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## Momentum and Aggregate Default Risk


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**Abstract**

In this paper, we explain momentum profits using innovations in aggregate economy-wide default risk. First, we show that momentum returns are positive only during high default shocks and nonexistent otherwise. Second, we present evidence suggesting that a conditional default shock factor is priced in the cross-section and can explain a large portion of the total momentum returns. According to our results, winners have potentially higher risk than losers during periods of high default shocks. We confirm this finding in alternate sub-periods where momentum is generally not observed and as well as in international data. We also provide an explanation for this finding by linking momentum profits to potential shareholder recovery during financial distress. We find that winners tend to have relatively higher risk in worsening aggregate default conditions due to lower shareholder bargaining power. These results indicate that momentum profits contain a systematic component related to aggregate default and can be explained in a rational framework.

*JEL Codes:* G11, G12

*Keywords:* Momentum, Aggregate Default Shocks, Shareholder Bargaining Power.

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# Momentum and Aggregate Default Risk

**Abstract**

In this paper, we explain momentum profits using innovations in aggregate economy-wide default risk. First, we show that momentum returns are positive only during high default shocks and nonexistent otherwise. Second, we present evidence suggesting that a conditional default shock factor is priced in the cross-section and can explain a large portion of the total momentum returns. According to our results, winners have potentially higher risk than losers during periods of high default shocks. We confirm this finding in alternate sub-periods where momentum is generally not observed and as well as in international data. We also provide an explanation for this finding by linking momentum profits to potential shareholder recovery during financial distress. We find that winners tend to have relatively higher risk in worsening aggregate default conditions due to lower shareholder bargaining power. These results indicate that momentum profits contain a systematic component related to aggregate default and can be explained in a rational framework.

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## 1. Introduction

Avramov, Chordia, Jostova, and Philipov (2011) find that the momentum strategy is profitable only among stocks with high firm-level default risk. This suggests that momentum profits should be higher during recessions when firm default risk is usually high. However, Chordia and Shivakumar (2002) document that momentum profits are mainly concentrated in periods of economic expansions. In this paper, we resolve these seemingly contradictory results obtained from cross-sectional and time-series analysis of momentum profitability. We identify unexpected increases in economy-wide default risk, i.e., high default shocks, as the key variable generating momentum profits. Specifically, we show that that in the time-series, momentum profits are only observed in periods of high default shocks to aggregate default. The previously documented momentum profits among stocks with high firm-level default or during periods of economic expansions evaporate absent high default shocks. We document that momentum profits exist both during expansions and recessions but only in periods of high default shocks.

We argue that firm-level default becomes more important when aggregate default unexpectedly increases[1], because high credit risk stocks are more likely to default in these states leading to lower performance and the observed momentum effect. Therefore, the returns to the momentum strategy are time-varying and they should be more (less) pronounced during periods of high (low) default shocks. Consistent with this prediction, we find that a trading strategy based on buying recent winners and selling recent losers produces 1.93% per month during high and -0.64% per month during low aggregate default shocks. We also observe that aggregate default shocks are not perfectly correlated with business cycles (the correlation is only 5% in our sample), which explains Chordia and Shivakumar (2002) findings, who do not find momentum in periods of economic recessions, when default concerns should be high. We find that momentum profits exist only during periods of high default shocks irrespective of the state of business cycle. Therefore, momentum is driven by unexpected changes in aggregate credit conditions rather than the general state of the economy.

Motivated by the above findings, we construct a conditional default shock factor[2] and examine its pricing in the cross-section. This factor is designed to capture the additional impact of default risk on excess returns during high default states. Our asset-pricing tests show that the premium on the conditional default factor is significant in the cross-section, controlling for the market return, HML, SMB, and industrial production growth factors.

[1]In the framework of this paper we will refer to unexpected increases (decreases) in aggregate default conditions as high (low) aggregate default shocks.

[2]The conditional default shock factor takes the value of the default factor during periods of high default shocks, and zero otherwise.

We further document that winners (losers) have higher (lower) exposure to the conditional default factor. The conditional default premium multiplied by the difference in exposure to this factor between winners and losers explains up to 89% of the difference between momentum profits in high and low aggregate default states.

Another unanswered question in the literature is why does momentum suddenly disappear in certain decades? For instance, Hwang and Rubesam (2008) document that the momentum effect experiences a sharp decline after 1995 and raise a question about the persistence of the momentum anomaly over time. One possible explanation for this result is that market efficiency has dramatically improved over recent years. However, Chordia and Shivakumar (2002) also do not find significant momentum prior to 1960, when we would expect the market to be less efficient. We argue that momentum does not disappear, but rather it is concentrated in periods of high default *shocks*. Indeed, we examine the two sub-periods: 1) prior to 1960 and 2) after 1995, and find that momentum exists in both, but it is conditional on high aggregate default *shocks*. To determine robustness of our findings we extend our analysis to incorporate U.K., German, French, and Dutch stock markets and document the same results as in the U.S.

Following Avramov, Chordia, Jostova, and Philipov (2011), we also analyze the subsample of firms with S&P debt ratings. We confirm that momentum does not exist among high investment grade firms and that the conditional default factor is not priced in this subsample. According to our results, momentum is primarily concentrated in the speculative grade group, but only during periods of high aggregate default shocks (4.33% per month). Consistent with our overall results, momentum within this subset is also driven by shocks to aggregate default. The momentum strategy during periods of low default shocks is not profitable and this result holds for all firms.

Jegadeesh and Titman (2001) and Griffin, Ji, and Martin (2003) document that winners only temporary outperform losers. Therefore, it is crucial to investigate whether the default risk explanation provided in this paper is also consistent with long-term reversal. Based on the evidence documented in the existing literature, we predict that the expected returns of winner (losers) should decrease (increase) after the hedge portfolio formation period and they should eventually converge. Consistent with our prediction, we observe that the spread in conditional default loadings between winners and losers disappears approximately one year after the portfolio formation.

Finally, we provide an explanation of why the risk exposure of winners to the conditional default factor differs from that of losers. Specifically, we link momentum to potential shareholder recovery.[3] Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) document that shareholders of certain firms can extract rents using their bargaining power when the firm cannot meet its financial obligations.[4] Shareholders with high (low) bargaining position face relatively lower (higher) risk as the probability of financial distress increases. Therefore, shareholders with relatively higher bargaining power or recovery potential will have greater ability to avoid liquidation and recover value in financial distress. Thus, they command relatively lower expected returns during periods of high default shocks.

To examine the efficacy of this argument to explain momentum, we follow Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) by using the firm's tangibility[5] (receivables, inventory, capital and cash holdings scaled by total book assets), the Herfindahl index[6] (the concentration of industry sales), and the ratio of R&D expenditures to total assets[7] as proxies for shareholder bargaining power. Using these three measures, we show that losers

[3]In the context of this paper we use the term "recovery" as shareholder bargaining power. It is not an actual recovery of the residual value, but rather the ability to negotiate with debtholders, because debtholder are not likely to dismantle the firm if they have high liquidation costs including losing real options and other intangible assets.

