models. We observe significantly bigger abnormal returns relative to momentum and reversal portfolio returns regressions. Most importantly, even though Carhart four factor model explains both reversal and momentum separately, it fails to explain fresh momentum effect. There is 0.42% alpha spread between fresh winners and fresh losers from Carhart model.

We exploit firm fundamentals data and find that there is significant information content in two-way sorting, which is not present in one-way momentum or reversal sorting of stocks. We follow the event study methodology of Fama and French (2008). Basically, we observe average quarterly earnings shocks progression of momentum, reversal and fresh momentum portfolios from one year before to three years after the portfolio sorting months. Earnings shocks move in a similar fashion to return spreads during matching time periods around sorting months.

Earnings shocks proxy for cash flow surprises. Matching patterns between earnings shocks and returns suggest that momentum, reversal and fresh momentum profits originate as responses to these unexpected cash flow news. Stock return spreads among extreme portfolios are actually justified by the consistent cash flows news spreads among them.

To pin down this interpretation, we examine forecast revisions around portfolio sorting months. We need to make sure that investors really revise their expectations on the face of these cash flow news. Again, we find matching dynamics with portfolio returns. Investors continuously revise their expectations of future cash flows as response to firm fundamentals news as first suggested by Chen, Moise and Zhao (2009). So, they are irrational and unable to incorporate information present in the past stock returns. This suggests financial markets do not even hold weak form efficiency.

The rest of part two is organized as follows. Section 2 presents a short literature review on the subject. Section 3 briefly summarizes momentum and reversal effects in our sample. Section 4 explains migration methodology and its implications for our study. Section 5 examines return and risk characteristics of fresh momentum portfolios in comparison with momentum and reversal sorting. Section 6 reports firm fundamental analysis for these portfolios. Section 7 examines expected cash flow revision dynamics for fresh momentum portfolios. Section 8 summarizes the empirical results of an event study for post-earnings announcement returns. Finally, section 9 concludes.

2 Literature Review

In finance literature, there is extensive research on time series and cross sectional patterns in average stock returns. One of these research subjects is reversal, first discovered by DeBondt and Thaler (1985). Reversal effect basically means that stocks with lower long term past returns tend to have higher future returns. Although, this effect has time series predictive property, it is about the cross-sectional return spread between stocks with low past returns and stocks with high past returns. Besides this, Jegadeesh and Titman (1993) document momentum effect which means stocks with relatively higher short term past returns tend to have higher future returns for a short period of time after.

Reversal effect is explained by Fama and French three factor asset pricing model (Fama, French 1996). In other words, cross sectional return spread between reversal winner and loser stocks can be justified by their risk exposures to certain risk factors, which are size, value and market risk. However, momentum remains being an anomaly since neither CAPM nor three factor model can explain momentum spread, which is the significant average excess return difference between momentum winner and loser stocks. Researchers show the difficulty in explaining momentum (Fama, French 1996-Grundy and Martin 2001-Griffin, Ji and Martin 2003). Both effects have been existing in stock returns even after they have been discovered (Jegadeesh and Titman 2001-Schwert 2003).

Return dynamics associated with reversal and momentum are explained by DeBondt, Thaler (1985) and Jegadeesh and Titman 2001. Basically, momentum profits only exist for up to one year, then reverse the course and turn into reversal in the long run. In this perspective, researchers tried to come up with economic stories (mostly behavioral explanations that assumes investor irrationality and existence of persistent psychological biases) to build a single framework that explains both momentum and reversal (Barberis, Schleifer, Vishny 1998-Danial, Hirshleifer, Subrahmanyam 1998). Fama (1998) suggested a rational explanation for these past returns effects, contradicting with the behavioral literature on this issue. He claimed momentum profits are due to chance events.

3 Momentum And Reversal Effects

To prepare the set up for our empirical study, we show momentum and reversal portfolios average excess returns on Table 8. We use monthly stock return data from January 1925 to December 2011 (inclusive)from CRSP database.

For each momentum portfolio month t, we sort stocks into short-term past return performance quintiles, depending on their cumulative returns from month t-12 to month t-2 (inclusive). We exclude one month before portfolio month t to avoid bid-ask bounce (see Fama-French 1996). Each quintile for any month t, gives one momentum portfolio for month t. First quintile contains the worst momentum performers, ”losers”. To get the monthly momentum portfolio excess returns, we calculate value-weighted cross sectional average excess stock returns in that portfolio for each month. (We use one month lagged market capitalization of stocks to calculate portfolio weights for each month). Portfolios are re-balanced every month.

To obtain reversal portfolios, we apply the same method that we use for momentum portfolios. Only exception is that formation period for portfolio month t is between month t-24 and month t-12 since we are interested in long term past cumulative return performance of stocks. (This time, we skip one year between the end of formation period and the portfolio month, following the standard methodology).

We confirm that we have momentum effect in our sample. On Table 8, we see that momentum winner portfolio (Q5) exceeds loser portfolio by 1.00% of average monthly excess return (time series average) in our sample period. This is significantly positive at 5% level with a t statistic of 5.02. We also observe that momentum is monotonic in the sense that from the worst loser portfolio to the best winner portfolio, there is monotonic increase in average monthly portfolio returns.

Similarly, reversal losers beat reversal winners by 0.31% of average monthly excess return with a significant t statistic of 1.94 at 5% level. Again, reversal pattern exists in our sample and it is monotonic like momentum. There is a monotonic decrease of short term holding period (one month) returns from worst losers to best winners. We notice that momentum spread (difference of average returns between extreme portfolios) is larger than reversal spread. This suggests that momentum is somewhat a bigger anomaly that is economically more significant.

Monotonic average excess return increase form momentum losers to winners indicates momentum effect is present and monotonic decrease in average excess returns from reversal winners to losers show that reversal effect exists. These regularities also suggest predictable migration patterns from all momentum and reversal portfolios (not only extreme portfolios) to first month performance quintiles. This leads into our examination of stock migration between long term past, short term past and future short term relative return performance ranks.

4 Stock Migration

We examine stock migration patterns between past return performance ranks and future return performance ranks. We expect that this will give us a better picture about stock return dynamics associated with momentum and reversal. This is because we can distinguish stocks further in each momentum or reversal portfolio in terms of their likely destination in the short term future.

Stocks are sorted into momentum and reversal portfolios depending on their short term and long term past returns as previously done with average returns analysis. Similarly, we build first month return performance quintiles depending on one month holding return of momentum and reversal portfolios. Momentum migration matrix is an average Markovian transition matrix, which has sample frequencies of stock migrations as its entries.

For each month, we build a momentum migration matrix. This shows the empirical distribution of stock migration frequencies from momentum portfolios into one month holding return performance portfolios for that specific month. We follow the same procedure to build monthly reversal migration matrices. Average migration matrices for momentum and reversal are time series averages of these monthly migration matrices.

Table 9 summarizes momentum and reversal migration patterns. In Panel A, we have the Markovian transition matrix from momentum performance quintiles into first month return performance quintiles. For instance, stocks which are in momentum quintile 5 (MQ 5) have 24% probability of becoming in top first month return quintile (FQ 1). In this sense, each row contains migration probabilities of stocks for each momentum portfolio. We see the momentum effect clearly by looking at this momentum migration matrix. Winners are likely to be winners since 25% is the highest number in the fifth row of the matrix. Losers are most likely to remain losers since 28% is again the highest number in the first row.

Further investigation in Table 9 displays another interesting pattern for our discussion in the paper. This is the U-shaped transition probability distribution in each row. We see that momentum winners most likely migrate into first-month winners portfolio, confirming momentum effect and the second highest migration likelihood is 24% into the worst first-month losers portfolio. Similarly, momentum losers are most likely end up in the worst first month losers quintile but after that the highest likelihood is for migrating to the best first-month winners quintile. This means momentum winners are most likely to be winners, however they are almost as likely to become worst losers. We see similar U-shaped migration patterns for reversal portfolios.

This indicates that migration dynamics of momentum and reversal are not uniform like average portfolio returns. This suggests it is theoretically possible to have subsequent momentum effects turn into a reversal effect. This can be possible through inter quintiles. Extreme quintiles imply the continuation of momentum or reversal depending on which effect one starts with. However, through inter quintiles, one can build theoretically feasible momentum and reversal matrices that agree with these two effects and can demonstrate the transition from momentum to reversal. At the end, this is an empirical question we address.

However, we find that this conversion between momentum and reversal does not hold. Panel C of Table 9 shows the square of the momentum migration matrix and it is pretty flat. We take the square of the momentum migration matrix since reversal formation period is equal to two consecutive momentum formation periods in our methodology. In this regard, it is not the case that momentum gradually turns into reversal.

The entries in each row of the squared migration matrix are very close to each other, meaning this new migration matrix does not have significant information from the past returns about future returns . Also, squared migration matrix is clearly different than the reversal matrix, even though reversal formation period is two subsequent momentum formation periods. Most importantly, these results show that first order auto-regressive process is not enough to explain the return predictability due to these anomalies.

5 Fresh Momentum Portfolios

5.1 Average Returns

Motivated by the observation that neither momentum nor reversal is enough to predict future return performance efficiently, we sort stocks into short term and long term past return performance quintiles. What we are aiming is to use both past return horizons to incorporate the predictive pattern coming from momentum and reversal simultaneously.

First, we get five independent momentum and reversal portfolios and take their intersection to get twenty-five double sorted portfolios. These are independent sorts that partition the stock universe into 25 equal numbered stock portfolios. For example, momentum winners are separated into five more portfolios depending on their reversal sorting returns, namely, cumulative returns in the long term before sorting month (sorting period is between two years before and one year before sorting month for reversal).

Intuitively, we expect stocks that are momentum winners and reversal losers (fresh momentum winners) to get the highest holding period returns, since momentum and reversal effect work together, supporting each other. Due to momentum, these stocks should be top winners in the future short run after sorting and due to reversal, these stocks again should be future best winners since they are long term past worst losers. Similarly, we expect stocks that are momentum losers and reversal winners (fresh momentum losers) to have the lowest short term holding period returns.

Moreover, we expect that fresh winners will exceed stale winners (stocks that are both momentum and reversal winners) and fresh losers will under-perform stale losers (stocks that are both momentum and reversal losers), confirming the increased efficiency of double sorting relative to single momentum or reversal sorting. Stocks that are stale winners are likely to be winners due to momentum, however they are likely to be losers due to reversal since they were long term past winners, too. This is indeed the case, as we confirm from double sorting US stocks between 1925 and 2011.

For these stale winner or loser stocks, momentum and reversal effects work against each other. It is interesting to see which one dominates the other. Empirically, we see that momentum effect is always dominant, meaning stale winners keep winning and stale losers keep losing, though their long past performance predict the opposite.

With these thoughts and projections in mind we calculate the average monthly excess returns of double sorted (fresh momentum) portfolios on Table 10. For any month t, we sort stocks into 25 portfolios depending on their long-term past return performance (t-24, t-13) and short-term past return performance (t-12, t-2) simultaneously. All the portfolios are value weighted as before. Portfolios are re-balanced each month. Portfolio holding period is one month after sorting. We could choose any number of months between one and twelve for holding period since both momentum and reversal, as well as fresh momentum hold for these different cases. The reason that we choose one month holding period is that this is the most strong case to observe these patterns.

For example, stocks that were top losers in reversal formation period and winners in momentum formation period are called fresh winners and they have on average 1.33% monthly excess returns. Stocks that are long term winners and short term losers are called fresh losers and they have the lowest average monthly excess return of -0.01%, as expected. This means there is a 1.35% spread on average excess returns between fresh winners and fresh losers. This return spread is significantly larger than both momentum and reversal spreads economically and statistically. Similarly, fresh losers perform the worst among 25 portfolios.

Portfolio number 11 contains the stocks which were long term and short term losers. This portfolio has 0.31% average monthly return. We call them stale losers. Here reversal predicts they should be winners in the first portfolio month and momentum effect predicts the opposite. In other words, two effects work against each other. Momentum effect is dominant in the sense that stale winners do better than stale losers. We observe the average monthly return spread between stale winners and losers is 0.59% which is statistically and economically significant.

We see that double sorting increases the profitability of both momentum and reversal strategies by incorporating them in one strategy. One way to confirm this is that fresh momentum extreme portfolio spread is much bigger than momentum and reversal spreads as explained above. Another way is to see the difference between fresh and stale winners/losers. Fresh winners exceed stale winners by 0.44% monthly, which is significant at 5% level with a t statistic of 2.70. At the other end of the spectrum, as expected, fresh losers do worse than the stale losers by 0.32% monthly. This is the source of higher zero cost profits of fresh momentum with respect to momentum and reversal.

This shows that our thought experiment about return dynamics in the face of considering momentum and reversal together has economic significance. We get economically and statistically larger spread between extreme fresh momentum portfolios and the improvement over stale counterparts are observed form both the winner and the loser sides of the return performance spectrum.

5.2 Abnormal Returns

To investigate the risk nature of cross sectional excess return spread of fresh momentum portfolios, we perform time-series CAPM and Fama-French factor regressions on monthly portfolio returns. First of all, we do these tests on momentum and reversal portfolios to confirm that in our sample period, these two anomalies prevail and are persistent.

First we perform time series factor regressions for momentum portfolios in order to validate that momentum is not explained by risk compensation relative to standard benchmarks. Table 11 shows that CAPM fails to explain the cross sectional difference on realized returns for extreme momentum portfolios since there is a significant abnormal excess return spread between momentum winners and losers, which is 1.14%. Fama-French three factor model also fails to explain momentum effect since we again see a significant positive alpha (1.26%).

Carhart four factor model explains momentum in our sample by construction since the fourth factor in this model is momentum factor itself. This validates that momentum is a unique phenomenon in stock returns that can not justified by compensation for holding risk associated with size, value and market risk.

We get expected results with reversal, too. On Table 12, we see that CAPM fails to explain reversal effect. There is a significant positive alpha spread of 0.28% monthly controlling for market risk as modeled by CAPM.

Three factor model, on the other hand captures this return predictability, giving a risk based rational explanation for reversal effect. This is mainly because of the fact that reversal portfolios behave as value stocks. Long term past losers are essentially high book to market stocks which load substantially on value premium in the three factor regression. Four-factor model also captures the reversal effect since it contains all of the three factors of the previous model.

After confirming that empirical findings of previous literature hold in our sample, we perform these regressions for our 25 two-way sorted portfolios on Table 13. As expected, we observe significantly larger abnormal returns relative to one-way sorted portfolio regressions. The alpha spread between fresh winners and fresh losers are significantly positive in all tests.

CAPM regression of fresh momentum portfolios give us a 1.44% monthly abnormal excess return spread between fresh winners and fresh losers. This spread is significantly larger than both momentum and reversal alpha spreads. As expected, fresh winners have significantly larger abnormal returns relative to stale winners and fresh losers have smaller abnormal returns relative to stale losers.

Fama-French three factor model also fails to explain fresh momentum profits. We have again a high alpha spread of 1.40% monthly between fresh winners and fresh losers. This clearly supports that fresh momentum is bigger an anomaly than momentum itself. As with CAPM, fresh winners exceed stale winners in terms of abnormal returns again in the three factor regression.

Most importantly, even though Carhart four factor model explains both reversal and momentum separately, it fails to explain fresh momentum effect. There is 0.42% alpha spread between fresh winners and fresh losers. This corresponds to approximately 5.1% annualized abnormal returns beyond what market, size, value and momentum risk justifies as compensation for holding risk. We also observe a significantly positive alpha spread between fresh and stale winners as well as a negative alpha spread between fresh and stale losers at a higher level relative to momentum and reversal cases.

All these results support our claim that two way sorting conveys significant information that one-way sorting or first order auto regressive approach can not deliver. Significant alpha coefficients from regressions suggest that two-way sorting can be used as a highly profitable investment strategy since this combined anomaly is persistent. This way, by making both momentum and reversal sorting more efficient, we can substantially increase the profitability of these investing styles.

6 Firm Fundamentals

We exploit firm fundamentals data to see if there is significant information content in two-way sorting, which is not present in one-way sorting of stocks (momentum or reversal). We follow event study methodology of Fama and French (2008). Main purpose of this section is to pin down systematic patterns in returns by relating them to fundamentals information in momentum, reversal and fresh momentum portfolios.

Basically, we examine quarterly earnings shocks progression of momentum, reversal and two-way sorted portfolios from one year before to three years after the portfolio sorting months and observe that they move in a similar fashion with average returns of these portfolios during matching time periods around sorting months. In our matching process between stock market data and firm fundamental data, we make sure that firm fundamental data were public information before the holding period of the relevant stock return.

All firm fundamentals data are extracted from COMPUSTAT universe covering the time period between 1985 and 2011. We define earning shocks as changes in earnings scaled by lagged assets (return on assets) between this quarter and four quarters ago. Our fundamentals data have quarterly frequency. As opposed to previous average return and risk analysis, we use terciles instead of quintiles since firm fundamental data are noisier than stock return data. Since momentum and reversal anomalies are more distinctive with higher number of portfolios, we can only hurt our results with low number of portfolios. So, our results are necessarily valid for other procedures with larger number of portfolios.

We start out investigation with momentum portfolios. In Panel A of Table 14, we report average earnings shocks around momentum portfolios. Momentum winners start of beating momentum losers twelve months ago in terms of earnings shocks. This relation goes until shortly after sorting month, t. This time period consistently matches with the period that momentum winners have superior returns than momentum losers. It is only natural to conclude that there is strong evidence for relating higher average returns to higher earnings shocks of winner portfolios. After two quarters post sorting, momentum losers start beating momentum winners and this is the point where we see that momentum actually starts to reverse in the sense that momentum investment strategy starts to generate negative returns.

Again, we observe intuitive and consistent earnings shocks progression for reversal. One year before sorting, reversal losers start lower than winners and gradually they exceed winners. This goes as long as reversal losers have superior returns relative to winners.

When we study earnings shocks progression of fresh momentum portfolios in the same fashion, we see that cross-sectional differences in returns are consistent with cross-sectional differences in earnings shocks before and after portfolio sorting months. Fresh winners have monotonically increasing higher earnings shocks than fresh losers till portfolio sorting month, t. After, this superior performance in earnings shocks monotonously decreases and eventually turns into reversal.

It is common practice in empirical finance literature to take twelve months lagged earnings as expected earnings for this month. In this sense, earnings shocks are unexpected earnings component of realized earnings. They represent earnings surprises.

Same pattern exists between fresh and stale winners. Fresh winners do better than stale winners between one year before and one year after month t in terms of returns and earnings shocks. However, reversal comes much later for fresh and stale winners, namely three years later, which is expected since, both portfolios are short term winners. This pattern is also consistent for fresh loser-stale loser earnings shocks spread. From earnings shocks patterns, we conclude that fresh and stale winners (losers) are fundamentally different.

The fact that fresh momentum winners have positive earnings shocks after the portfolio sorting months supports the market irrationality view. Investors don't perceive any of the predictable trend and reversion patterns in earnings and keep being surprised. This creates fresh momentum profits.

7 Analyst Earnings Forecast Revisions

7.1 Short Term Earnings Forecasts

We know that stock prices are forward looking and earning shocks affect stock prices if they make investors revise their forecasts on future cash flows. With this motivation, we investigate analysts' one-year forward earnings forecast revisions for momentum, reversal and fresh momentum portfolios. We expect continuous forecast revisions progression around portfolio sorting months, which is consistent with return and earnings shocks dynamics discussed above, to be able to support market irrationality explanation mentioned previously.

Our analyst forecasts data is from I/B/E/S data set. We define forecast revisions as this month's forecast minus the forecast of twelve months ago, scaled by the stock price of twelve months ago. We use quarterly data.

Table 15 shows quarterly changes in 4-quarter forward earnings forecasts. This table confirms that investors really get surprised around portfolio sorting month since forecast revisions follow the same progression pattern as earnings shocks and returns of momentum, reversal and fresh momentum portfolios.

In Panel A, we see that momentum winners start having lower revisions in twelve month before portfolio sorting month, t relative to momentum winners. This difference gradually increases and becomes positive right before portfolio sorting month and keep being positive after this point on till one year later. Finally, winners-losers spread become negative. This is the same pattern with return and earnings shocks progression of momentum portfolios, having momentum and reversal dynamics around portfolio sorting month.

Panel B gives us similar results. Reversal losers beat reversal winners from shortly before portfolio month until 24 months after. This is the time period which higher returns are obtained by reversal losers. We observe that this period overlaps with the shifted momentum period to the right. This confirms reversal effect follows after momentum effect when we consider post portfolio sorting returns.

Panel C summarizes these forecast revisions for fresh momentum portfolios. As expected, we observe a similar but more dramatic pattern for fresh winner- fresh loser spread than the one with momentum. Fresh winners exceed fresh losers from three quarters before the portfolio sorting month t and this goes on until two years after. This clearly shows double sorting effect in terms of higher returns compared to both momentum and reversal is confirmed with analyst forecast revisions for future earnings. However, time period that fresh winners beat fresh losers in terms of forecast revisions is slightly shifted to the right. This is possibly due to reversal component in the double sorting.

We see that the progression of forecast revision spreads between fresh winner and stale winner portfolios has the exact same pattern with the spread between reversal loser and winner portfolios. Since we control for momentum and check the reversal effect, it is natural we got this result. This confirms that after controlling for momentum, we still have the reversal effect. For fresh loser minus stale loser portfolio we can make the same argument. Again, we observe reversal effect in forecast revisions even after we control for momentum.

7.2 Long Term Earnings Forecasts

We have further evidence that market does not understand the predictable pattern in earnings shocks and keep revising their forecasts. This shows irrationality of market participants since they misprice earnings news and revise their expectations to correct this mispricing continuously. Otherwise, we would observe persistent revisions in long term earnings growth forecasts.

Table 16 summarizes long term earnings growth forecast revisions dynamics around portfolio sorting months. Long term earnings growth rate forecast revisions are quarterly differences between subsequent forecasts. Since there is no seasonality, we choose to analyze quarterly changes rather than 12-month changes.

We observe similar patterns with earnings shocks progressions. This means forecast revisions are not persistent and follow earnings surprises quarter by quarter.

Panel A of Table 16 summarizes long term growth revisions for momentum portfolios. Momentum winners start having lower revisions in twelve month before portfolios sorting month, t relative to momentum losers. This difference gradually increases and becomes positive right before portfolio sorting month and keep being positive after this point until one year later. Finally, winners-losers spread become negative. This is the same pattern with return and earnings shocks progression of momentum portfolios.

We see that convergence pattern from momentum into reversal is shifted to the right, compared to the one-year forward earnings forecasts revisions progression. This suggests investors are relatively more sluggish to revise their long term expectations.

Panel B summarizes long term growth revisions for reversal portfolios which are consistent with quarter by quarter changing of expectations story. We include this panel since it is useful when we examine the forecast revision patterns of two-way sorted portfolios.

We get consistent results for fresh momentum portfolios as shown in Panel C. Fresh winners exceed fresh losers starting from two quarters before portfolio sorting month until three years after since reversal and momentum effects work together to create this spread.

Controlling for momentum, we see that reversal still plays a significant part because fresh winners have higher forecast revisions than stale winners before and after portfolio sorting month. Similar argument holds in the case of fresh and stale losers forecast revision spread. Again, these progressions are consistent with return and earnings shocks dynamics of fresh momentum portfolios.

8 Earnings Announcement Returns

Finally, we check earnings announcement returns, showing that investors get surprised with earnings announcements. We examine average three-day cumulative returns of momentum, reversal and fresh momentum portfolios around earnings announcement dates. This event study is quite useful especially because three day risk free rate (discount rate) is close to zero, so this cumulative return is due cash flow news part of earnings surprises.

Panel A of table 17 shows average announcement returns for momentum portfolios. The average announcement returns are significantly positive for all momentum portfolios. As expected, there is a significant 0.18% return spread between momentum winners and losers.

As we can see on Panel B, we find significantly positive average announcement returns for reversal portfolios. Reversal losers exceed reversal winners by 0.41%, which is significantly positive at 5% level. This supports the earnings surprises explanation of momentum and reversal cross-sectional return differences.

We obtain consistent results for fresh momentum portfolios in Panel C. All double sorted portfolios have significant average announcement returns. Fresh winners exceed fresh losers by 0.61% which is more than both momentum and reversal winner-loser spreads. This number is significant with a t statistic of 4.58. So double sorting improves on momentum and reversal sorting also in terms of earnings announcement return spreads between winners and losers. Fresh winners have 0.39% more average announcement returns than stale winners do and fresh losers have 0.51% less announcement returns than stale losers do.

All these numbers are significantly positive in statistical and economic sense. All of these results support our argument that return spreads between winners and losers, as well as fresh winners and losers and stale winners and losers are due to price adjustments as response to earnings surprises.

The fact that we observe significant returns around earnings announcements imply investors revise their expectations of future cash flows unrelated to changes in discount rates. More interestingly, we observe significant average announcement return spreads between winners and losers for all three anomalies, which are consistent with the return and firm fundamentals spreads.

As expected, fresh momentum average announcement return spread is significantly bigger relative to momentum and reversal average announcement return spreads.

9 Conclusion

With the motivation of solving the mentioned inconsistency of momentum and reversal effect in terms of explaining stock return dynamics, we examined migration patterns of stocks among momentum, reversal and first month return performance ranks. This thought experiment helped us understand better how these two phenomena exist together.

Momentum sorting is shown to be inefficient in terms of predicting stock migrations from short term past return performance into short term future return performance. Two-way sorting respect to long term (reversal) and short term (momentum) past returns is found to bring key information to explain stock return dynamics.

As our main result, we find a higher average monthly return spread between fresh winners and fresh losers, compared to the spreads between winners and losers in both momentum and reversal portfolios. Double sorting also creates important economic value from an investment perspective since it creates higher positive alphas from standard factor pricing models, including Carhart four factor model.

Significant information content of two-way sorting is confirmed with firm fundamentals. Fresh winner and fresh loser portfolios have different earnings shocks progressions between one year before and three years after portfolio sorting months. This difference reflects upon investor expectations as observed from earnings forecast revision and post-earnings announcement return patterns for fresh momentum portfolios.

Matching contemporaneous patterns of return, earnings shocks and expected earnings revisions for fresh momentum portfolios, justify the return spreads among these portfolios being fundamental. These ”fresh” systematic patterns in average returns are due to investor irrationality coming from the fact that investors do not understand the predictable pattern in earnings progression and keep revising their expectations on future cash flows, which turn into contemporaneous returns.

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Table 8 Average Excess Returns

This table reports average value-weighted excess returns of momentum and reversal portfolios. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are rebalanced at the begining of each month. The sample period is from 1925 to 2011. Portfolios are designated with momentum (reversal) formation period rank quintile. Excess returns are percentages.

Panel A: Price Momentum							
M1	M2	M3	M4	M5	M5-M1	(S.E.)	(t)
0.10	0.45	0.57	0.82	1.10	1.00	(0.20)	(5.02)
Panel B: Price Reversal							
R1	R2	R3	R4	R5	R1-R5	(S.E.)	(t)
0.85	0.77	0.66	0.56	0.54	0.31	(0.16)	(1.94)

Table 9 Migration

This table reports average migration patterns of stocks from momentum (reversal) quintiles, MQ (RQ), into first month return quintiles, FQ. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are rebalanced at the begining of each month. The sample period is from 1925 to 2011. Portfolios are designated with momentum (reversal) formation period rank quintile. Following tables are transition probability matrices from momentum (reversal) quintiles into first month return performance quintiles.

Panel A: Momentum Migration

	FQ				
MQ	1	2	3	4	5
1	0.28	0.19	0.15	0.15	0.23
2	0.18	0.22	0.22	0.21	0.17
3	0.15	0.22	0.24	0.23	0.16
4	0.16	0.21	0.22	0.22	0.19
5	0.24	0.18	0.16	0.18	0.25

Panel B: Reversal Migration

	FQ				
RQ	1	2	3	4	5
1	0.28	0.19	0.15	0.15	0.23
2	0.18	0.22	0.22	0.21	0.17
3	0.15	0.22	0.24	0.23	0.16
4	0.16	0.21	0.22	0.22	0.19
5	0.24	0.18	0.16	0.18	0.25

Panel C: Momentum Migration Squared

	FQ				
MQ	1	2	3	4	5
1	0.21	0.20	0.19	0.19	0.21
2	0.20	0.21	0.20	0.20	0.20
3	0.19	0.21	0.20	0.20	0.19
4	0.20	0.20	0.20	0.20	0.20
5	0.21	0.20	0.19	0.19	0.20

Table 10 Fresh Momentum Returns

This table reports average value-weighted first-month excess returns of fresh momentum portfolios. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1925 to 2011. Portfolios are designated with momentum and reversal formation period rank quintile. Portfolios are value-weighted. Returns are in percentages.

	MQ				
RQ	1	2	3	4	5
1	0.31	0.56	0.90	0.98	1.33
2	0.31	0.64	0.73	0.83	1.24
3	0.11	0.52	0.65	0.85	1.26
4	0.09	0.37	0.42	0.78	1.01
5	-0.01	0.28	0.39	0.69	0.90
15-51	1.35				
S.E	0.22				
t	6.22				
15-55	0.44				
S.E	0.16				
t	2.70				
51-11	-0.32				
S.E	0.21				
t	-1.54				

Table 11 Abnormal Returns-Momentum

This table shows alphas from regressions of momentum portfolios' excess returns on market, Fama-French HML, SMB and momentum factors. Momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Portfolios are designated with momentum formation period rank quintiles. Portfolios are re-balanced at the beginning of each month. The sample period is from 1925 to 2011. All portfolios are value-weighted. ** indicates statistical significance at the 5% level. Alphas are in percentages.

Panel A: CAPM-ALPHA					
M1	M2	M3	M4	M5	M5-M1
-0.71	-0.21	-0.04	0.21	0.43	1.14**
Panel B: Fama-French 3 Factor-ALPHA					
M1	M2	M3	M4	M5	M5-M1
-0.81	-0.26	-0.06	0.21	0.45	1.26**
Panel C: Carhart 4 Factor-ALPHA					
M1	M2	M3	M4	M5	M5-M1
-0.01	0.17	0.00	-0.01	-0.08	-0.07

Table 12 Abnormal Returns-Reversal

This table shows alphas from regressions of reversal portfolios' excess returns on market, Fama-French HML, SMB and momentum factors. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are designated with reversal formation period rank quintiles. Portfolios are re-balanced at the beginning of each month. The sample period is from 1925 to 2011. All portfolios are value-weighted. ** indicates statistical significance at the 5% level. Alphas are in percentages.