[4]Note that commonly accepted measures of firm-level financial distress do not take into account the effect of shareholder bargaining power.

[5]Firms with highly tangible assets can be more easily liquidated in the case of bankruptcy, while liquidation may lead to a greater loss in value for firms with more intangible assets.

[6]Firms with high Herfindahl index should have highly specific assets and may also face higher liquidation costs in default; such firms are relatively more valuable as going concerns, giving shareholders higher bargaining power.

[7]Firms with high R&D expenditures to total book assets are more difficult to liquidate due to high potential growth options and product specialization.

have higher shareholder bargaining power and, therefore, these stocks should have relatively lower expected returns during periods of high aggregate default shocks.

Ever since Jegadeesh and Titman (1993) documented the momentum effect[8], the most widely considered explanation for momentum profits has been behavioral overreaction or underreaction to firm-specific information.[9] Several papers look for risk-based evidence to explain momentum profits but have been unable to document convincing results.[10] On the other hand, some papers document a significant relation between risk and momentum.[11] These studies focuses primarily on one aspect of the momentum anomaly, i.e., the difference in *unconditional* expected returns between winners and losers. However, a more convincing explanation for the existence of momentum profits has to incorporate other aspects of this anomaly, which have been previously documented. We extend this literature by examining one additional aspect of momentum related to its time-series behavior, i.e. the momentum premium is time-varying and depends on shocks to aggregate economy-wide default.

We contribute to the momentum literature on two dimensions. First, we extend the literature by establishing a link between momentum returns and aggregate economy-wide default risk. Using historical information for the estimation of unexpected shocks to default, we find that momentum profits occur only during periods of high *shocks* to aggregate default.

[8] Moskowitz and Grinblatt (1999) and Lewellen (2002) show that momentum exists in industry, size and book-to-market portfolios, respectively. Jegadeesh and Titman (2001) document that momentum persists in the period after 1993. Rouwenhorst (1998) documents momentum internationally.

[9] For example, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) analyze the overreaction or underreaction explanation for momentum in the context of different psychological biases such as conservatism, self-attributive overconfidence, and slow information diffusion.

[10] Fama and French (1996) show that their three-factor model does not explain momentum; similarity, Grundy and Martin (2001) and Avramov and Chordia (2006) find that controlling for time-varying exposures to common risk factors does not affect momentum profits. Finally, Griffin, Ji, and Martin (2003) show that the Chen, Roll, and Ross (1986) model does not explain momentum either.

[11] Pástor and Stambaugh (2003) show that liquidity risk accounts for half of momentum profits. Sadka (2006) finds that shocks to the variable component of liquidity are priced in the cross-section of momentum portfolios. Bansal, Dittmar, and Lundblad (2005) show a relation between consumption risk and momentum portfolios. Ahn, Conrad, and Dittmar (2003) show that a nonparametric risk adjustment can account for roughly half of momentum profits. Liu and Zhang (2008) document that winners have higher loadings on the growth rate of industrial production than losers.

This discovery allows us to reconcile contradictory findings of past research. Second, at the firm level, we link momentum to firm fundamentals related to shareholder bargaining power during financial distress. In doing so, we provide a risk-based explanation of the momentum anomaly related to shareholder recovery and time-varying exposure to aggregate default risk. Our results suggest that the existence of momentum is consistent with a risk-based explanation - a large portion of momentum profits can be explained by equity holders' exposure to conditional default.

The remainder of the paper is structured as follows. Section II presents the sorting procedures and pricing of the conditional default factor. Section III describes the relation between financial distress, shareholder recovery, and momentum. Section IV presents robustness checks. Section V concludes the paper.

## 2. Momentum and Aggregate Default Shocks

### *2.1. Data and Portfolio Construction*

We obtain stock returns, number of shares outstanding, and prices from the Center for Research in Security Prices (CRSP) monthly file. The sample is comprised of all stocks traded on AMEX/NYSE/NASDAQ from January 1960 to December 2009. We exclude stocks that are priced below $1, foreign stocks, and American Depositary Receipts (ADR).

We follow the methodology introduced by Jegadeesh and Titman (1993) and sort stocks into deciles based on their cumulative performance over months $t-6$ through $t-1$. Since it is not uncommon to observe a short-term return reversal, we also skip a month after the formation period. The momentum portfolios are formed by equally weighting firms in each of the deciles. The top decile represents winners and the bottom decile consists of losers. We form momentum portfolios every month and hold them for the next six months (referred to as the 6-1-6 strategy).

Table 1 presents the average monthly returns and other descriptive statistics for equally-weighted momentum portfolios over the period January 1960 to December 2009. Portfolio

1 and portfolio 10 are comprised of loser and winner stocks, respectively. Basic descriptive statistics, such as median, standard deviation, and percentiles are presented in the corresponding columns.

According to Table 1 winners outperform losers by 0.79% per month which is consistent with previous studies. The distribution of losers tends to be flatter than that of winners. The standard deviation of winners is 6.81% and of losers is 9.65%. The fact that losers are more volatile than winners makes their performance differential even more puzzling.

*2.2. Momentum and Aggregate Default Shocks*

While Avramov, Chordia, Jostova, and Philipov (2011) show that the profitability of momentum is driven by firm-level credit risk, Chen, Roll, and Ross (1986) present an asset-pricing model that incorporates innovation to aggregate default. Also, Campbell (1996) and Petkova (2006) suggest that innovations in macro-economic variables such as aggregate default should be able to forecast future investment opportunities. We proposed that innovations in economy-wide default risk ignored by previous studies play a critical role in explaining momentum profits. According to our proposition, innovations in aggregate default shocks are better suited for capturing default risk. We begin our analysis by examining momentum profits conditional on unexpected changes in aggregate default risk.

We measure the aggregate default premium as the yield spread between Moody's CCC corporate bond index and the 10-year U.S. Treasury bond. To capture unexpected changes in aggregate default, we derive innovations in the default premium as the residual from the following model:

$$DEF_t = \alpha_0 + \alpha_1 DEF_{t-1} + \alpha_2 DEF_{t-2} + \xi_t, \tag{1}$$

where, $DEF_t$ is default spread in month $t$, and unexpected shocks to default are represented by $\xi_t$. The values of residuals above (below) median correspond to positive (negative) shocks in aggregate default. To avoid a look-ahead bias, we estimate equation (1) using information up to time $t-1$.[12] First, we estimate model (1) using the pre-sample period (from January of 1954 to December of 1959). Then we add one observation to the sample and estimate the model to obtain the value of the residual in January of 1960. We continue this procedure until residuals are estimated for every observation of the time-series. By implementing this approach the residuals at time $t$ are conditional on information known from January 1954 to $t-1$.

We argue that using shocks rather than levels of the default spread is more suitable for capturing unexpected changes in aggregate default conditions. Figure 1 shows the time-series of default shocks and levels. Shaded areas of the graph correspond to periods of recessions as defined by the National Bureau of Economic Research (NBER). This figure documents that the default spread and recessions are fairly correlated (the correlation is approximately 30%), however, default shocks do not appear to follow the same pattern (the correlation is only 5%). This suggests that default shocks potentially capture default conditions that are less related to general economic states such as recessions and expansions. For example, during the expansion in October of 1996 the U.S. Small Business Administration (SBA) reported that their loan default rate was greater than the overall national default rate. The following reform forced SBA to repurchase millions of dollars worth of credit, even though, about 50% of defaulted loans were never recovered. These events affected investors' perception of default risk and led to an increase in the default spread by almost 3%, but such events can only be captured by innovations to default as opposed to a recession dummy.

We use the median value of aggregate default shocks to split the sample in high and low default shock periods and NBER definition of business cycles (recessions account for 20% of the total sample). We then estimate momentum profits for each state of aggregate default. The results presented in Panel A of Table 2 suggest that momentum is highly correlated with shocks to aggregate default. The return to the momentum strategy is on average 1.93% per month during high default periods, with a t-statistics of 7.35. On the other hand, momentum

[12]Ignoring this bias yields results very similar to those reported in the paper.

returns are close to zero during periods of low default shocks. We repeat this analysis using the residuals from the AR(1) and AR(3) models instead of equation (1) and obtain similar results. Moreover, since default is related to liquidity (Ericsson and Renault (2006)) and volatility we control for aggregate liquidity and market volatility as follows.

$$DEF_t = \alpha_0 + \alpha_1 DEF_{t-1} + \alpha_2 DEF_{t-2} + \alpha_3 LIQ_{t-1} + \alpha_4 MVOL_{t-1} + \xi_t, \tag{2}$$

where, LIQ represents aggregate market liquidity (measured using the Amihud (2002) ratio), MVOL stands for market volatility (as defined in French, Schwert, and Stambaugh (1986)). Controlling for liquidity and market volatility does not affect the results. For different model specifications, we consistently observe that momentum is mainly pronounced in periods of high aggregate default shocks.

Previous empirical studies suggest that the momentum anomaly is primarily concentrated in periods of economic expansions. Chordia and Shivakumar (2002) find that momentum is correlated with variables related to the business cycle and it is mainly observed during expansions. Further, Stivers and Sun (2010) provide evidence suggesting that the momentum anomaly is a pro-cyclic phenomenon. Specifically, they argue that an increase (decrease) in cross-sectional dispersion in recent stock returns, which is likely to be associated with bad (good) times, causes the subsequent momentum profits to decline (increase). Hence, they conclude that the momentum premium is higher in good times. However, credit risk is likely to be less important during expansions; therefore, the previous finding that momentum is profitable in expansions presents a puzzle. We attempt to explain this apparent inconsistency by focusing on aggregate default shocks rather than the general state of the economy.

We next examine whether results documented in previous research hold in our sample. Specifically, we calculate the return of the momentum strategy that buys winners and shorts losers during expansions and recessions.[13] The results of this sorting procedure are presented

[13] Expansions and recessions and are defined according to National Bureau of Economic Research (NBER) recession dates.

in Panel B of Table 2. Winners significantly outperform losers during expansions. The return to the momentum strategy during these periods is 0.85% per month and statistically different from zero. On the other hand, momentum profits during periods of contraction are essentially zero (0.18% with a t-statistics of 0.44).

Since the correlation between the NBER recession dummy and shocks to aggregate default is not perfect (it is only 5% in our sample), our findings do not contradict previously documented results. To show this, we use independent sorts on business cycles and shocks to aggregate default. The results of this procedure are presented in Panel C of Table 2. Clearly, default shocks occur during expansions as well as during contractions. Panel C of Table 2 documents that momentum profitability is concentrated during periods of high default shocks irrespective of the state of the business cycle. The average return to the momentum strategy during high default shocks is 1.74% per month during expansions and 2.76% in recessions. Both of them are statistically significant. In contrast, there is virtually no momentum when aggregate default decreases in good times and there is negative momentum when aggregate default decreases in bad times (-3.75% per month). These results reveal that poor momentum performance during recessions (documented in Panel A, as well as by previous research) can be explained by the fact that positive momentum in high default states (2.76%) is offset by negative momentum returns during low default states (-3.76%).

In summary, the results thus far indicate that momentum profits are pronounced in periods of high default shocks. Without conditioning on aggregate default shocks, it is possible to erroneously conclude that momentum is primarily concentrated in periods of economic expansions. However, conditioning on aggregate default shocks, we find that momentum profitability is related to states of high default. This result is new to the best of our knowledge and has important implications for explaining the momentum anomaly. It is in line with the observation that momentum profitability is concentrated in stocks that are likely to be more sensitive to aggregate default conditions (stocks of low credit rated firms). Moreover, the relation between momentum and positive shocks to aggregate default that we uncover reveals important time-series properties of momentum returns.

In the next section, we examine whether shocks to aggregate default have the ability to explain the cross-sectional behavior of momentum returns. In other words, we want to answer the question: do winners and losers have different exposures to high unexpected default states and furthermore, are high shocks to default priced in the cross-section of momentum portfolios?

### *2.3. Conditional Default Risk*

We start with a general asset-pricing model of the form:

$$E[r_i] = \gamma_0 + \beta_1' \gamma_i, \tag{3}$$

where, $E[r_i]$ represents the expected excess return on asset $i$, $\gamma_i$ is a vector of factor prices of risk, $\beta_1'$ is a vector of factor loadings, and $\gamma_0$ is a constant. For parsimony, we initially consider two risk factors: the market return and unexpected default shocks. Since our empirical results imply that the relation between momentum and unexpected default shock depends on the nature of the shock, we further model aggregate default as a scaled factor. We scale only the default factor and, therefore, allow the default betas of different assets to vary across the two different default states, i.e., (high (positive) default shocks and low (negative) default shocks). Specifically, we introduce a conditional default factor:[14]

$$C\xi_t = I_t \xi_t, \tag{4}$$

where $\xi_t$ denotes a non-traded default factor measured by default shock at time $t$ (the residual from (1), and $I_t$ is an indicator function that equals 1 if the economy is in a period of high default shock and 0 otherwise.[15] Therefore, the conditional default variable takes a non-zero value only during periods of positive default shocks.

[14] Watanabe and Watanabe (2008) apply a similar approach for the analysis of time-varying liquidity.