Panel A: CAPM-ALPHA					
R1	R2	R3	R4	R5	R1-R5
0.15	0.17	0.05	-0.03	-0.13	0.28**
Panel B: Fama-French 3 Factor-ALPHA					
R1	R2	R3	R4	R5	R1-R5
0.00	0.08	-0.01	-0.01	-0.06	0.06
Panel C: Carhart 4 Factor-ALPHA					
R1	R2	R3	R4	R5	R1-R5
0.16	0.14	0.05	-0.05	-0.13	0.29

Table 13 Abnormal Returns-Fresh Momentum

This table shows alphas from regressions of two-way sorted portfolio excess returns on market, Fama-French HML, SMB and momentum factors. Portfolios are designated with momentum and reversal formation period rank quintiles. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1925 to 2011. All portfolios are value-weighted. ** indicates statistical significance at the 5% level. Alphas are in percentages.

Panel A: CAPM-Alpha					
	MQ				
RQ	1	2	3	4	5
1	-0.56	-0.19	0.16	0.30	0.60
2	-0.49	-0.04	0.10	0.23	0.60
3	-0.68	-0.14	0.06	0.28	0.64
4	-0.66	-0.24	-0.17	0.18	0.40
5	-0.83	-0.45	-0.28	0.03	0.19
Q15-Q51	1.44**				
Q15-Q55	0.41**				
Q51-Q11	-0.27				

Panel B: Fama-French 3 Factor-Alpha					
	MQ				
RQ	1	2	3	4	5
1	-0.82	- 0.38	- 0.04	0.15	0.50
2	-0.68	- 0.17	-0.01	0.13	0.57
3	-0.82	- 0.25	0.00	0.23	0.65
4	-0.74	- 0.27	-0.17	0.19	0.44
5	-0.91	- 0.46	-0.24	0.08	0.26
Q15-Q51	1.40**				
Q15-Q55	0.24				
Q51-Q11	-0.08				

Panel C: Carhart 4 Factor-Alpha					
	MQ				
RQ	1	2	3	4	5
1	0.01	0.11	0.21	0.11	0.12
2	0.04	0.22	0.13	-0.01	0.06
3	-0.07	0.13	0.09	0.04	0.12
4	-0.12	0.04	-0.15	-0.03	-0.07
5	-0.29	-0.08	-0.25	-0.11	-0.22
Q15-Q51	0.42**				
Q15-Q55	0.34**				
Q51-Q11	-0.30				

Table 14 Changes in ROA

This table reports 12-month changes in return on assets (ROA) in percentage for the price momentum, price reversal and price fresh momentum portfolios. ROA is measured as the ratio of income before extraordinary items to lagged total assets . Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1985 to 2011. Portfolios are equally weighted and designated with momentum and reversal formation period rank terciles. ** indicates statistical significance at the 5% level.

Panel A: Momentum

					Month						
MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.91	-1.02	-1.13	-1.21	-1.23	-1.18	-1.11	-1.01	-0.90	-0.35	0.12
2	-0.04	-0.02	0.01	0.01	-0.01	-0.03	-0.01	-0.02	-0.03	-0.09	-0.07
3	0.68	0.74	0.80	0.86	0.89	0.85	0.76	0.68	0.59	0.18	-0.17
M3-M1	1.59**	1.77**	1.93**	2.08**	2.11**	2.03**	1.87**	1.69**	1.49**	0.54**	-0.28**

Panel B: Reversal

					Month						
RQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.33	-0.22	-0.10	- 0.01	-0.08	0.17	0.21	0.24	0.24	0.27	0.25
2	-0.06	-0.07	-0.10	-0.11	-0.10	-0.09	-0.0.6	-0.05	-0.02	0.00	-0.02
3	0.32	0.22	0.12	0.03	-0.07	-0.17	-0.24	-0.28	-0.31	-0.34	-0.30
R1-R3	-0.66**	-0.44**	-0.23**	-0.04	0.14**	0.34**	0.45**	0.52**	0.56**	0.60**	0.56**

Panel C: Fresh Momentum

					Month							
	MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
RQ	1	-1.31	-1.27	-1.22	-1.15	-1.07	-0.89	-0.72	-0.51	-0.35	0.20	0.30
1	2	-0.07	-0.06	-0.05	- 0.02	0.05	0.05	0.06	0.00	-0.05	-0.07	0.07
	3	0.96	1.17	1.31	1.39	1.21	1.07	0.91	0.81	0.70	0.24	-0.22
	1	-1.09	-1.19	-1.25	-1.20	-1.10	-0.93	-0.77	-0.64	-0.50	-0.14	0.15
2	2	-0.07	-0.07	-0.04	-0.06	-0.05	-0.07	-0.08	-0.06	-0.04	-0.07	-0.02
	3	0.60	0.61	0.66	0.68	0.69	0.63	0.61	0.52	0.41	0.09	-0.25
	1	-1.04	-1.23	-1.32	-1.35	-1.33	-1.26	-1.15	-1.04	-0.93	-0.39	-0.12
3	2	0.20	0.14	0.05	-0.02	-0.06	-0.10	-0.13	-0.19	-0.22	-0.32	-0.30
	3	1.07	1.03	0.89	0.65	0.47	0.35	0.19	0.03	-0.13	-0.45	-0.50
	13-31	2.00**	2.39**	2.64**	2.74**	2.53**	2.33**	2.06**	1.86**	1.63**	0.62**	-0.10
	13-33	-0.10	0.14	0.43**	0.74**	0.74**	0.72**	0.73**	0.78**	0.82**	0.69**	0.28**
	31-11	0.27**	0.04	-0.11	-0.19**	-0.25**	-0.37**	-0.43**	-0.54**	-0.58**	-0.59**	-0.42**

Table 15 Analyst Forecast Revisions

This table reports 12-month changes in 4 quarter-ahead Earnings Forecasts, in percentage (scaled by stock price of 12 months ago) from 3 quarters ago to the beginning of next quarter for the price momentum, price reversal and price fresh momentum portfolios. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1985 to 2011. Portfolios are equally weighted and designated with momentum and reversal formation period rank terciles. ** indicates statistical significance at the 5% level.

Panel A: Momentum

	Month										
MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.19	-0.21	-0.26	-0.28	-0.29	-0.27	-0.25	-0.23	-0.18	0.09	0.29
2	0.09	0.11	0.11	0.10	0.11	0.11	0.11	0.14	0.13	0.19	0.19
3	0.64	0.67	0.73	0.79	0.74	0.71	0.69	0.67	0.60	0.34	0.09
M3-M1	0.81**	0.87**	1.00**	1.09**	1.03 **	0.97**	0.93**	0.88**	0.76**	0.26**	-0.19

Panel B: Reversal

	Month										
RQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	0.01	0.10	0.19	0.22	0.31	0.31	0.34	0.36	0.39	0.41	0.34
2	0.14	0.15	0.15	0.17	0.19	0.18	0.17	0.18	0.16	0.13	0.15
3	0.30	0.26	0.22	0.17	0.14	0.07	0.07	0.06	0.03	0.02	0.07
R1-R3	-0.27**	-0.15**	-0.03	0.06	0.17**	0.24**	0.30**	0.32**	0.37**	0.39**	0.29**

Panel C: Fresh Momentum

		Month										
	MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
RQ	1	-0.40	-0.40	-0.37	-0.39	-0.34	-0.24	-0.21	-0.21	-0.08	0.29	0.55
1	2	-0.14	0.00	0.03	0.06	0.07	0.08	0.19	0.30	0.30	0.37	0.40
	3	0.58	0.68	0.84	0.96	0.98	0.95	0.92	0.89	0.89	0.60	0.24
	1	-0.21	-0.16	-0.19	-0.19	-0.16	-0.15	-0.17	-0.10	-0.09	0.01	0.25
2	2	0.10	0.06	0.07	0.05	0.09	0.09	0.06	0.06	0.10	0.15	0.17
	3	0.58	0.62	0.62	0.60	0.61	0.62	0.59	0.60	0.53	0.26	0.11
	1	0.01	- 0.05	-0.17	-0.22	-0.30	-0.27	-0.25	- 0.26	-0.23	-0.04	0.25
3	2	0.27	0.28	0.27	0.19	0.12	0.11	0.05	0.09	0.07	0.05	0.02
	3	0.75	0.69	0.68	0.65	0.62	0.55	0.52	0.47	0.41	0.14	0.03
	13-31	0.52**	0.73**	1.00**	1.15**	1.24**	1.19**	1.16**	1.12**	1.06**	0.62**	0.07
	13-33	-0.17**	0.00	0.13	0.25**	0.29**	0.39**	0.39**	0.44**	0.51**	0.44**	0.22**
	31-11	0.38**	0.25**	0.18**	0.11	0.01	-0.07	-0.10	-0.13	-0.12	-0.38**	-0.32**

Table 16 Analyst Forecast Revisions-Long Term Growth

This table reports quarterly changes in long term EPS growth forecasts in percentage for the price momentum, price reversal and price fresh momentum portfolios. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. The sample period is from 1985 to 2011. Portfolios are equally weighted and designated with momentum and reversal formation period rank terciles. ** indicates statistical significance at the 5% level.

Panel A: Momentum

	Month										
MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.59	-0.62	-0.63	-0.63	-0.60	-0.55	-0.50	-0.46	-0.41	-0.27	-0.19
2	-0.17	-0.17	-0.17	-0.17	-0.17	-0.18	-0.18	-0.18	-0.17	-0.16	-0.13
3	0.07	0.08	0.08	0.08	0.06	0.02	-0.02	-0.06	-0.10	-0.20	-0.27
M3-M1	0.66**	0.69**	0.71**	0.71**	0.66**	0.57**	0.48**	0.40**	0.32**	0.07**	-0.08**

Panel B: Reversal

	Month										
RQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
1	-0.26	-0.24	-0.22	-0.21	-0.20	-0.17	-0.15	-0.14	-0.13	-0.12	-0.11
2	-0.15	-0.14	-0.14	-0.13	-0.13	-0.13	-0.14	-0.14	-0.14	-0.13	-0.11
3	-0.18	-0.20	-0.22	-0.24	-0.25	-0.27	-0.27	-0.28	-0.28	-0.28	-0.28
R1-R3	-0.09**	-0.04**	0.00	0.03	0.06**	0.09**	0.12**	0.15**	0.16**	0.17**	0.17**

Panel C: Fresh Momentum

		Month										
	MQ	t-12	t-9	t-6	t-3	t	t+3	t+6	t+9	t+12	t+24	t+36
RQ	1	-0.56	-0.55	-0.55	-0.52	-0.49	-0.44	-0.39	-0.34	-0.29	-0.15	-0.10
1	2	-0.23	-0.21	-0.19	-0.19	-0.18	-0.17	-0.16	-0.14	-0.12	-0.11	-0.05
	3	0.00	0.04	0.06	0.06	0.06	0.06	0.05	0.05	0.02	-0.09	-0.17
	1	-0.46	-0.48	-0.49	-0.49	-0.46	-0.41	-0.38	-0.36	-0.32	-0.21	-0.12
2	2	-0.13	-0.12	-0.12	-0.11	-0.11	-0.11	-0.12	-0.11	-0.12	-0.11	-0.08
	3	0.08	0.10	0.13	0.13	0.11	0.06	0.02	-0.01	-0.04	-0.11	-0.17
	1	-0.62	-0.66	-0.68	-0.71	-0.68	-0.64	-0.58	-0.53	-0.48	-0.32	-0.24
3	2	-0.15	-0.18	-0.18	-0.19	-0.21	-0.23	-0.24	-0.25	-0.25	-0.24	-0.21
	3	0.16	0.15	0.12	0.09	0.05	0.00	-0.07	-0.13	-0.18	-0.31	-0.38
	13-31	0.62**	0.70**	0.74**	0.76**	0.74**	0.70**	0.64**	0.59**	0.49**	0.24**	0.07**
	13-33	-0.16**	-0.10**	-0.07**	-0.04	0.01	0.07**	0.12**	0.18**	0.20**	0.23**	0.21**
	31-11	-0.06**	-0.10**	-0.14**	-0.18**	-0.20**	-0.19**	-0.19**	-0.19**	-0.19**	-0.17**	-0.14**

Table 17 Earnings Announcement Returns

This table shows average 3-day cumulative returns around quarterly announcements of annual EPS (earnings per share) for momentum, reversal and fresh momentum portfolios. Window period is from one day before announcement to one day after. Price momentum portfolios are formed based on cumulative monthly returns from month t-12 to t-2. Price reversal portfolios are formed based on cumulative monthly returns from month t-24 to t-13. Portfolios are re-balanced at the beginning of each month. Sample period is from 1985 to 2011. Portfolios are designated with momentum and reversal formation period rank terciles. Returns are in percentages.

Panel A: Price Momentum

M1	M2	M3	M3-M1	(S.E.)	(t)
0.30	0.41	0.48	0.18	0.08	2.40

Panel B: Price Reversal

R1	R2	R3	R1-R3	(S.E.)	(t)
0.62	0.43	0.21	0.41	0.08	4.89

Panel C: Fresh Momentum

	M1	M2	M3
R1	0.58	0.62	0.68
R2	0.33	0.41	0.56
R3	0.07	0.28	0.28
(13-31)	0.61		
(S.E.)	0.13		
(t)	4.58		
(13-33)	0.39		
(S.E.)	0.11		
(t)	3.50		
(31-11)	-0.51		
(S.E.)	0.10		
(t)	-4.88		

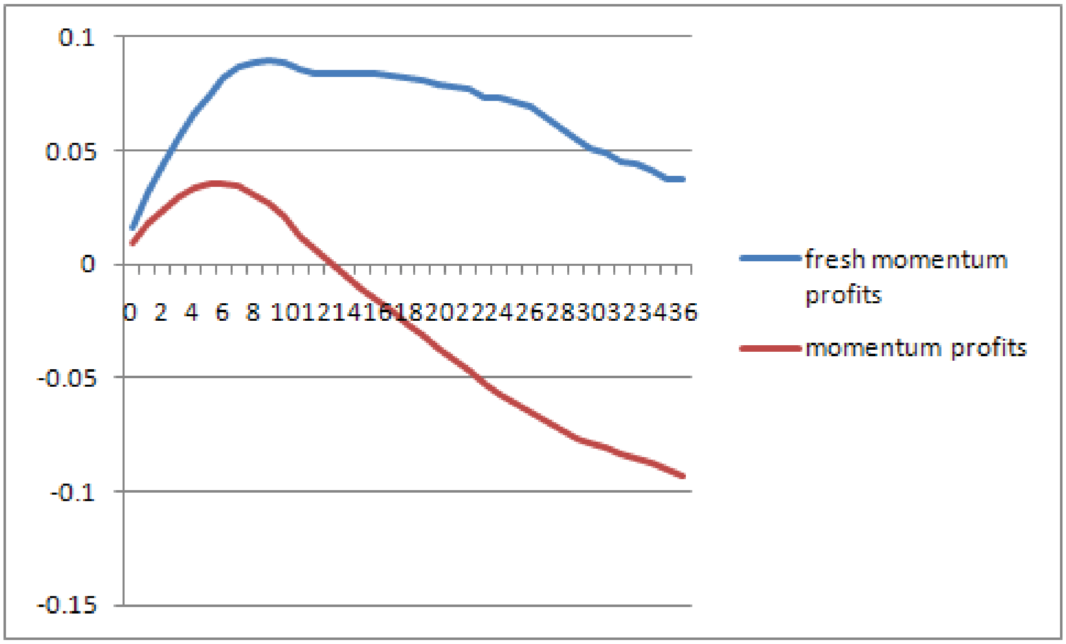

Figure 4 Cumulative Profits

This figure shows cumulative monthly profits from holding winner portfolio and shorting loser portfolio for momentum and fresh momentum strategies up to three years after portfolios sorting months. Sample period is from 1985 to 2011.