[15] The indicator function is estimated using the cumulative recursive procedure explained in section 2.2

The return-generating process can be written as:

$$R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_{i,t}, \tag{5}$$

where, $MKTRF_t$ is the excess return of the CRSP value-weighted portfolio. Given our previous results that momentum profits only occur during states of high unexpected default, we are particularly interested in the $\beta_i^{CDEF}$ coefficients of winners and losers. The $\beta_i^{CDEF}$ coefficient measures the beta spread for each asset between the two states of aggregate default. Therefore, the default beta of an asset during low default shock periods is $\beta_i^{DEF}$, and its default beta during high default shock periods is $(\beta_i^{DEF} + \beta_i^{CDEF})$.

We follow the Fama and MacBeth (1973) two-pass procedure to estimate the factor risk premia in equation (5). We use the full sample from 1960 to 2009 in the first-pass beta estimation. We do not use a rolling beta approach since the default beta is already state-dependent. Since the betas are generated regressors, we use a standard error correction proposed by Shanken (1992) to account for the errors-in-variables problem in the second stage of Fama-MacBeth. In order to estimate the factor risk premia in equation (5), we use 30 test assets. These assets include 10 momentum portfolios, 10 size portfolios, and 10 book-to-market portfolios.[16]

Table 3 presents the loadings of the momentum portfolios with respect to the market return ($\beta^{MKTRF}$), unexpected default ($\beta^{DEF}$), and conditional default ($\beta^{CDEF}$). According to the results presented in the table, the loser portfolio has a negative loading on default (-3.83) and a positive conditional default loading (2.70). Therefore, the loser portfolio loading in high default states is -1.13. The winner portfolio has a loading of -0.09 on default and a loading of -0.47 on conditional default. Therefore, the winner portfolio loading in high default states is -0.56. The spread between the winners' and losers' loadings on conditional

[16] 10 size and 10 book-to-market portfolios are obtained from Kenneth R. French's web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). Liu and Zhang (2008) and Bansal, Dittmar, and Lundblad (2005) also use 10 size, 10 book-to-market, and 10 momentum portfolios for momentum analysis. Adding 10 industry portfolios to the sample yields similar results.

default is significant with a $t$-statistic of -2.38.

Untabulated results show that the unconditional default betas of losers and winners are both negative (-2.40 and -0.33, respectively), and the difference is statistically significant. Therefore, losers (winners) do better (worse) in states of high default than their unconditional default betas would suggest. This implies that losers might have a hedging ability during states of high unexpected default, controlling for their market betas. Table 3 reveals the familiar U-shape pattern in the market betas of momentum portfolios. This pattern suggests that exposure to the market return alone is not able to capture the momentum anomaly.

The results so far indicate that losers perform better than the CAPM model (augmented with unconditional default shocks) predicts in periods of high unexpected default. In contrast, winners perform worse than the CAPM model (augmented with unconditional default shocks) predicts in high default states. This suggests that losers might offer lower expected returns than winners in high default states since they offer insurance against such states. To examine this possibility in more detail, we need to estimate the price of risk for conditional default.

We estimate factor prices of risk in the second stage of the Fama-MacBeth procedure using 30 portfolios sorted on momentum, size, and book-to-market. The size and book-to-market portfolios are necessary to create a larger cross-section of test assets. Table 4 reports the estimates of the prices of risk and their corresponding $t$-statistics, adjusted for errors-in-variables. Model 1 corresponds to the CAPM. The market risk premium is not significant which is consistent with previous empirical findings. Model 2 augments the CAPM with the unexpected default factor, and the results reveal that the default factor is not priced. Model 3 is our main specification that introduces the conditional default factor $CDEF$; it has a negative and significant premium.

To examine the economic significance of the conditional default premium, we compare the actual difference in momentum profits during high and low default states to the expected difference. As shown in Table 2, the momentum profit in high default states is 1.93%

and -0.64% in low default states. The difference between the two is 2.57%. The expected difference in momentum profits between high and low default states equals the conditional default premium (-0.0072, Model (3) of Table 4) multiplied by the spread in conditional default betas between winners and losers (-3.18, Table 3), i.e., 2.29%. Therefore, conditional default exposure of winners and losers explains 89% of the difference between momentum profitability in high and low default states.

Interestingly, the premium on unexpected default in low default states is also negative and marginally significant. As shown previously, losers have high expected returns in states of low default shocks. This observation is in line with their loadings on this factor. In the next section we attempt to explain and justify the hedging ability of losers in periods of high unexpected default.

## 3. Financial Distress, Shareholder Bargaining Power, and Momentum

We start with the observation that losers perform better than predicted by the CAPM during high unexpected default shocks. In addition, losers, by definition, experience a series of price declines before portfolio formation and, therefore, they are likely to be financially distressed and closer to bankruptcy. The question is: why do stocks with a high probability of distress do better than expected when the aggregate risk of defaulting increases? We rely on a model by Garlappi and Yan (2011) to answer this question.

Garlappi and Yan (2011) argue that shareholders have an ability to recover a part of the residual firm value when the firm is on the verge of bankruptcy. However, the possibility of shareholder recovery varies significantly based on shareholders' bargaining power that depends on the characteristics of a firm. The authors document that the expected equity returns of high bargaining power firms decrease as bankruptcy risk increases, because the shareholders have a strong bargaining position, which leads to lower risk in financial distress. Therefore, if the probability of financial distress should increase, the shareholders with high (low) bargaining power can benefit in this state, because of high recovery possibility. We hypothesize that losers are high bankruptcy risk and high shareholder recovery stocks. Then, they should have lower expected returns in high default states because their shareholders do not require additional premium for holding. In the next section we examine whether losers indeed posses these characteristics.

### *3.1. Firm-level Bankruptcy Risk*

We use two measures to capture financial distress risk at the firm level. The first proxy is based on an option-pricing measure proposed by Bharath and Shumway (2008). It is essentially an extension of the Merton (1974) model that incorporates reasonable assumptions to simplify the estimation process. Bharath and Shumway (2008) demonstrate that this modified measure of financial distress performs reasonably well. One of the advantages of using this approach is that it allows a simplified methodology that captures the firm-specific probability of bankruptcy. The major assumptions underlying this measure are that 1) the market value of debt is equal to its face value, 2) the volatility of debt is a function of stock volatility, and 3) the expected return is equal to the stock return from the previous period.

Then, if $E$ and $F$ represent the market value of equity and the face value of debt, respectively, the "naive" distance to financial distress measure can be defined as:

$$DD_{naive} = \frac{ln[(E+F)/F] + (r_{it-1} - 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}}, \tag{6}$$

where, $\sigma_V$ is the standard deviation of the firm's value and $T$ is the estimation period.

The naive probability of financial distress is

$$\pi_{naive} = N(-DD_{naive}). \tag{7}$$

The distance to financial distress is based on the assumption that equity is a call option on the firm value with a strike price equal to the value of the firm's debt. This procedure estimates the probability of debt value being higher than the fundamental value of the firm at time $T$, or the probability that the "option" is out-of-money (this is why $DD_{naive}$ is negative in (7)). In other words, this estimates the probability that the equity "option" on the firm is out-of-the-money, and the equity holders choose to let the option expire, that is, let the firm default on its obligations.