Part III

Industry Level Anomalies

1 Introduction

In the third part, we provide an extensive analysis of all known firm-level anomalies at the industry level. First, we verify if these anomalies still exist with the most recent data[16]. We find that the anomalies mentioned in this paper exist in our sample and quite robust to controlling for several standard benchmark risk factors.

Then, we test if these anomalies exist at the industry level. We use the Fama and French 12 industry specification to define industries. We aggregate firm level return and fundamental information to construct industry returns and fundamentals. We find that size, value, investment and inventory change anomalies also exist at the industry level.

More specifically, smaller industries, industries with lower investment and industries with lower change in inventory levels have bigger average industry returns. So, the effect of these variables on the returns are consistent with the ones at the firm level.

Interestingly, the value industries, which are the ones with lower market to book asset ratios have lower industry returns in contrast to the higher stock returns of value firms.

Moreover, we show that industry level anomalies are robust to most known firm level risk factors. Some of these factors are confirmed to explain the corresponding anomaly return spreads at the firm level.

Also, we find that after controlling for industries, firm level anomaly return spreads change in magnitude but do not disappear. This shows that industries do not fully explain firm level anomaly patterns. Also, significant changes in magnitudes show that industry level spreads are not fully explained by the firm level anomalies.

[16]Many of the anomalies are discovered several years ago.

We study the time series properties of anomaly spreads at the firm and industry level and find evidence which supports the significant difference of these effects. Also, we show that none of the industry anomaly spreads are highly correlated with their corresponding firm level ones.

Size, investment and inventory change spreads behave in a similar fashion at the firm and industry levels during recessions, which is consistent with the finding that the average effect of these variables on returns are in the same direction. On the other hand, there are differences with the business cycle dynamics of industry and firm level value spreads, just like the opposite effect of value on stock and industry returns.

Rest of part three is organized as follows. Section 2 provides a concise literature review on the stock return anomalies that are relevant for the paper. Section 3 examines the anomaly returns and corresponding abnormal returns at the firm level. Section 4 studies the existence of these anomalies at the industry level. Section 5 reports our results on firm-level anomalies after controlling for industries. Section 6 contains our time series analysis on the return spreads for the anomalies that are shown to exist at the industry level. Section 7 examines another measure for value and growth to provide further evidence for our results on the value effect on industry returns. Finally, section 8 concludes.

2 Literature Review

Several patterns in average stock returns are identified in the financial economics literature that are not explained by conventional asset pricing theory (Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965)). Following is the list of these anomalous return dynamics relevant to this paper.

First anomaly analyzed in this paper is momentum. Stocks with lower returns over the last year tend to have lower returns for the next couple of months and stocks with higher past returns tend to have higher future returns (Jegadeesh and Titman (1993)).

Banz (1981) finds that stocks with low market capitalization (small stocks) have abnormally high average returns. In the cross section of stocks, smaller stocks have on average significantly higher excess returns than the larger ones.

Value stocks, which are the ones with higher book to market equity ratios have higher average returns than the growth stocks, which are the ones with lower book to market equity ratios(Rosenberg, Reid, and Lanstein (1985), Chan, Hamao, and Lakonishok (1991), Fama and French (1992)).

Haugen and Baker (1996) and Cohen, Gompers, and Vuolteenaho (2002) find that more profitable firms have higher average stock returns which is not explained by CAPM and Fama and French three factor model.

Fairfield, Whisenant, and Yohn (2003) and Titman, Wei, and Xie (2004) show that firms that invest more have lower average returns in the cross sections of stocks relative the firms that invest less. In relation to the investment anomaly, firms that have higher asset growth recently have lower stock returns (Cooper, Gulen and Schill, 2008).

Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008) document that high-default-probability firms tend to have lower future stock returns. So, firms that are more financially distressed have lower stock returns on average.

It is also noted in literature that average returns after stock re-purchases are high (Ikenberry, Lakonishok, and Vermaelen (1995)) and returns after stock issues are low (Loughran and Ritter (1995)), Daniel and Titman (2006) and Pontiff and Woodgate (2008) show that average returns are negatively correlated with net stock issues.

Finally, Belo and Lin (2010) shows that firms with higher levels of inventory change have lower average stock returns in the cross section of stocks. This pattern is not explained by standard benchmark risk factors either.

Moskowitz and Grinblatt (1999) document that a significant component of the momentum effect on stock returns originates at the industry level. They show that controlling for industries, momentum profits decline substantially. They further discover that momentum based on industry returns is quite strong in the economic sense.

3 Firm Level Anomalies

Before analyzing anomalies at the industry level, we confirm the robustness of known firm level anomalies in our sample. This is important for comparison purposes. We adopt portfolio based approach following Fama and French (1992). As we form portfolios, we effectively average out idiosyncratic risk of each firm and only systematic risk associated with the sorting measure remains in portfolio average returns. Then, time series averages of these portfolio returns are taken to get the average returns. Average returns proxy for expected returns, so we can observe the relationship between the relevant sorting measure and expected returns. Portfolio method mitigates the measurement error problem inherent in realized returns proxy for expected returns due to averaging every month among a big set of stock returns cross section and eventually taking time series averages.

Stocks are sorted into ten equally populated portfolios respect to their matched relevant anomaly fundamental levels. Portfolios are held for twelve months till next sorting occurs. In this sense portfolios are balanced annually. In the entirety of the following analysis, highest numbered portfolios contain one tenth of the stocks with the highest level of the sorting measure.

For completeness of analysis, we investigate both equal weighted and value weighted average excess returns. We know that our sample is populated mostly with small firms. So, using equal weighted portfolios puts more emphasis on patterns among small firms. In other words, the results will come from mostly small firms. Also, to keep an equally weighted portfolio, frequent re-balancing other than annual re-balancing due to fundamental levels will occur due to changing share prices. More specifically, if we have a fixed amount of capital and want to invest in equal number of shares for all stocks, than we need to re-balance our portfolio since the previous number of shares for each stock will sum up to a different dollar amount than our capital due to constantly changing prices. Since our study ignores transaction costs, investment profitability results due to equal weighted average returns may not be robust to these costs. Still, to get an overall picture and not to ignore small firms that have a large population, we investigate equally weighted average returns, too.

Value weighting essentially creates equal ownership portfolios, in other words, we do not have to re-balance due to price changes of stocks. Price changes will exactly reflect on changes in portfolio weights of each share so we don't actually need to change the number of shares we have in order to keep our value weights as prices change. This means value weighted portfolios can be held for a long time, decreasing the effect of transaction costs.

The sample period of each anomaly test is different and different matching methods are used so we present our methodologies and results independently. Differences in sample periods originate from different start dates of samples. We choose them with respect to the availability of data. More specifically, we make sure that there is a reasonable number of firms that have the relevant market and fundamental data so that we have well diversified anomaly portfolios.

3.1 Momentum and Reversal

We use monthly stock return data from CRSP universe from 1925 up to 2010, inclusive. Ten portfolios are constructed using the short term return performance for momentum and long term past return performance for reversal.

More specifically, for each momentum portfolio's month t, we sort stocks into short-term past return performance deciles, depending on their cumulative returns from month t-12 to month t-2 (inclusive). We exclude one month before portfolio month t to avoid bid-ask bounce [17]. Each decile for any month t, gives one momentum portfolio for month t. First decile contains the worst momentum performers, losers. To get the monthly momentum

[17] see Fama-French (1996).

portfolio excess returns, we calculate equal- and value-weighted cross sectional average excess stock returns in that portfolio for each month. We use one month lagged market capitalization of stocks to calculate portfolio weights for each month. Portfolios are re-balanced every month. In a way, portfolio construction is following an investment strategy in stocks using short term past returns information in this specific manner.

To obtain reversal portfolios, we apply the same method that we use for momentum portfolios. Only exception is that reversal formation period for portfolio month t is between month t-24 and month t-13 since we are interested in long term past cumulative return performance of stocks. This time, we skip one year between the end of formation period and the portfolio month, following the standard methodology.

Table 18 reports the average excess return results on momentum and reversal stock portfolios. In Panel A, we see the results obtained using equally weighted excess returns. The momentum portfolio number 1 has on average 0.72% monthly return in our sample. The excess return spread between extreme momentum portfolios is 0.51% monthly which corresponds to an annualized return spread of 6.12% and a significant t statistic of 2.39. The equally weighted average return spread between extreme reversal portfolios is -0.89% corresponding to a significant t statistic of -5.24.

The spreads for momentum and reversal obtained using value weighted portfolio returns is also impressive and consistent with the previous studies. The value weighted return spread for momentum is a very big 1.10% monthly and the reversal spread is -0.44% as shown in Panel B of table 18. It is interesting to see that in equally weighted returns, reversal effect is much larger than the momentum effect. This relation is the other way around when we use value weighted returns instead. This suggests that larger stocks are more responsible for the momentum effect relative to the reversal one.

We further investigate the robustness of these spreads to well known risk factors such as market, size, value, momentum, investment and profitability. We regress average excess portfolio spreads onto standard benchmark risk models. The alphas from these regressions are abnormal returns associated with the return spreads by taking the model as a proxy for the expected returns.

In table 18, we see in the first two columns of Panel A that from CAPM and Fama and French three factor model, we get significant alphas for equally weighted return spreads for momentum. The CAPM alpha is 0.67% monthly for the momentum spread which is significant. The three factor alpha is also significant and 0.83%. In Panel B, we see that the Carhart alpha is insignificant (0.06%) for momentum. This is as expected since one of the factors in the Carhart model is the momentum factor and this model explains momentum by construction.

For reversal, we get a significant value weighted alpha (-0.38%) from CAPM and an insignificant alpha (-0.03%) from the three factor model. Naturally, we get an insignificant alpha from Carhart model since this model includes all the three factors from the Fama and French model.

The last factor regression is done using the CNZ model[18]. In the equal weighted case, we have an insignificant alpha (-0.16%) for momentum and a significant alpha for reversal (-0.79%). Interestingly, for the value weighted case, we have a significant alpha for momentum (1.21%) and an insignificant alpha for reversal (-0.23%).

3.2 Size and Value

For the size anomaly, we use June of each year to sort stocks into size deciles and keep these portfolios for one year starting at the following July up to the June of next year. We follow a similar procedure for studying the value effect in stock returns. We use CRSP monthly stock return data for the size effect analysis and merge the returns with the firm fundamental data from Compustat for the value effect analysis.

To obtain the size effect, our sample goes back to 1925. As a robustness check, we verify that the size spread also exists for the time period starting 1963 up to 2011. For the

[18]Chen, Novy-Marx and Zhang (2010)

value effect we start our sample in 1963 to make sure there is adequate number of firms with the relevant accounting information. Size is defined as the market capitalization of June in each year for each stock in the CRSP universe. Value is the ratio of the market values of assets to book values of assets. Detailed definitions are given in the appendix.

For the value anomaly, we make sure that accounting variables are publicly known before the returns they are used to explain. Following Fama and French (1992), we match the accounting data for the fiscal year-end in calendar year t-1 with the monthly returns for July of year t to June of year t+1 for each stock. This way, we leave a minimum of six-month time interval between fiscal year ends and the returns. Finally, we hold stocks in portfolios for twelve months and calculate equal and value weighted average monthly returns of our portfolios built on relevant accounting information. Portfolio weights are one month lagged market capitalization values. Market capitalization is shares outstanding times closing price of the month. This way, we make sure that most recent market and accounting data are used to explain stock returns at the time of building portfolios.

Then, we take the difference between extreme portfolios to obtain the return spread due to the relevant fundamental measure. In Table 18, we see that the size spread is an equal weighted -1.50% monthly. So, the group of biggest stocks have on average 1.50% monthly excess returns less than the group of smallest stocks in our sample. The size spread in value weighted portfolios is -0.73%. Both spreads are significant and economically very big. As expected, CAPM fails to explain the size spread for equal and value weighted returns. Again as expected, Fama and French three factor model explains the size effect by construction giving insignificant alphas in the value weighted case. We see from Table 18 that CNZ model also fails to explain size effect at the firm level giving significant alphas for both equal and value weighted cases, (-1.72% and -0.84%, respectively).

The existence of value/growth effect on expected stock returns is also verified in our sample. In Table 18, Panel A; we see that the growth stocks have -1.24% monthly excess return less than the value stocks, which are captured by highest and lowest value/growth portfolios, respectively. This corresponds to a significant return spread with a t statistic of -6.49. Using value weighted portfolios, we obtain the growth spread as -0.48% monthly, again significant with a t statistic of -2.53.

In Panel B of table 18, we see that CAPM fails to explain the value effect giving a significant alpha of -0.53%. By construction the three factor model and Carhart four factor model explains the growth spread in our sample with insignificant alphas. We also note that the CNZ model is successful in terms of generating an insignificant alpha of -0.07% for the growth spread.

3.3 Investment and Asset Growth

We define investment as the net change in fixed assets and investment capital scaled by lagged assets. Asset growth is simply calculated as the change in the value of book value of assets scaled by lagged assets. Detailed definitions are given in the appendix. We match annual fundamental data with monthly stock returns. Starting from July of each year, the investment and asset growth measures from the previous year's fiscal end is matched with monthly returns up to the June of next year, inclusive. Then, ten stock portfolios are constructed and return averages are taken to measure the relation between investment, asset growth and expected stock returns. The sample period used for both anomalies is from 1963 to 2010.

In Table 19, Panel A; we have the results on average returns for portfolios sorted on investment. We see that the the firms that invest a lot have -1.27% less equal weighted returns than the firms that invest less. This corresponds to a significant t statistic of -9.57. For the value weighted case, the return spread due to investment levels is -0.68% monthly, which is also significant. This corresponds to an annualized return difference of -8.16%.

From the factor regressions on investment portfolios, we see that CAPM fails to explain the return spreads in both equally and value weighted cases. This result is similar to the other regressions. From CAPM, we get two significant alphas for the equal and value weighted cases (-1.33% and -0.72%, respectively). In the three factor model, we get -1.20% and -0.43% alphas and for the Carhart model, we get -1.04% and -0.38% significant alphas. The outcome is similar for the CNZ regressions and the alphas are -1.24% and -0.48%.

We obtain similar results for the asset growth anomaly. In the first panel of Table 19, we see that the return spread is -1.39% monthly. This corresponds to a CAPM alpha of -1.44%, three factor alpha of -1.18%, Carhart alpha of -1.14% and CNZ alpha of -1.67%. In the second panel of the same table, we have the results for the value weighted case. The asset growth return spread is a significant -0.62% monthly. This gives a CAPM alpha of -0.70%, a three factor alpha of -0.32%, a Carhart alpha of -0.24% and a CNZ alpha of -0.61%. Among these alphas, only the Carhart alpha is insignificant.