However, the naive probability of financial distress incorporates the market value of the firm, which is related to the recent performance of the firm's equity and, therefore, momentum returns. To avoid this potential problem, we also introduce another measure of individual distress based on the modified Altman Z-score. This measure incorporates financial statements data and is not affected by market value of equity. We follow Graham, Lemmon, and Schallheim (1998) and estimate the modified Altman Z-score as:

$$\text{Z-score} = \frac{1.2 \times WC + 1.4 \times RE + 3.3 \times EBIT + SALES}{TA}, \tag{8}$$

where, $WC$, $RE$, $EBIT$, and $SALES$ correspond to working capital, retained earnings, earnings before interest and taxes, and sales, respectively. TA represents book value of total assets. An increase in the modified Z-score implies a decline in the firm's probability of bankruptcy.

We estimate each of these two measures of financial distress for losers and winners portfolios separately and present the results of this analysis in Panel A of Table 5. Specifically, we find that the probability of bankruptcy for losers is 18.03% higher than for winners. Moreover, the modified Z-score of losers (0.61) is lower than that of winners (1.63). The difference between winners and losers is statistically significant for both measures of financial distress.

In summary, the above evidence is consistent with our hypothesis that losers are more financially distressed than winners. This is not surprising given that they have recently experienced a series of price declines. More importantly, observing that losers have a higher probability of default explains their higher sensitivity to worsening aggregate default conditions.

*3.2. Shareholder Recovery and Bargaining Power*

To proxy for shareholder recovery and bargaining power Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) use measures capturing the costs entailed in liquidating the firm. The shareholders of firms that are relatively difficult/costly (easy/less costly) to liquidate will have a stronger (weaker) position in distress negotiations. It is potentially more beneficial for creditors to negotiate with shareholders to restructure the obligations of the firm that is difficult/costly to liquidate rather than continue with the actual liquidation. We follow Garlappi, Shu, and Yan (2008) and use three measures of shareholder recovery based on expected liquidation value (tangibility), liquidation costs (Herfindahl index), and R&D expenses to estimate the shareholders' bargaining power in financial distress negotiations.

The first measure of shareholder recovery is based on the tangibility of the firm's assets. Firms with high concentration of tangible assets are easier/less costly to liquidate in case of bankruptcy. Claimants of such a firm in financial distress have less incentive to negotiate with shareholders and restructure the firm's obligations. Therefore, the expected residual recovery and the bargaining power of this firm's shareholders in distress negotiations will be relatively low.

On the other hand, firms with a high concentration of intangible assets can be more difficult/costly to liquidate. Since the expected liquidation value and, therefore, recovery by creditors of this type of firm will be relatively low, it will make reorganization preferable, giving shareholders higher bargaining power and the possibility to recover some of the residual value of the firm. Thus, low tangibility is favorable for shareholders when such a firm gets closer to financial distress.

Berger, Ofek, and Swary (1996) estimate that one dollar of total book value, depending upon the type of asset, generates: 71.5 cents for receivables, 54.7 cents for inventory, and 53.5 cents for property plant and equipment, in case of liquidation. Following Garlappi, Shu, and Yan (2008), we add cash holdings, and use their approach to estimate the expected asset liquidation value or tangibility as

$$Tng = \frac{(0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times PPE + Cash)}{TotalAssets}. \tag{9}$$

Low tangibility implies low expected liquidation value and high shareholder recovery and bargaining power.

The second proxy of shareholder recovery is based on asset specificity. Firms with highly specific assets face higher liquidation costs and their creditors are more likely to choose restructuring the obligations of the firm over liquidation. Hence, high asset specificity provides the shareholders of the firm with a superior bargaining position during financial distress negations.

The Herfindahl index serves as a measure of the specificity of the firm's assets. If the index is relatively high (low), it indicates that asset specificity is high (low) and, therefore, it is more (less) costly to liquidate the firm. Hence, the bargaining power and shareholder recovery increase when the value of the Herfindahl index rises. To capture asset specificity, we follow Garlappi, Shu, and Yan (2008) and use the Herfindahl index (HI) based on sales and two-digit SIC codes:

$$HI_{j,t} = \sum_{i=1}^{N_{j,t}} s_{i,t}^2, \tag{10}$$

where, $s_{i,t}$ represents sales of firm $i$ at time $t$ as a proportion of total sales of its industry $j$. Firms belonging to an industry with a higher Herfindahl index should have higher asset specificity and, therefore, higher shareholder recovery and bargaining power.

Finally, the last measure of shareholder bargaining power is based on the ratio of R&D expenses to book total assets. Titman and Wessels (1988) argue that R&D is a good proxy of product specialization. Besides, Opler and Titman (1994) predict that high R&D firms are more sensitive to financial distress and, therefore, the shareholders of these firms should have high bargaining power during periods of high default shocks.

Panel B of Table 5 reports the shareholder recovery measures of winners and losers. The results show that winners tend to have higher tangibility on average. More importantly, the difference in tangibility between the two groups is statistically significant (0.02 with a t-statistics of 9.01). Moreover, the specificity of assets as measured by the Herfindahl index is higher for losers. Finally, we find that losers have a higher R&D ratio (6.51% vs. 7.87% for winners and losers, respectively) suggesting that it is more costly to liquidate of these firms. Therefore, shareholders of losers have higher bargaining power, leading to lower risk and lower expected returns. Overall, these results suggest that losers are likely to be firms with low tangibility, high asset specificity, who spend relatively more on R&D, and, therefore, they are likely to have high shareholder bargaining power.

In summary, the results in this section show that losers tend to have high shareholder bargaining power and also face a higher probability of financial distress than winners. Therefore, losers do not require additional premium in states of high unexpected default, because their shareholders have an ability to recover some of the residual value of the firm. These results help to justify why losers have low expected returns during periods of high aggregate default shocks.

## 4. Robustness Checks

### *4.1. Controlling for Other Risk Factors*

Recent studies suggest that innovations in default spread are correlated with the Fama-French factors. Petkova (2006), for example, documents that SMB is significantly correlated with shocks to the aggregate default spread. Furthermore, Hwang, Min, McDonald, Kim, and Kim (2010) use the credit spread as a proxy for shareholder limited liability and show that it is related to HML and SMB. Given these results, a potential concern is that default shocks and the Fama-French factors may capture the same risk exposure. To address this concern, we augment our model in (5) with SMB and HML. Therefore, we examine the model of the following form

$$R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \epsilon_{i,t}, \quad (11)$$

where, SMB and HML stand for size and value factors, respectively.[17] To estimate factor risk premia, we follow the procedure described in section 2.3 and use 30 test assets: 10 momentum, 10 size, and 10 book-to-market portfolios.