3.4 Net Stock Issuance

Following Fama and French (2008),net stock issues is calculated as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year-end in t-1 to the split-adjusted shares outstanding at the fiscal year-end in t-2. The split-adjusted shares outstanding is shares outstanding times the adjustment factor. This measure is matched with the monthly returns of year t's July up to following year's June, inclusive. The sample period is from 1963 to 2010.

In the third column of the first panel of Table 19, we see that the excess return spread associated with net stock issuance is -0.99%. This is a significant spread with an annualized return of -11.88% and a t statistic of -7.46. From the factor regressions, we get significant alphas. The CAPM alpha is -1.12%. The three factor alpha is -0.95%, the Carhart alpha is -0.76% and the CNZ alpha is -0.62%.

For the value weighted portfolios, we get similar results. The difference between extreme portfolios sorted on net stock issuance is -0.74%. So, stocks with high net stock issuance have significantly lower average stock returns than the stocks with low net stock issuance. We get a significant CAPM alpha of -0.82%, a three factor alpha of -0.70%, a Carhart alpha of -0.63% and a CNZ alpha of -0.61%. All these alphas are significant and economically important.

3.5 Change in Inventories

We define inventory change as the annual change in inventories scaled by lagged value of total inventories. In this sense, we capture the percentage change in inventories for each firm. Similar to net stock issuance anomaly, we use annual fundamental information of inventory levels and match them with monthly returns. Previous fiscal year's fundamental information on inventories is matched with the monthly returns of July, this year, up to the June of next year.

In the fourth columns of two panels in Table 19, we see the results on average stock returns for portfolios sorted on inventory change measure. The firms with highest level of inventory change have 1.00% equally weighted average return less than the ones with lowest levels of inventory change. The value weighted portfolio return spread is also significant (-0.63%).

The results of the factor regressions on the equally weighted portfolio spread is as follows; we get a CAPM alpha of -1.05%, a three factor alpha of -0.88%, a Carhart alpha of -0.82% and a CNZ alpha of -0.99%. All these alphas are significant. For the value weighted case, the CAPM, three factor, Carhart and CNZ alphas are -0.68%, -0.41%, -0.30% and -0.46%, respectively.

3.6 Profitability

We define profitability as the return on assets, which is calculated as the quarterly income before extraordinary items scaled by the lagged book value of total assets. We use quarterly data instead of annual data. We match these fundamentals with the returns of the months after the the announcement date of the quarterly firm fundamental information. For example, if the two subsequent quarterly accounting information reports are made public in April and July of a given year, the first set of fundamental data is matched with the returns of May, June and July of that year. Our sample period of the profitability anomaly is from 1972 to 2011.

In the first column of the first panel of Table 20, we see that the equally weighted excess return spread between the extreme portfolios (highest minus lowest) is a significant 1.17% monthly. This corresponds to an annualized return spread of 14.04% with a t statistic of 3.85. So, consistent with previous studies, more profitable firms have higher expected returns than less profitable ones. For the value weighted case, the return spread is again significant. It is 1.09% monthly with a t statistic of 3.91.

The results from factor regressions are also consistent with previous studies. For the equal weighted case, the CAPM alpha is 1.26%, the three factor alpha is 1.34%, the Carhart alpha is 0.88% and the CNZ alpha is 0.28%. All of the alphas other than the CNZ alpha are significant. The CNZ factor model explains the profitability anomaly by construction since one of its factors is built on the profitability information.

For the value weighted case, the factor alphas are as follows; the CAPM, three factor, Carhart and CNZ alphas are 1.25%, 1.42%, 1.14% and 0.36%, respectively. Again, all alphas are significant except the CNZ alpha.

3.7 Financial Distress

We use Ohlson's O-score (1980) as the measure of financial distress and sort stocks into ten equally populated portfolios respect to their O-score. The calculation of O-score is given in the appendix. We use quarterly data to construct the O-score and match this financial distress measure with the returns of months following the most recent quarterly firm fundamental announcements. As in the case of matching profitability information with returns in the previous subsection; if the two subsequent quarterly accounting information reports are made public in April and July of a given year, the first set of fundamental data is matched with the returns of May, June and July of that year.

In table 20, we see that the average excess return spread for financial distress is an insignificant -0.25% monthly for the equal weighted case. This corresponds to insignificant alpha spreads for all the standard factor models we use. However, in the value weighted case, we have a significant spread between extreme O-score portfolios. The financially more distressed firms have 1.22% less average excess returns than financially less stressed firms. This is a large number with a significant t statistic of 3.91. It corresponds to an annualized return spread of 13.08%.

We get significant alpha spreads from most of the benchmark risk factor models. The CAPM alpha is -1.44%, the three factor alpha is -1.63% and the Carhart alpha is -1.17%. These alpha spreads are all statistically significant and big in the economic sense. The CNZ factor model is successful in explaining the financial distress anomaly and produces an insignificant alpha of -0.48% monthly.

3.8 Earnings Surprises

We define Standardized Unexpected Earnings (SUE) as the change in the quarterly earnings per share from its value announced four quarters ago divided by the standard deviation of the change in quarterly earnings over the prior eight quarters.[19]

In Table 20, last columns of both panels show the results on average returns for portfolios sorted on SUE. In the first panel, we see that the equally weighted average portfolio spread is a significant 0.96%. This corresponds to a t statistic of 11.50. The alphas from the factor regressions are 0.97%, 0.99%, 0.83% and 0.83% for CAPM, three factor, Carhart and CNZ models, respectively. These alphas are all highly significant.

In the second panel of Table 20, we see that the value weighted return spread for SUE is a significant 0.29%, which gives significant alphas for CAPM and three factor models (0.32% and 0.30% respectively). The Carhart and CNZ alphas are insignificant (0.19% and

[19]please see Chan, Jegadeesh, and Lakonishok (1996)

0.21%).

4 Industry Level Anomalies

Firms within an industry compete in the same product market and their operating decisions reflect strategic interactions among them. They move closely with each other in product and technology innovations, and react similarly to shifts in supply and demand conditions, as well as changes in regulatory environment. In addition, as the industry experiences expansions and contractions, these firms' growth opportunities and investing and financing decisions are highly correlated. In this regard, we investigate if certain anomalies that are known to exist at the firm level also exist at the industry level.

4.1 Industry Specification and Variables

We use Fama and French 12 industries. Assigning firms into 12 industries represents a compromise between having a reasonable number of distinct industries and having enough firms within each industry so that sorting within industries will not produce portfolios that are too thin. We take value weighted cross sectional averages of market and fundamental information to get industry aggregates. We will explain this aggregation process in detail as we go through the empirical tests in each subsection below since there is not a general method for all anomalies.

4.2 Momentum and Reversal

We take cross sectional value weighted averages of the stock returns each month to get the monthly time series of industry level returns. Then, using the cross section of 12 industries, we calculate the short term and long term past industry return performance. We use terciles instead of deciles in this analysis since there are only 12 industries.

More specifically, for each momentum industry portfolio's month t, we sort industries into short-term past return performance terciles, depending on their cumulative returns from month t-12 to month t-2 (inclusive). We exclude one month before portfolio month t to avoid bid-ask bounce (see Fama-French 1996). Each tercile for any month t, gives one momentum portfolio for month t. First tercile contains the worst momentum performers, losers. To get the monthly momentum portfolio excess returns, we calculate equal and value-weighted cross sectional average excess industry returns in that portfolio for each month. We use one month lagged market capitalization of industries to calculate portfolio weights for each month. Industry market capitalization is the value weighted average of stock market capitalizations in the industry portfolio. Portfolios are re-balanced every month. In a way, portfolio construction is following an investment strategy in stocks using short term past returns information in this specific manner.

To obtain reversal portfolios, we apply the same method that we use for momentum portfolios. Only exception is that formation period for portfolio month t is between month t-24 and month t-13 since we are interested in long term past cumulative return performance of industries. This time, we skip one year between the end of formation period and the portfolio month, following the standard methodology.

Table 21 reports our results on industry level momentum and reversal. In the first panel, we see that there is a significant momentum spread of 0.45% between the third and first portfolios. This gives an annualized return of 5.40% and a t statistic of 4.00. In the second panel, the value weighted return spread for momentum is also significant (0.46%).

The alphas we obtain from the standard firm level benchmark risk factor models are 0.45%, 0.52%, -0.11% and 0.35% for CAPM, three factor, Carhart and CNZ model for the equal weighted portfolios. All of these alphas are significant except the Carhart alpha. In the value weighted case, we also get significant alphas from all factor models except the Carhart model. The CAPM, three factor and CNZ model alphas are 0.46%, 0.53% AND 0.42%. The Carhart alpha is -0.15%.

For reversal, we do not have a significant spread either in equal or in value weighted cases. The equal weighted return spread is -0.09% and the value weighted return spread is -0.13%. Also, from standard factor models, we get insignificant alphas for the reversal spread in both averaging methods.

4.3 Size and Value

Again we build industry portfolios using Fama French 12 industry specification. Value weighted avarages of market capitalizations are taken to get the industry market capitalization. For the size anomaly we use June of each year to sort industries into size terciles and keep these portfolios for one year starting at the following July up to the June of next year. We follow a similar procedure for studying the value effect in industry returns. Value is the ratio of the market values of assets to book values of assets. We take the ratio of the total market value of assets to the total book value of assets in each industry. Detailed definitions are given in the appendix.

To obtain the size effect, our sample goes back to 1925. As a robustness check, we verify that the size spread also exists for the time period starting 1963 up to 2011. For the value effect we start our sample in 1963 to make sure there is adequate number of industries with the relevant accounting information.

For the value anomaly, we make sure that accounting variables are publicly known before the returns they are used to explain. We match the aggregate accounting data for the fiscal year end in calendar year t-1 with the monthly returns for July of year t to June of year t+1 for each industry[20]. This way, we leave a minimum of six-month time interval between fiscal year ends and the returns. Finally, we hold industries in value portfolios for twelve months and calculate equal and value weighted average monthly returns of our portfolios built on relevant accounting information. Portfolio weights used in calculating value weighted averages for portfolios that are held from July of year t to the June of year

[20]Following Fama and French (1992)

t+1 are average industry market capitalization values in June of year t. This way, we make sure that most recent market and accounting data are used to explain industry returns at the time of building portfolios.

Then, we take the difference between extreme portfolios to obtain the return spread due to the relevant fundamental measure. In Table 21, we see that the size spread is an equal weighted -0.24% monthly. So, biggest industries have on average 0.24% monthly excess returns less than the group of smallest industries do in our sample. The size spread in value weighted portfolios is -0.31%. Both spreads are significant and economically very big. As expected, CAPM fails to explain the size spread for equal and value weighted returns. Again as expected, Fama and French three factor model explains the size effect by construction giving insignificant alphas in the value weighted case. We see from Table 21 that CNZ model explains size effect at the industry level giving insignificant alphas for both equal and value weighted cases, (0.13% and 0.15%, respectively).

The existence of value effect on expected industry returns is also verified in our sample. In table 21, Panel A; we see that the growth industries have 0.31% monthly excess return more than the value industries, which are captured by highest and lowest value portfolios, respectively. This corresponds to a significant return spread with a t statistic of 2.26. Using value weighted portfolios, we obtain the growth spread as 0.31% monthly, again significant with a t statistic of 1.97.

The results on the value effect on returns at the industry level are very interesting since it goes in the opposite direction with the firm level effect. Value firms, which are ones with low market to book ratios have higher average returns than growth firms, which are the ones with high market to book ratios. This was confirmed in our sample in one of the previous sections. We find that value industries actually have lower industry returns relative to growth industries.

In the first panel of Table 21, we see that CAPM explains the growth spread at the industry level giving an insignificant equal weighted alpha spread of 0.22%. However, three factor model fails to explain the growth spread at the industry level. We have the opposite result for the growth spread at the firm level, more specifically, CAPM fails to explain it and the three factor model explains the firm level growth spread by construction. This is another difference between the value effects at the firm and industry level. We also get significant equally weighted alpha spreads for industry level growth spread from the Carhart and CNZ models (0.47% and 0.35%, respectively).

In Panel B of Table 21, we again see that CAPM explains the value effect giving an insignificant alpha of 0.20%. However, interestingly the three factor firm level risk model fails to explain the value effect at the industry level. The alpha we get from the three factor model is 0.51%, which is significant with a t statistic of 4.06. Carhart model creates a significant alpha of 0.45%. We also note that the CNZ model is successful in terms of generating an insignificant alpha of 0.29% for the growth spread.

4.4 Investment and Asset Growth

We define investment as the net change in fixed assets and investment capital scaled by lagged assets. Asset growth is simply calculated as the change in the value of book value of assets scaled by lagged assets. Detailed definitions are given in the appendix. We match annual fundamental data with monthly stock returns. Starting from July of each year, the investment and asset growth measures from the previous year's fiscal end is matched with monthly returns up to the June of next year, inclusive. We take the net change in the sum of fixed assets and investment scaled by the sum of assets across the industry to get the industry aggregate of investment. Similarly, industry level asset growth is the change in the sum of total assets scaled by total lagged assets across the industry.

Then, three industry portfolios are constructed and return averages are taken to measure the relation between investment, asset growth and expected industry returns. The sample period used for both anomalies is from 1963 to 2010.

In Table 22, Panel A; we have the results on average returns for industry portfolios sorted on investment. We see that the the industries that invest a lot have -0.28 % less equal weighted returns than the industries that invest less. This corresponds to a significant t statistic of -2.21. For the value weighted case, the return spread due to investment levels is -0.33% monthly, which is also significant. This corresponds to an annualized return difference of -3.96%.

From the factor regressions on investment portfolios, we see that CAPM fails to explain the return spreads in both equally and value weighted cases. This result is similar to the other regressions. From CAPM, we get two significant alphas for the equal and value weighted cases (-0.25% and -0.32%, respectively). In the three factor model, we get -0.22% and -0.29% alphas and for the Carhart model, we get -0.24% and -0.30% significant alphas. The outcome is similar for the CNZ regressions and the alphas are -0.33% and -0.45%, which are both significant.

In the first panel of Table 22, we see that the return spread due to asset growth measure is 0.13% monthly. This corresponds to a CAPM alpha of 0.01%, three factor alpha of 0.23%, Carhart alpha of 0.26% and CNZ alpha of 0.23%. In the second panel of the same table, we have the results for the value weighted case. The asset growth return spread is a significant 0.08% monthly. This gives a CAPM alpha of -0.05%, a three factor alpha of 0.20%, a Carhart alpha of -0.28% and a CNZ alpha of 0.24%. Among these alphas, only the Carhart alpha is significant.

4.5 Net Stock Issuance

Following Fama and French (2008),net stock issues is calculated as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year-end in t-1 to the split-adjusted shares outstanding at the fiscal year-end in t-2. The split-adjusted shares outstanding is shares outstanding times the adjustment factor. Then, we take the value weighted averages of the net stock issuance measure at the firm level to get the industry net stock issuance in the cross section of firms in each industry. This measure is matched with the monthly industry returns of year t's July up to the following year's June, inclusive. The sample period is from 1963 to 2010.

In the third column of the first panel of Table 22, we see that the excess return spread associated with net stock issuance is 0.09%. This is an insignificant spread with an annualized return of 1.08% and a t statistic of 0.99. From the factor regressions, we get insignificant alphas for most of the risk factor models. The CAPM alpha is 0.08%. The three factor alpha is 0.05%, the Carhart alpha is 0.12% and the CNZ alpha is 0.25%. Only the CNZ alpha is significant.

For the value weighted portfolios, we get similar results. The difference between extreme portfolios sorted on net stock issuance is 0.10%. We get a CAPM alpha of 0.07%, a three factor alpha of 0.07%, a Carhart alpha of 0.15% and a CNZ alpha of 0.22%. All these alphas are insignificant in the statistical sense.

4.6 Change in Inventories

We define inventory change as the annual change in inventories scaled by lagged value of total inventories. In this sense, we capture the percentage change in inventories for each firm. Similar to net stock issuance anomaly, we use annual fundamental information of inventory levels and match them with monthly returns. Previous fiscal year's fundamental information on inventories is matched with the monthly returns of July, this year, up to the June of next year. Then, we take the percentage change in the sum of inventories in each industry to get the aggregate industry level inventory change. Our sample period is from 1963 to 2010.

In the fourth columns of two panels in Table 22, we see the results on average industry returns for portfolios sorted on inventory change measure. The industries with highest level of inventory change have 0.30% equally weighted average return less than the ones with lowest levels of inventory change. The value weighted portfolio return spread is also significant (-0.32%).

The results of the factor regressions on the equally weighted portfolio spread is as follows; we get a CAPM alpha of -0.29%, a three factor alpha of -0.27%, a Carhart alpha of -0.30% and a CNZ alpha of -0.32%. All these alphas are significant. For the value weighted case, the CAPM, three factor, Carhart and CNZ alphas are -0.31%, -0.29%, -0.30% and -0.38%, respectively.

4.7 Profitability

We define profitability as the return on assets, which is calculated as the quarterly income before extraordinary items scaled by the lagged book value of total assets. We use quarterly data instead of annual data. We match the returns of the months after the the announcement date of the quarterly firm fundamental information. For example, if the two subsequent quarterly accounting information reports are made public in April and July of a given year, the first set of fundamental data is matched with the returns of May, June and July of that year. then, we take the value weighted averages of the ROA measures in each industry to get the industry level profitability measure. Our sample period of the profitability anomaly is from 1972 to 2010.

In the first column of the first panel of Table 23, we see that the equally weighted excess return spread between the extreme portfolios (highest minus lowest) is an insignificant 0.08% monthly. For the value weighted case, the return spread is again insignificant. It is 0.20% monthly with a t statistic of 1.26.

The results from factor regressions are as follows; for the equal weighted case, the CAPM alpha is 0.05% , the three factor alpha is 0.05%, the Carhart alpha is 0.05% and the CNZ alpha is -0.10%. All of the alphas are insignificant. For the value weighted case, the factors are as follows; the CAPM, three factor, Carhart and CNZ alphas are 0.09%, 0.03%, -0.10%, -0.03%, respectively. Again, all alphas are insignificant.

4.8 Financial Distress

We use Ohlson's O-score (1980) as the measure of financial distress. The calculation of this measure is given in the appendix. We use quarterly data to construct the O-score and match this financial distress measure with the returns of months following the most recent quarterly firm fundamental announcements. For instance, if the two subsequent quarterly accounting information reports are made public in April and July of a given year, the first set of fundamental data is matched with the returns of May, June and July of that year as an example. Then, we take the value weighted averages of these scores in each industry to get the industry level financial distress measure.

In table 23, we see that the average excess industry return spread for financial distress is an insignificant -0.02% monthly for the equal weighted case. This corresponds to insignificant alpha spreads for all the standard factor models we use. In the value weighted case, we again have an insignificant spread between extreme O-score portfolios (-0.06%).

We get insignificant alpha spreads from most of the benchmark risk factor models. For the equal weighted case all the alphas are insignificant. For the value weighted case; the CAPM alpha is 0.00%, the three factor alpha is -0.32% and the Carhart alpha is -0.21% and the CNZ alpha is -0.23%. All of these alphas are insignificant except the three factor alpha, which is significant with a t statistic of -2.75.

4.9 Earnings Surprises

We define Standardized Unexpected Earnings (SUE) as the change in the quarterly earnings per share from its value announced four quarters ago divided by the standard deviation of the change in quarterly earnings over the prior eight quarters.[21] Then, we take the value weighted averages of firm level SUE to get the industry level SUE in each industry.

In Table 23, last columns of both panels show the results on average returns for portfolios sorted on SUE. In the first panel, we see that the equally weighted average portfolio

[21] Chan, Jegadeesh, and Lakonishok (1996)

spread is an insignificant 0.01%. This corresponds to a t statistic of 0.08. The insignificant alphas from the factor regressions are 0.04%, -0.11%, -0.11% and -0.06% for CAPM, three factor, Carhart and CNZ models, respectively.

In the second panel of Table 23, we see that the value weighted return spread for SUE is an insignificant 0.06%, which gives insignificant alphas for all factor models. CAPM and three factor alphas are 0.09% and 0.03% respectively. The Carhart and CNZ alphas are also insignificant (-0.10% and -0.03%).

5 Industry Adjusted Stock Returns

In the previous section, we find that size, value, investment and inventory change anomalies also exist at the industry level. We also showed that the industry return spreads due to these measures are robust to controlling for several standard risk factors such as market, size, value and momentum. In this section, we want to see if industry level effects of these measures can explain the return spreads at the firm level. In other words, we want to see what proportion of the firm level anomaly spreads originate from the industries.

We control for industries by calculating the industry adjusted stock returns. As in previous sections, we use Fama, French 12 industries and allocate all firms into these industries. We take value weighted cross sectional averages in each industry in each month to get the industry monthly return. Then, we subtract this industry return from each of the stock return in that industry to get the industry adjusted stock returns.

After getting these industry adjusted returns, we repeat the portfolio analysis at the firm level using the adjusted returns. We also report the results using unadjusted returns for comparison. We use three portfolios in each test and repeat the portfolio analysis for the four anomalies that are shown to exist at the industry level.[22]

[22]Please refer to the previous sections and appendix for the definition of the anomaly measures and portfolio sorting methods.

5.1 Equally Weighted Anomaly Portfolios

Table 24 reports the results on average returns for equally weighted portfolios. In Panel A, we have the average unadjusted returns for anomalies. In Panel B, we have the corresponding industry adjusted returns. In this analysis we used terciles instead of deciles and we get significant results even though low number of portfolios work against us.

For the size anomaly, we have an average equally weighted return spread of -0.52%. The corresponding industry adjusted return spread is -0.44%. So, some of the size spread come from the industry level. Controlling for the industry effect, the size spread naturally gets smaller in magnitude. This is also consistent with that size effects are at the same direction for both the industry and the firm level. We get significant alphas from the CAPM model for both unadjusted and adjusted size spreads (-0.38% and -0.32%, respectively). The three factor alphas and Carhart alphas for both unadjusted and adjusted spreads are insignificant. The CNZ alphas are on the other hand are significant (-0.63% and -0.59%, respectively).

For the value anomaly, we have an unadjusted equally weighted return spread of -0.83%. which corresponds to a t statistic of -6.11. After controlling for industries, we obtain again -0.83% return spread but a stronger t statistic, which is -7.94. As expected CAPM fails to explain both unadjusted and adjusted growth spreads with significant alphas of -0.94% and -0.92%. We get significant alphas from other factor models, too.

We have a significant spread for investment for both unadjusted and adjusted returns (-0.70% and -0.64%). Controlling for industries, the investment return spread diminishes in magnitude. This is consistent with that the effect of investment on returns is at the same direction for both industry and firm levels. We get significant alphas from all factor models for both unadjusted and adjusted cases.

The inventory change spread also diminishes in magnitude when we control for the industries. We have -0.60% for the unadjusted case and -0.58% for the adjusted case. We also get significant alphas from all the factor models for the unadjusted and adjusted return spreads.

5.2 Value-Weighted Anomaly Portfolios

We get quite similar results for the value weighted portfolios. Table 25 reports these results in two panels for unadjusted and adjusted excess returns. Size, investment and inventory change anomalies exist at the firm level for the value weighted case, too. As expected the magnitude of the anomaly spreads gets smaller after we control for industries. The unadjusted spreads for size, investment and inventory change are -0.36%, -0.35% and -0.35%, respectively. The corresponding adjusted spreads are -0.23%, -0.27% and -0.29%.

CAPM model gives -0.44% and -0.38% for the value anomaly unadjusted and adjusted return spreads. CAPM fails to explain the investment and inventory change spreads for both unadjusted and adjusted returns. For the investment anomaly, we get -0.38% and -0.30% for the unadjusted and adjusted cases, which are significant. For the inventory change anomaly, we have -0.42% and -0.33% for the unadjusted and adjusted cases. CAPM explains both the unadjusted and adjusted size spreads.

The three factor model explains the size and investment unadjusted return spreads (alphas are 0.07% and -0.10%) and fails to explain the inventory change unadjusted spread (-0.25%). The three factor model fails to explain the adjusted size and inventory change spreads (0.12% and -0.23%) but gives an insignificant alpha for the investment industry adjusted spread (-0.11%). The three factor alphas for the growth spread are 0.07% and -0.12%, which are both insignificant.

Carhart model gives an insignificant alpha for the unadjusted size spread (0.03%). We get insignificant alphas for the investment and inventory change unadjusted spreads (-0.04% and -0.12%). The alphas for size, investment and inventory change adjusted spreads are 0.10%, -0.05% and -0.17%, respectively, which are insignificant except the one for inventory change. The Carhart alphas for growth are 0.07% and -0.15%, which are both insignificant, too.

The CNZ alphas for the growth unadjusted and adjusted spreads are -0.20% and -0.41% which the only latter is significant. The unadjusted spreads for size, investment and inventory change are -0.44%, 0.13% and -0.18%. The corresponding adjusted spreads are -0.42%, -0.02% and -0.19%. These alphas are significant except for the investment anomaly.

6 Time series Analysis

6.1 Correlations Among Spreads

Previous tests suggest that using a cross section of industries, we capture several anomalous return behavior that are different than the corresponding ones at the firm level. As an example, size spread at the industry level is not just another manifestation of the size effect at the firm level. Since smaller industries are the ones that have smaller firms, average industry returns of a group of smaller industries will reflect the stock returns of small firms to a certain extent. We want to confirm that this is not the source of industry level anomalies.

First of all, we saw in the previous section that controlling for industries, firm-level anomaly spreads diminish in magnitude for size, investment and inventory change anomalies. This shows that industry level spreads can not be explained fully by firm level spreads. Secondly, industry level spreads are robust to controlling for some firm level risk factors. For instance, the Fama French three factor model explains the value effect at the firm level[23]. However, the three factor model fails to explain the value spread at the industry level.

As an additional check, we want to understand the time series correlation between anomaly spreads. If, for instance size spread at the industry level can be explained by the size spread at the firm level, we expect that the time series of industry level and firm level size spreads to be highly correlated.

[23]Table 18, fourth column of the second Panel

Table 26 reports the pairwise correlations between spreads. The first entries are the correlation coefficients and the second entries under the coefficients are p values. For example, the correlation between size spread at the industry and firm level is 0.24% with a p-value of 0.00. This shows that there is a significant positive correlation but the magnitude is very small (only a quarter).

The correlation between the value spread at the firm and industry level is 0.54% even though these effects are in opposite direction; The value effect at the firm level is positive and it is negative at the industry level. The correlation between the industry level and firm level investment spreads is an insignificant 0.05%. Finally the correlation between the industry and firm level inventory change spreads is 0.19%.

6.2 Business Cycles

Next, we investigate how the anomaly return spreads behave in different states of the economy and compare the time series patterns of industry level spreads to firm level spreads. In Figure 5, time series of the anomaly spreads are graphed for the ones that are significant at the firm and industry level. NBER designated recession periods are also depicted on the graphs. We compare how spreads behave in recessions.

In the first plot, we see that size spread at the firm and industry level behave very similar in most of the recessions. They usually peak during recessions. So, the size spread is countercyclical and is negative on average. Also, this is consistent with that the average spreads at the firm and industry level are both negative.

We also see from the third and fourth plot that investment and inventory change spreads behave quite similarly at the firm and industry level. This is consistent with the fact that their effect on returns are at the same direction.

We see that for the value anomaly, the firm level and industry level spreads behave similarly for the first four recessions from 1963 to 1991. However, in the last two recessions, they start to behave in the opposite direction. This suggests that the opposite sign of value spreads at the firm and industry level that is determined in previous sections may be due to the second half of the sample.

7 Book-to-Market Equity Measure

Throughout the paper, we used market to book ratio of assets as the measure of growth. Another conventional measure of value (opposite of growth) is the book to market equity ratio, BE/ME.[24]

7.1 Firm Level Effects

First, we study the effect of BE/ME on returns at the firm level. Table 27 reports the results on average returns. We use five portfolios and sort stocks into five equally populated portfolios according to their BE/ME measure. In Panel A; the equally weighted value spread using this measure is 1.00% in the whole sample, which starts from 1926 and goes up to 2010. The value weighted return spread in the entire sample period is 0.24%.

The equal weighted value spread corresponds to significant alpha spreads from all the benchmark factor models. However, all the factor models are successful in terms of explaining the value-weighted value spread.

In the previous sections, we mentioned that the value effects at the firm and industry level behave differently in the time series at the second half of the sample period. For this reason, we investigate the effect of value on returns in the early sample and in the late sample.

In Panel B of Table 27, we have the results for the early sample period. It goes between 1926 and 1949. We find that the equal weighted value spread is a significant 1.42%. However the value weighted spread is insignificant in this sub-period. The equal weighted spread corresponds to significant alphas from all of the factor models. The CAPM, three

[24] Please refer to French Kenneth's online data library for the definition of BE/ME.

factor, Carhart alphas are 0.91%, 0.50% and 0.73%, respectively. The CNZ factors do not go back to this period so we do not have any results for the CNZ regressions.

In Panel C of Table 27, we see the results for the late sample period. It goes between 1980 and 2010. We find that the equal weighted spread is 1.01%. The value weighted spread is 0.46%. These two spreads correspond to significant alphas from CAPM (1.13% and 0.50%). We get a significant alpha (0.64%) for the equal weighted spread from the three factor model and we get an insignificant alpha (-0.11% for the value weighted spread. The Carhart alphas for equal and value weighted cases are 0.81% and 0.03%, where only the first one is significant. The CNZ alphas are 0.90% and 0.58%, which both are significant.

7.2 Industry Level Effects

Next, we study the effect of BE/ME on returns at the industry level. Table 28 reports the results on average returns. We use five portfolios and sort industries into five equally populated portfolios according to their BE/ME measure. Industry level BE/ME measure is obtained by taking the ratio of sum of book equity to the sum of market equity for each industry.

In Panel A; the equally weighted value spread using this measure is 0.02% in the whole sample, which starts from 1926 and goes up to 2010. The value weighted return spread in the entire sample period is 0.04%.

The equal weighted value spread corresponds to significant alpha spreads from the three factor and CNZ models (-0.22% and -0.37%). The CAPM and Carhart alphas are insignificant (0.03% and -0.11%). We have similar results for the value weighted case.