Panel A of Table 6 presents the betas from the first stage of the Fama and MacBeth (1973) estimation. We observe that in the presence of SMB and HML, the $\beta^{CDEF}$ spread between losers and winners is still negative and significant (-3.35 with a t-statistics of -2.49). Model 1 of Table 7 presents the second stage of the Fama and MacBeth (1973) estimation. The magnitude of the conditional default premium declines from -72 (Model 3 in Table 4) to -45 basis points, however, the factor remains statistically significant.

Further, Liu and Zhang (2008) link the growth rate of industrial production MP[18] to momentum. Specifically, they document that this factor is priced in the cross-section of momentum portfolio returns and winners have higher MP loadings than losers. Moreover, the spread between the MP loadings of winners and losers combined with the size of the MP premium explain a large portion of the realized momentum profits. We, on the other hand, use the conditional default factor (CDEF) as the main determinant of the cross-sectional variation of momentum portfolio returns. Since the default premium is also used as an important macroeconomic indicator, it can be correlated with the growth rate of industrial production. Therefore, a potential concern is that our conditional default factor may proxy for the growth rate of industrial production. To address this concern, we extend our analysis

[17] The SMB and HML factors are obtained from Kenneth R. French's web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

[18] It is defined as $MP_t = \log IP_t - \log IP_{t-1}$. $IP$ is the index of industrial production and is obtained from the Federal Reserve Bank of St. Louis.

by incorporating the MP factor in the model (5)

$$R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \beta_i^{MP} MP_t + \epsilon_{i,t}, \tag{12}$$

where, $MP_t$ represents the growth rate of industrial production computed as in Liu and Zhang (2008).

Panel B of Table 6 presents the beta loadings of the 10 momentum portfolios in the first stage of the Fama and MacBeth (1973) procedure. Consistent with previous results, losers (winners) have positive (negative) CDEF loadings. More importantly, the CDEF spread between the two is statistically significant (-3.23 with t-statistics of -2.37). Note that $\beta^{MP} \approx 0$.

Model 2 of Table 7 documents that the conditional default premium stays negative and significant (-0.0075 with a t-statistics of -2.56) after including the MP factor in the model. The growth rate of industrial production is no longer priced in the cross-section of momentum portfolios. These results are robust to excluding the market returns from the model to avoid a potential concern that MP and the market return may be correlated. Finally, in Model 3 of Table 7, we include both the Fama-French and MP factors in the specification. The economic significance of the conditional default premium is -48 basis points, and it remains significant. The expected difference in momentum profits between high and low default states equals the conditional default premium (-0.0048) multiplied by the spread in conditional default betas between winners and losers (-3.36), i.e., 1.61%. As shown in Table 2, the realized difference in momentum profits between high and low default states is 2.57%. Therefore, conditional default exposure for winners and losers still explains 63% of the realized momentum profits.

In summary, the results described in this section reveal that shocks to default spread contain information about the cross-section of returns, which is independent of its correlation with HML, SMB, and MP. Furthermore, it appears that the CDEF factor has a large economic significance and captures between 62% and 89% of the difference in momentum returns in high and low default shocks.

### *4.2. Analysis by Credit Risk Groups*

This section presents further evidence on the relation between momentum and aggregate default shocks. We investigate whether high credit risk stocks, which drive the momentum anomaly, are also sensitive to aggregate default shocks. Besides, this test will also ascertain whether our previous findings are unique to our specific sample and test-period or not. Our prediction is that firms with low rated debt are sensitive to worsening default conditions and, therefore, the high credit risk group should have the largest difference between the CDEF loadings of losers and winners. Moreover, if our prediction is correct, the conditional default factor should not be priced for low credit risk stocks.

Here we also test whether investment grade stocks[19] are affected by aggregate default shocks. A central prediction of Garlappi and Yan (2011) is that the expected returns of high recovery stocks should decrease in bankruptcy risk. However, the investment grade firms have lower bankruptcy risk on average and, therefore, we are less likely to observe the same relation among these stocks.

#### *4.2.1. Momentum Profits by Credit Risk Group*

Avramov, Chordia, Jostova, and Philipov (2011) show that momentum profits exist only in stocks of low credit rated firms. To further scrutinize our proposition, we extend this study's cross-sectional analysis by analyzing how shocks to aggregate default affect returns of different credit rating groups. According to our proposition, low credit rating stocks are less sensitive to aggregate default shocks than stocks with high credit ratings. We porpose that the shareholders of speculative grade losers face relatively lower risk as aggregate default increases (because of a higher recovery potential) and, therefore, they should have lower expected returns. Investment grade losers are less likely to display the same behavior, since

[19]Those with high credit rated bonds.

their initial credit risk is too low to create any recovery concerns. If our proposition is correct, momentum profits will be observed mainly in low credit risk stocks during high default states and driven mostly by losers.

To analyze the momentum anomaly by different credit risk groups, we obtain the S&P domestic long-term issuer credit ratings from the Compustat Rating database. This database contains detailed information about total credit risk of the firm, rather than of its individual bonds. Following Avramov, Chordia, Jostova, and Philipov (2011), we assign numeric equivalents to the ratings. Higher numbers correspond to lower ratings (for example, 1 represents AAA rating and 22 corresponds to D). We split the sample into three credit risk categories: investment grade, middle grade, and speculative grade firms, based on the numeric values. The time period of the sample is from 1986 to 2009.

We estimate the performance of the momentum strategy for each of the three credit risk groups, conditional on aggregate default shocks. Table 8 presents the results of this analysis. Panel A documents the profitability of the momentum strategy among speculative grade firms. As predicted, momentum profits are generated during high default periods (4.33% per month with a $t$-statistics of 6.83). On the other hand, there is no significant difference between the performance of speculative grade winners and losers during periods of low default shocks (-1.52% per month with a $t$-statistics of -1.25). We emphasize that high credit risk stocks do not always generate positive momentum profits. One explanation of this result is that these stocks are less sensitive to default shocks in periods of low default.

Panels B and C of Table 8 contain the results for middle and investment grade firms. Consistent with our predictions, momentum profits become less pronounced for firms with higher investment grades. Specifically, Panel B documents that the returns from the momentum strategy using middle grade firms are 1.41% and -0.90% per month during periods of high and low default shocks, respectively. Finally, in Panel C we observe that for investment grade stocks there is no statistically significant difference between the returns of losers and winners in high or low default shock states. It is interesting that in periods of high default shocks, winners generate similar performance across all three credit risk groups (0.60%, 0.70% and 0.91% for speculative, middle and investment grade stocks, respectively). This result provides further evidence that *losers* drive the momentum anomaly.