In Panel B of Table 28, we have the results for the early sample period. It goes between 1926 and 1949. We find that the equal weighted value spread is a significant 0.62%. The value weighted spread is also significant in this sub-period (0.60%). The equal weighted spread corresponds to significant alphas from all of the factor models. The CAPM, three factor, Carhart alphas are 0.50%, 0.38% and 0.44%, respectively. The CNZ factors do not go back to this period so we do not have any results for the CNZ regressions.

In Panel C of Table 28, we see the results for the late sample period. It goes between 1980 and 2010. We find that the equal weighted spread is -0.44%. The value weighted spread is -0.51%. These two spreads correspond to insignificant alphas from CAPM (-0.29% and -0.30%). We get a significant alpha (-0.72%) for the equal weighted spread from the three factor model and we also get a significant alpha (-0.74%) for the value weighted spread. The Carhart alphas for equal and value weighted cases are -0.61% and -0.70%, where both are significant. The CNZ alphas are -0.49% and -0.62%, which also are significant.

So, we conclude that the opposite effect of the value measure on returns at the firm and industry level originate from the late sample period where these two spreads also behave in opposite manner in recessions[25].

8 CONCLUSION

In the third part, we document extensive stock return anomalies at the industry level. We take value weighted cross sectional averages of stock returns and several firm fundamentals in each industry to get industry returns and fundamentals. Then, we match industry fundamental information with monthly industry returns, following a portfolio based methodology.

We use Fama French 12 industries. Assigning firms into 12 industries represents a compromise between having a reasonable number of distinct industries and having enough firms within each industry so that sorting within industries will not produce portfolios that are too thin. We get well diversified industry portfolios with negligible firm specific risk.

We find that smaller industries, industries that invest less and industries with lower levels of change in inventory have higher average industry returns. These return patterns are

[25]Please refer to the Business Cycles section

consistent with the ones at the firm level, more specifically firms with smaller market size, less investment and lower change in inventory have higher average returns as documented in previous studies.

The value effect on returns go in the opposite direction for the firm and industry levels. We know that value firms, which are firms with higher book to market asset ratios, have higher average returns than growth firms. However, value industries have lower average returns than growth industries.

These anomalies are robust even controlling for some known firm-level sorted risk factors. We get this conclusion by two different analysis. First, we regress industry level anomaly spreads onto CAPM, Fama French and Carhart models and get some significant alpha spreads. So, these standard factor models fail to explain industry level significant return spreads for size, investment, value and change of inventory.

We also adjust stock returns for industries by subtracting the relevant industry returns from them. Then, we repeat the firm level portfolio analysis to see if the size of anomaly return spreads at the firm level change. As expected, we find that size, investment and change-in-inventory spreads get smaller after controlling for industries since both industry and firm level effects of these measures on returns are in the same direction. Also, we find that value spread gets bigger in magnitude. This is due to the opposite direction of value spread at the firm and industry level.

All these findings suggest that investing based on anomalies are risky. Portfolios based on firm fundamentals such as investment and change in inventory or market information such as size are not well diversified. This supports the behavioral explanations for anomalies being reasonable. The major criticism against these explanations is that if certain systematic profitable stock return patterns, due to irrational investor biases and not due to higher risk, exist in the market, these must be exhausted very quickly by rational investors. Otherwise, there are persistent arbitrage opportunities in the market. So, market can not be even weakly efficient. However, we show that trading on these anomalies are actually riskier than previously thought since some of the anomaly profits originate from stocks that belong to the same industries and are highly correlated.

One important result of part three that should be studied further is the opposite effect of value on stock and industry returns. This finding definitely calls for an extensive and concentrated analysis on this issue.

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Appendix

Definition of Anomaly Variables

The variables used in the paper are given with corresponding Compustat and CRSP data item names.

Definitions for Raw Data Variables

at: total assets.
prc: stock price.
shrout: number of shares outstanding.
prcc-f: fiscal year closing price.
cshpri: common shares used to calculate earnings per share.
dlc: debt in current liabilities.
dltt: debt in long term liabilities.
pstkl: preferred stock.
txditc: deferred taxes and investment tax credit.
act: total current assets.
ni: net income.
pi: funds provided by operations.
ebit: earnings before interest and taxes.
ib: income before extraordinary items.
dp: depreciation and amortization.
ppent: net property, plant and equipment.
txdb: deferred taxes.
dvc: dividends common.
dvp: dividends preferred.
prstkc: purchase of common and preferred stock.
csho: common shares outstanding.
adjex-c: cumulative adjustment factor.
invt: total inventories.

Formulas for Constructed Variables

Market capitalization, (SIZE) = prc * shrout.

Total assets, (AT) = at.

Market-to-Book Asset, (MB) = (prcc-f * cshpri + dlc + dltt + pstkl - txditc) / at.

Profitability, (ROA) = ib /at,(t-1).

Asset Growth, (ASSETGRTH) = (at-L.at)/L.at

Investment, (INVEST) = (ppegt-L.ppegt+invt-L.invt)/L.at

Standardized Unexpected Earnings, (SUE) = (epspx-L.epspx)/s.d.(epspx-eightmonths)

Inventory Change, (DELTAINV) = (invt-L.invt)/L.invt

Ohlson's Score, (OSCORE) = -1.32-0.407*log(mktasset[26]/cpi) + 6.03*(dlc+dltt)/mktasset - 1.43*(act-lct)/mktasset + 0.076*lct/act - 1.72*oeneg[27] - 2.37*ni/mktasset - 1.83*pi/lt + 0.285*intwo[28] - 0.521*(ni-L.ni)/(abs(ni)+abs(L.ni))

Net Stock Issuance, (NETSIS) = log(csho*adjex-c(t)/csho*adjex-c(t-1))

[26] $mktasset = prcc_f * cshpri + lt + 0.1 * (prcc_f * cshpri - at + lt)$

[27] $oeneg = 0, \quad oeneg = 1 \quad if \quad lt > at$

[28] $intwo = 0 \quad and \quad intwo = 1 \quad if \quad ni < 0 \quad and \quad L.ni < 0$

Table 18 Average Excess Returns-Firm Level

This table reports average excess returns for firm level portfolios built on momentum (MOM), reversal (REV), size and value (MB) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Sample period is from 1925 to 2010 for momentum, reversal and size, and from 1963 to 2010 for value. Momentum and reversal portfolios are re-balanced every month and size and value portfolios are re-balanced every twelve months. All returns are in percentages.

	Panel A: Equally Weighted Returns				Panel B: Value Weighted Returns			
	MOM	REV	SIZE	MB	MOM	REV	SIZE	MB
P1	0.72	1.64	2.10	1.42	-0.13	0.99	1.30	0.72
P2	0.63	1.32	1.22	1.23	0.18	0.94	0.96	0.68
P3	0.68	1.16	1.02	1.04	0.31	0.80	0.93	0.69
P4	0.82	1.04	0.92	0.88	0.51	0.77	0.87	0.52
P5	0.90	1.00	0.83	0.80	0.53	0.79	0.81	0.50
P6	0.98	1.03	0.85	0.74	0.60	0.78	0.85	0.47
P7	1.10	0.95	0.74	0.59	0.77	0.67	0.76	0.39
P8	1.18	1.03	0.74	0.60	0.84	0.64	0.73	0.39
P9	1.33	0.88	0.73	0.41	1.02	0.57	0.72	0.33
P10	1.23	0.95	0.60	0.18	0.94	0.59	0.56	0.25
P10-P1	0.51	-0.80	-1.50	-1.24	1.10	-0.44	-0.73	-0.48
Annualized	6.12	-9.60	-18.00	-14.88	13.2	-5.28	-8.76	-5.76
t	2.39	-5.24	-6.03	-6.49	4.49	-2.63	-3.02	-2.53
CAPM	0.67	-0.73	-1.28	-1.39	1.34	-0.38	-0.47	-0.53
t	3.27	-4.78	-5.30	-7.85	5.86	-2.22	-2.02	-2.83
FF	0.83	-0.42	-0.80	-0.76	1.52	-0.03	-0.01	0.17
t	4.18	-3.45	-5.19	-6.89	6.97	-0.29	-0.01	1.61
CARHT	-0.35	-0.49	-1.04	-0.71	0.06	-0.11	-0.16	0.17
t	-2.78	-3.90	-6.67	-6.27	0.60	-0.85	-1.30	1.60
CNZ	-0.16	-0.79	-1.72	-0.89	1.21	-0.23	-0.84	-0.07
t	-0.56	-4.24	-7.56	-4.85	3.22	-1.01	-3.54	-0.04

Table 19 Average Excess Returns-Firm Level

This table reports average excess returns for firm level portfolios built investment (INVEST), asset growth (ASSETGRTH), net stock issuance (NETSIS) and inventory change (DELTAINV) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Sample period is from 1963 to 2010. Portfolios are re-balanced every twelve months. All returns are in percentages.

	Panel A: Equally Weighted Returns				Panel B: Value Weighted Returns			
	INVEST	ASSETGRTH	NETSIS	DELTAINV	INVEST	ASSETGRTH	NETSIS	DELTAINV
P1	1.38	1.45	1.19	1.28	0.84	0.76	0.80	0.79
P2	1.09	1.19	1.09	1.11	0.62	0.65	0.63	0.76
P3	1.06	1.04	1.04	1.00	0.62	0.64	0.42	0.52
P4	0.99	0.93	0.73	0.96	0.50	0.58	0.47	0.54
P5	0.96	0.86	0.74	0.95	0.48	0.46	0.47	0.46
P6	0.94	0.79	0.82	0.87	0.44	0.43	0.45	0.42
P7	0.78	0.76	0.90	0.81	0.35	0.48	0.48	0.41
P8	0.73	0.70	0.73	0.72	0.49	0.34	0.38	0.43
P9	0.60	0.56	0.45	0.60	1.35	0.47	0.21	0.28
P10	0.10	0.06	0.19	0.27	0.16	0.14	0.06	0.16
P10-P1	-1.27	-1.39	-0.99	-1.00	-0.68	-0.62	-0.74	-0.63
Annualized	-15.24	-16.68	-11.88	-12.00	-8.16	-7.44	-8.88	-7.56
t	-9.57	-8.41	-7.46	-9.04	-4.69	-3.52	-6.92	-4.45
CAPM	-1.33	-1.44	-1.12	-1.05	-0.72	-0.70	-0.81	-0.68
t	-10.08	-8.74	-9.12	-9.52	-5.07	-4.10	-7.79	-4.87
FF	-1.20	-1.18	-0.95	-0.88	-0.43	-0.32	-0.70	-0.41
t	-9.09	-7.81	-8.49	-8.32	-3.27	-2.09	-6.92	-3.11
CARHT	-1.04	-1.14	-0.76	-0.82	-0.38	-0.24	-0.63	-0.30
t	-8.29	-7.32	-7.00	-7.59	-2.84	-1.57	-6.11	-2.26
CNZ	-1.24	-1.67	-0.62	-0.99	-0.48	-0.61	-0.57	-0.46
t	-9.27	-9.45	-5.34	-8.29	-3.80	-3.42	-4.95	-3.01

Table 20 Average Excess Returns-Firm Level

This table reports average excess returns for firm level portfolios built on return on assets (ROA), Ohlson's score (OSCORE) and Standardized Unexpected Earnings (SUE) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Sample period is from 1972 to 2010 for ROA and SUE and from 1981 to 2010 for OSCORE. Quarterly firm fundamental data is used for all three measures. All returns are in percentages.

	Panel A: Equally Weighted Returns			Panel B: Value Weighted Returns		
	ROA	OSCORE	SUE	ROA	OSCORE	SUE
P1	0.17	0.89	0.34	-0.50	0.53	0.35
P2	0.19	0.87	0.54	-0.02	0.53	0.57
P3	0.32	0.79	0.56	0.07	0.46	0.42
P4	0.51	0.78	0.63	0.30	0.44	0.45
P5	0.75	0.71	0.84	0.44	0.41	0.31
P6	0.81	0.62	1.00	0.51	0.36	0.42
P7	0.90	0.55	1.05	0.46	0.40	0.45
P8	0.96	0.52	1.02	0.48	0.44	0.52
P9	1.04	0.67	1.05	0.46	0.12	0.59
P10	1.34	0.64	1.30	0.59	-0.69	0.63
P10-P1	1.17	-0.25	0.96	1.09	-1.22	0.29
Annualized	14.04	-3.00	11.52	13.08	-14.64	3.48
t	3.85	-0.76	11.50	3.91	-3.37	2.18
CAPM	1.26	-0.25	0.97	1.25	-1.44	0.32
t	4.18	-0.76	11.50	4.63	-4.19	2.44
FF	1.34	-0.56	0.99	1.42	-1.64	0.30
t	4.77	-1.83	11.67	5.93	-6.13	2.26
CARHT	0.88	-0.11	0.83	1.14	-1.17	0.19
t	3.27	-0.39	10.42	4.81	-4.91	1.41
CNZ	0.28	0.29	0.83	0.36	-0.48	0.21
t	1.39	1.02	9.93	1.99	-1.87	1.54

Table 21 Average Excess Returns-Industry Level

This table reports average excess returns for industry level portfolios built on momentum (MOM), reversal (REV), size and value (MB) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Sample period is from 1925 to 2010 for momentum, reversal and size, and from 1963 to 2010 for value. Momentum and reversal portfolios are re-balanced every month and size and value portfolios are re-balanced every twelve months. All returns are in percentages.

	Panel A: Equally Weighted Returns				Panel B: Value Weighted Returns			
	MOM	REV	SIZE	MB	MOM	REV	SIZE	MB
P1	0.91	1.19	1.21	0.84	0.85	1.18	1.18	0.72
P2	1.07	1.03	1.14	1.04	1.05	0.99	1.16	0.98
P3	1.35	1.04	0.96	1.14	1.31	1.01	0.87	1.03
P3-P1	0.45	-0.09	-0.24	0.31	0.46	-0.13	-0.31	0.31
Annualized	5.40	-1.08	-2.88	3.72	5.52	-1.56	-3.72	3.72
t	4.00	-0.92	-2.86	2.26	3.80	-1.18	-3.43	1.97
CAPM	0.45	-0.14	-0.23	0.22	0.46	-0.18	-0.24	0.20
t	4.05	-1.34	-2.68	1.70	3.80	-1.63	-2.70	1.33
FF	0.52	-0.02	-0.11	0.55	0.53	-0.04	-0.11	0.51
t	4.72	-0.18	-1.40	5.64	4.50	-0.43	-1.40	4.06
CARHT	-0.11	-0.07	-0.13	0.47	-0.15	-0.08	-0.13	0.45
t	-1.58	-0.70	-1.62	4.74	-1.86	-0.82	-1.58	3.49
CNZ	0.35	0.09	0.13	0.35	0.42	0.12	0.15	0.29
t	2.07	0.69	1.10	2.39	2.19	0.78	1.25	1.73

Table 22 Average Excess Returns-Industry Level

This table reports average excess returns for industry level portfolios built investment (INVEST), asset growth (ASSETGRTH), net stock issuance (NETSIS) and inventory change (DELTAINV) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Sample period is from 1963 to 2010. Portfolios are re-balanced every twelve months. All returns are in percentages.

	Panel A: Equally Weighted Returns				Panel B: Value Weighted Returns			
	INVEST	ASSETGRTH	NETSIS	DELTAINV	INVEST	ASSETGRTH	NETSIS	DELTAINV
P1	1.11	0.89	0.93	1.18	1.10	0.88	0.92	1.17
P2	1.11	1.05	0.99	1.08	1.09	1.03	0.94	1.05
P3	0.83	1.02	1.02	0.88	0.77	0.95	1.01	0.85
P3-P1	-0.28	0.13	0.09	-0.30	-0.33	0.08	0.10	-0.32
Annualized	-3.36	1.56	1.08	-3.60	-3.96	0.96	1.20	-3.84
t	-2.21	1.09	0.99	-2.67	-2.28	0.58	0.95	-2.37
CAPM	-0.25	0.01	0.08	-0.29	-0.32	-0.05	0.07	-0.31
t	-2.09	0.11	0.86	-2.53	-2.21	-0.44	0.73	-2.31
FF	-0.22	0.23	0.05	-0.27	-0.29	0.20	0.07	-0.29
t	-1.84	2.60	0.59	-2.38	-2.00	1.94	0.64	-2.18
CARHT	-0.24	0.26	0.12	-0.30	-0.30	-0.28	0.15	-0.30
t	-1.96	2.86	1.26	-2.56	-2.04	-2.66	1.38	-2.17
CNZ	-0.33	0.23	0.25	-0.32	-0.45	0.24	0.22	-0.38
t	-2.42	2.00	2.33	-2.50	-2.71	1.84	1.90	-2.44

Table 23 Average Excess Returns-Industry Level

This table reports average excess returns for industry level portfolios built on return on assets (ROA), Ohlson's score (OSCORE) and Standardized Unexpected Earnings (SUE) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Sample period is from 1972 to 2010 for ROA and SUE and from 1981 to 2010 for OSCORE. Quarterly firm fundamental data is used for all three measures. All returns are in percentages.

	Panel A: Equally Weighted Returns			Panel B: Value Weighted Returns		
	ROA	OSCORE	SUE	ROA	OSCORE	SUE
P1	0.98	1.12	0.98	-0.91	1.10	0.95
P2	1.06	1.20	1.10	1.06	1.12	1.09
P3	1.05	1.09	0.99	1.11	1.04	1.01
P3-P1	0.08	-0.02	0.01	0.20	-0.06	0.06
Annualized	0.96	-0.24	0.12	2.40	-0.72	0.72
t	0.56	-0.19	0.08	1.26	-0.42	0.39
CAPM	0.05	-0.01	0.04	0.15	0.00	0.09
t	0.38	-0.12	0.33	0.92	0.01	0.60
FF	0.05	-0.13	-0.11	0.46	-0.32	0.03
t	0.42	-1.16	-0.88	3.38	-2.75	0.21
CARHT	0.05	-0.13	-0.11	0.22	-0.21	-0.10
t	0.42	-1.16	-0.88	1.67	-1.75	-0.70
CNZ	-0.10	-0.12	-0.06	0.15	-0.23	-0.03
t	-0.80	-0.93	-0.51	0.95	-1.62	-0.22

Table 24 Industry-Adjusted Stock Returns

This table reports industry adjusted and non-adjusted average excess returns for firm level portfolios built on size, market to book ratio (MB), investment (INVEST) and inventory change (DELTAINV) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Sample period is from 1925 to 2010 for size, from 1963 to 2010 for MB, INVEST and DELTAINV. All returns are in percentages.

Equally Weighted Returns

Panel A:Industry Non-Adjusted					Panel B: Industry Adjusted			
	SIZE	MB	INVEST	DELTAINV	SIZE	MB	INVEST	DELTAINV
P1	1.22	1.23	1.18	1.14	-0.28	-0.33	-0.40	-0.41
P2	0.80	0.76	0.92	0.90	-0.69	-0.75	-0.61	-0.61
P3	0.70	0.40	0.48	0.54	-0.73	-1.15	-1.04	-0.98
P3-P1	-0.52	-0.83	-0.70	-0.60	-0.44	-0.83	-0.64	-0.58
Annualized	-6.24	-9.96	-8.40	-7.20	-5.28	-9.96	-7.68	-6.96
t	-3.54	-6.11	-8.32	-8.43	-3.10	-7.94	-8.26	-9.13
CAPM	-0.38	-0.94	-0.75	-0.64	-0.32	-0.92	-0.70	-0.61
t	-2.66	-7.52	-9.23	-9.27	-2.31	-9.53	-9.42	-9.97
FF	-0.11	-0.50	-0.59	-0.52	-0.06	-0.64	-0.56	-0.51
t	-1.35	-6.50	-7.93	-7.89	-0.75	-8.68	-8.18	-8.67
CARHT	-0.17	-0.44	-0.55	-0.49	-0.12	-0.58	-0.52	-0.50
t	-2.07	-5.63	-7.21	-7.33	-1.37	-7.85	-7.49	-8.23
CNZ	-0.63	-0.54	-0.69	-0.60	-0.59	-0.71	-0.68	-0.58
t	-3.86	-4.16	-8.92	-8.73	-3.69	-6.91	-8.99	-9.13

Table 25 Industry-Adjusted Stock Returns-continued

This table reports industry adjusted and unadjusted average excess returns for firm level portfolios built on size, market to book ratio (MB), investment (INVEST) and inventory change (DELTAINV) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Sample period is from 1925 to 2010 for size, from 1963 to 2010 for MB, INVEST and DELTAINV. All returns are in percentages.

Value Weighted Returns

	Panel A:Industry Non-Adjusted				Panel B: Industry Adjusted			
	SIZE	MB	INVEST	DELTAINV	SIZE	MB	INVEST	DELTAINV
P1	0.95	0.74	0.71	0.64	-0.53	-0.73	-0.83	-0.80
P2	0.78	0.48	0.45	0.50	-0.70	-0.90	-0.95	-0.90
P3	0.60	0.33	0.36	0.29	-0.76	-1.12	-1.10	-1.09
P3-P1	-0.36	-0.41	-0.35	-0.35	-0.23	-0.39	-0.27	-0.29
Annualized	-4.32	-4.92	-4.20	-4.20	-2.76	-4.68	-3.24	-3.48
t	-2.53	-3.27	-3.16	-3.64	-1.76	-5.40	-3.66	-4.56
CAPM	-0.18	-0.44	-0.38	-0.42	-0.09	-0.38	-0.30	-0.33
t	-1.37	-3.48	-3.51	-4.54	-0.76	-5.25	-4.12	-5.45
FF	0.07	0.07	-0.10	-0.25	0.12	-0.12	-0.11	-0.23
t	1.41	0.98	-1.08	-2.95	2.16	-2.39	-1.75	-4.03
CARHT	0.03	0.07	-0.04	-0.12	0.10	-0.15	-0.05	-0.17
t	0.51	0.95	-0.42	-1.50	1.67	-2.84	-0.85	-2.92
CNZ	-0.44	-0.20	0.13	-0.18	-0.42	-0.41	-0.02	-0.19
t	-2.40	-1.43	1.84	-1.94	-2.40	-5.57	-0.36	-3.05

Table 26 Correlations Among Spreads

This table reports pairwise time series correlations among industry level and firm level return spreads for size, market to book ratio (mb), investment (invest) and inventory change (dinv) measures. Correlation coefficients are given in percentages and p values are reported. Sample period is from 1963 to 2010 for all correlations except the one between the industry size and firm size measures. The sample period for this correlation is from 1925 to 2010.

	size-ind	mb-ind	invest-ind	dinv-ind	size-firm	mb-firm	invest-firm	dinv-firm
size-ind	1							
mb-ind	-0.09	1						
p	0.03							
invest-ind	-0.06	-0.12	1					
p	0.17	0.01						
dinv-ind	0.01	-0.10	0.68	1				
p	0.81	0.03	0.00					
size-firm	0.24	-0.21	0.18	0.19	1			
p	0.00	0.00	0.00	0.00				
mb-firm	0.23	0.54	-0.06	0.00	0.11	1		
p	0.00	0.00	0.19	0.98	0.01			
invest-firm	0.07	0.23	0.05	0.12	0.22	0.39	1	
p	0.08	0.00	0.30	0.01	0.00	0.00		
dinv-firm	0.10	0.27	0.06	0.19	0.10	0.43	0.48	1
p	0.02	0.00	0.16	0.00	0.01	0.00	0.00	

Table 27 BE/ME Measure-Firm Level

This table reports average excess returns for firm level portfolios built on book to market equity ratio (BE/ME) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Various sample periods are used and designated in Panels. Equal weighted (EW) and value weighted (VW) returns are presented. All returns are in percentages.

	Panel A: 1926-2010		Panel B: 1926-1949		Panel C: 1980-2010	
	EW	VW	EW	VW	EW	VW
P1	0.57	0.54	0.85	0.70	0.32	0.32
P2	0.77	0.61	0.98	0.79	0.60	0.42
P3	0.97	0.70	1.18	0.85	0.82	0.50
P4	1.16	0.82	1.55	1.12	0.98	0.58
P5	1.57	1.02	2.27	1.38	1.33	0.78
P5-P1	1.00	0.24	1.42	0.68	1.01	0.46
Annualized	12.00	2.88	17.04	8.16	12.12	5.52
t	5.39	2.60	2.50	1.24	6.55	2.87
CAPM	0.83	0.24	0.91	0.11	1.13	0.50
t	4.61	1.38	1.93	0.27	7.79	3.16
FF	0.36	-0.23	0.50	-0.16	0.64	-0.11
t	3.86	-2.98	2.77	-0.99	6.38	-1.05
CARHT	0.59	-0.03	0.73	0.08	0.81	0.03
t	6.43	-0.36	4.17	0.52	8.4	0.25
CNZ	0.99	0.58			0.99	0.58
t	5.95	3.20			5.95	3.20

Table 28 BE/ME Measure-Industry Level

This table reports average excess returns for industry level portfolios built on book to market equity ratio (BE/ME) and corresponding factor regression alphas. CAPM, FF, CARHT and CNZ are Capital Asset Pricing, Fama and French three factor, Carhart four factor and Chen, Novy-Marx and Zhang three factor models, respectively. Various sample periods are used and designated in Panels. Equal weighted (EW) and value weighted (VW) returns are presented. All returns are in percentages.

	Panel A: 1926-2010		Panel B: 1926-1949		Panel C: 1980-2010	
	EW	VW	EW	VW	EW	VW
P1	1.11	1.07	0.89	0.87	1.35	1.32
P2	1.09	1.04	1.45	1.35	1.17	1.17
P3	1.20	1.12	1.41	1.29	1.17	1.09
P4	1.03	1.05	0.99	0.96	1.28	1.29
P5	1.13	1.11	1.51	1.47	0.91	0.81
P5-P1	0.02	0.04	0.62	0.60	-0.44	-0.51
Annualized	0.24	0.48	7.44	7.20	-5.28	-6.12
t	0.15	0.32	2.27	2.22	-2.09	-2.18
CAPM	0.03	0.07	0.50	0.48	-0.29	-0.30
t	0.26	0.56	1.89	1.83	-1.45	-1.41
FF	-0.22	-0.19	0.38	0.35	-0.72	-0.74
t	-2.47	-2.09	2.11	2.04	-4.70	-4.66
CARHT	-0.11	-0.10	0.44	0.43	-0.61	-0.70
t	-1.24	-1.10	2.37	2.37	-3.99	-4.34
CNZ	-0.37	-0.45			-0.49	-0.62
t	-2.02	-2.38			-2.41	-2.91

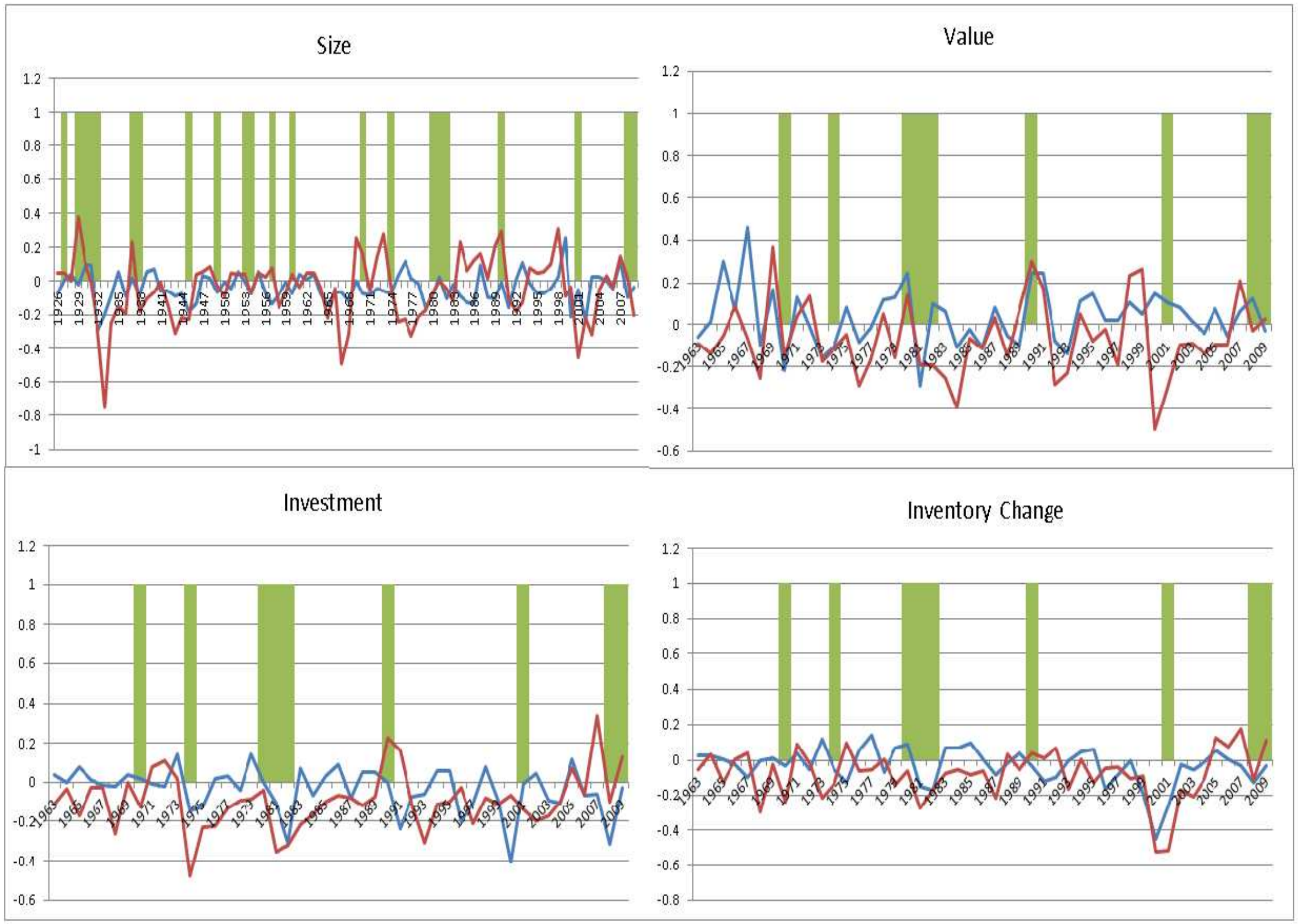

Figure 5 Business Cycles

Each graph shows the times series of the anomaly spreads at the firm and industry level. NBER recessions are depicted in green. Firm level spreads are depicted in red and industry level spreads are depicted in blue. The sample period is from 1925 to 2010 for the size anomaly. The sample starts at 1963 for the other anomalies.