Controlling for different credit risk groups, the results confirm our previous conclusion that momentum is profitable only in states of high default shocks. While Avramov, Chordia, Jostova, and Philipov (2011) show that momentum is driven by high credit risk stocks, our time-series analysis reveals that this is true only in periods of high aggregate default shocks. The immediate implication of this result is that momentum profits can be increased by focusing on speculative grade firms but only in high default states. This implies that momentum is observed under very specific circumstances, namely, at the intersection of firm-level distress and aggregate default shocks.

*4.2.2. Conditional Default Premium by Credit Risk Groups*

This section analyzes the conditional default loadings of portfolios comprised of stocks from each of the three credit risk groups. We hypothesize that speculative grade stocks, which have a higher probability of financial distress, are more sensitive to the conditional default factor than stocks of investment grade firms.

We estimate conditional default loadings of the 10 momentum portfolios in each credit rating group using equation (5). Table 9 reports the results of this analysis. Columns $\beta_{SG}^{CDEF}$, $\beta_{MG}^{CDEF}$, and $\beta_{IG}^{CDEF}$ correspond to the conditional default loadings of speculative, middle, and investment grade stocks, respectively. The results suggest that the sensitivity of momentum portfolio returns to the conditional default factor ($\beta^{CDEF}$) is higher for speculative grade firms. In particular, as we move from the speculative to the investment grade group of firms, the conditional default loadings of losers decrease from 4.48 to 1.25, and that of winners increase from -0.87 to -0.74.

We also estimate the CAPM model augmented with unexpected default and conditional default variables for each credit risk category. As before, we add 10 size and 10 book-to-market portfolios to the set of test assets in order to create a larger cross-section for the Fama-

MacBeth estimation. Table 10 presents the estimated prices of risk and their corresponding $t$-statistics for the market, unexpected default, and conditional default variable. The test assets used to obtain results reported in Column 1 are 10 momentum portfolios from the speculative grade group, 10 size, and 10 book-to-market portfolios. Similarly, the test assets used for Column 2 (3) are 10 momentum portfolios from the middle (investment) grade group, 10 size, and 10 book-to-market portfolios. We find the conditional default premium is negative, however, it is only significant in the cross-section of speculative grade stocks. The magnitude and significance of the premium are slightly lower than the ones reported previously for the whole cross-section of momentum portfolios. One of the possible reasons for this result is the shorter length of the time series adopted for this test. Since credit ratings are only available after 1986, the sample size in this case is smaller.

Overall, the results show that speculative grade losers are more sensitive to conditional default shocks than middle grade or investment grade losers. Speculative grade losers do better in times of high default shocks than predicted by the CAPM (augmented with unexpected aggregate default risk). Further, the conditional default factor affects speculative grade winners more than middle and investment grade winners. However, the difference in sensitivity this factor is less pronounced than the one for losers. This finding suggests that momentum profits are driven by the short side of the strategy, namely, the losers.

*4.3. Evidence from Earlier and Later Sub-periods*

Chordia and Shivakumar (2002) do not find significant momentum prior to 1960. Similarly, Hwang and Rubesam (2008) document that momentum profits are non-existent after the early 90s. In this section, we attempt to answer the question why the momentum anomaly cannot be directly observed during these sub-periods. To make sure that our results are not driven by the time-specific period, we present the analysis of two sub-periods: 1) prior to 1960 and 2) after 1995. We hypothesize that momentum does not simply disappear, but it is instead concentrated during high default states.

We follow the methodology described in section 2.2 and repeat the analysis for the first sub-period from 1928 to 1960. We confirm the finding of Chordia and Shivakumar (2002) and show that there is no significant momentum during this sub-period (the difference between winners and losers is 37 basis points with a t-statistics of 0.94). We then use shocks to aggregate default adjusted for look-ahead bias and estimate the performance of the momentum strategy during periods of high and low default shocks separately. Figure 2 presents the results of this analysis. We find *positive and significant momentum* during high default shocks (2.46%). At the same time, momentum is negative during low default shocks (-1.15%, significant at 10%). This result clearly shows that momentum existed in earlier periods; however, it was conditional on high default shocks.

Further, we continue the analysis and track momentum performance conditionally on both business cycles (as defined by NBER.) and default shocks. Figure 3 reveals a similar pattern - momentum is positive and significant during high default states irrespective of the state of the business cycle. However, it is more pronounced during recessions than expansions (3.42% and 1.96 during recessions and expansions, respectively), when the shocks are expected to be higher. Similarly, there is virtually no difference between performance of winners and losers during low default shocks in expansion (-0.42% and statistically insifnicant). Finally, momentum is negative and significant during default shocks in recession (-4.50%). Similarly, we repeat this procedure again for the sub-period from 1995 to 2010 and document almost identical results (untabultaed). Again, momentum is not significant for this sub-period (19 basis points with a t-statistics of 0.28). However, we observe high and significant momentum (2.58% basis points with a t-statistics of 4.02) conditional on high default shocks. These findings are consistent with our previous results and show that momentum is not time-specific; instead it is conditional on high default shocks states of nature.

We also find that the CDEF spread between winners and losers is negative prior to 1960. Results presented in Table 11 show that winners (losers) have negative (positive) $\beta^{CDEF}$, which is also consistent with the results reported in Table 3. Specifically, the difference between the CDEF loadings of winners and losers is -5.51 with a t-statistics of -2.24. Note that the difference between the market betas ($\beta^{MKTRF}$) is not significant, therefore, market risk is not likely to drive the momentum profits during this period. We repeat this analysis for the sub-period after 1995 and find a similar pattern. Untabulated results show that the CDEF spread is -6.61 with a t-statistics of -2.80

Results discussed above show that our primary proposition is not sample specific and our findings hold even during periods when momentum was not observed directly by previous studies. Momentum is mainly driven by unexpected increases in aggregate default risk.

*4.4. International evidence*

Rouwenhorst (1998) and Griffin, Ji, and Martin (2003) document the momentum anomaly internationally and find that business cycle risk cannot explain it. To provide additional support to our results and show that they are not specific to the US sample, we test sensitivity of the momentum anomaly to aggregate default shocks in international markets. Furthermore, if our primary proposition is correct, we should also observe higher shareholder bargaining power associated with losers than with winners on average.

We obtain data for four large European economies, i.e. United Kingdom, Germany, France, and the Netherlands from DataStream. To improve the reliability of the DataStream data, we apply the screens proposed by Ince and Porter (2006). We do not have data on aggregate default risk in each of these countries over our test period. While Baele (2005) provides evidence suggesting that the US shocks spillover to the global markets, we use US aggregate default risk data in this test out of necessity. To the extent, foreign and US default shocks are not perfectly correlated, our results will be biased against our proposition. Table 12 presents the results using international data and aggregate US default shocks. Panels A through D are based on the United Kingdom, German, French, and Netherlands samples. The findings are similar to the results observed in the US market. They confirm that momentum is *more pronounced during periods of high default shocks.* In particular, we find that the profitability of momentum in the UK, German, French, and Netherlands markets are 2.29%, 1.00%, 1.57%, and 2.09%. Consistent with the US results, we find lower or no momentum during periods of low default shocks.

Finally, we estimate average shareholder bargaining power of losers and winners for each of the four markets using the tangibility variable. The results of this analysis are presented in Table 13 and confirm that losers tend to have lower tangibility, and, therefore, should have higher bargaining power in distress negotiations. In particular, we show that the difference in tangibility between winners and losers varies between 0.017 (for Netherlands) and 0.012 (for Germany) and is significant across all countries. This result is consistent with our evidence obtained using the US data.

### *4.5. Time-Series Evolution of Conditional Default Loadings, Shareholder Recovery, and Financial Distress*

Jegadeesh and Titman (2001) and Griffin, Ji, and Martin (2003) document that the returns to momentum strategies gradually decline and become negative approximately one year after the portfolio formation period. This implies that winners only temporary outperform losers. Therefore, the difference in expected returns between losers and winners should steadily decline after the portfolio formation period to be consistent with a risk-based explanation. Therefore, we hypothesize that the difference in investors' risk perception between winners and losers should be only temporary.

To estimate the evolution of conditional default loadings for every month $t$ from January 1960 to December 2009, we calculate average returns of losers and winners for month $t+k$, where $k = +1, \ldots, +12$. We then estimate equation (5) for portfolios of losers and winners across calendar months and estimate CDEF loadings for event month $t+k$.

Figure 4 shows the dynamics of the CDEF loadings for winners and losers after the formation period. During the first holding month, we observe a high and positive CDEF loading for the loser portfolio; however loadings consistently decline over time. Given our earlier finding that the conditional default premium is -72 basis points (Table 4), this result suggests that *ceteris paribus*, the expected returns of losers consistently increase. On the other hand, the CDEF loadings of winners are negative at the beginning of the holding period, implying that they should perform better than what the CAPM model predicts. Then the CDEF loadings increase with time, become positive after the sixth month, and eventually the loadings of winners and losers converge. The CDEF loadings spread between losers and winners in our sample is indeed temporary and consistent with the findings of Jegadeesh and Titman (2001) and Griffin, Ji, and Martin (2003). This finding suggests that expected returns of winners (losers) decrease (increase) after the formation period is consistent with our proposal and supports a risk-based explanation for the momentum anomaly.

We next continue the analysis and examine how shareholder bargaining power and financial distress evolve before and after the portfolio formation period. Our results indicate that the difference in the exposure to the conditional default factor for winners and losers is potentially due to the difference in shareholder bargaining power in financial distress negotiations. Therefore, we hypothesize that the shareholder recovery of winners (losers) decreases (increases) before the formation period making them relatively riskier (safer) and increases (decreases) after the formation period making them relatively safer (riskier). That is, momentum profits should decrease as the difference in recovery decreases over time. As a result, the expected returns of winners (losers) should become lower (higher) over time leading to reversal.

Figure 5 presents tangibility of the losers and winners portfolios over a 36-month post-formation period. For every month $t$ from January 1960 to December 2009, we calculate average tangibility of losers and winners for month $t+k$, where $k = -12, \ldots, +36$. We then average tangibility for $t+k$ across portfolio formation months.

Consistent with Jegadeesh and Titman (2001) we observe that the returns of losers consistently increase and the returns of winners consistently decline after the formation period. More importantly, we document that the shareholder bargaining power of winners increases (tangibility decreases) after the portfolio formation period, leading to lower risk of financial distress and to the observed decline in winners' performance. At the same time, the strength of the shareholders' bargaining power of the loser portfolio stocks decreases after the formation period leading to lower risk and return. Finally, we sort stocks into deciles based on the most recent tangibility and document that buying high and selling low tangibility stocks produces nearly 60 basis points of profit per month, which is 76% of the total momentum performance in our sample. Figure 5 also documents that the duration of the tangibility spread is about 12 months, which is close to the duration of momentum.

Finally, we find that the probability of financial distress (based on Merton (1974)) follows a similar pattern. Figure 6 presents the dynamics of the probability of financial distress for winners and losers before and after the formation period. Specifically, we document that winners (losers) experience a decrease (increase) in the probability of distress before the formation period and an increase (decline) afterwards, which is consistent with the our previous results.

## 5. Conclusion

There are two main findings in this paper. First, we establish a link between momentum and aggregate default. Specifically, momentum profits are mainly concentrated during periods of high aggregate default *shocks*. The result holds after controlling for business cycles and subsume with previously documented results that momentum exists only among high credit risk stocks. We further use a cross-section of momentum portfolios to test an empirical asset pricing model that contains the market return and a conditional default shock factor. We find that losers (winners) have lower (higher) conditional default risk. Since, the conditional default factor is priced and has high economic significance; losers should have lower expected returns in states of high aggregate default. The combined effect of a conditional default premium and exposure to this risk explains a large portion of momentum profits.

Second, we examine why the risk exposures of winners on the conditional default factor differ from those of losers. We do this by relying on a model by Garlappi and Yan (2011) that links the default characteristics of a firm to its shareholders' bargaining power in bankruptcy negotiations. Garlappi and Yan (2011) argue that shareholders with a better (worse) ability to recover a part of the residual firm value face relatively lower (higher) risk as the probability of default increases. As a result, firms with high shareholder recovery potential should have lower expected returns than firms with low recovery, however, this relation should be most pronounced in high default states. We show that losers are indeed stocks with high shareholder recovery potential. Therefore, they require relatively lower returns during periods of high default shocks. As noted earlier, the low expected return of losers in times of high default drives the profitability of the momentum strategy in those times.

The results have immediate implications for the previously suggested relation between default risk and expected returns (Vassalou and Xing (2004), Chava and Purnanandam (2010) and Campbell, Hilscher, and Szilagyi (2008)). We argue that shareholder recovery affects expected returns through aggregate default shocks. More importantly, these shocks are better suited for capturing default risks because they are more difficult to predict by investors (by construction these shocks are unexpected). Therefore, investors are more likely to adjust their expectations to reflect current economic conditions.

Overall we interpret our results as suggesting that momentum profits have an important component related to default risk. These results are important in light of previous studies that have been unable to document a relation between risk measures and momentum returns.[20] Our results suggest that behavioral arguments are not necessary to explain momentum.

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Table 1: Summary statistics

Table 1 presents descriptive statistics for monthly returns of equally-weighted momentum portfolios over the period 1960 - 2009. The momentum portfolios are based on the 6-1-6 strategy. W and L are comprised of winners and losers, respectively. The momentum strategy is represented by portfolio W - L.

| Portfolio | Mean | Sd. | 5% | 25% | Median | 75% | 95% |
|---:|---:|---:|---:|---:|---:|---:|---:|
| L | 0.95% | 9.65% | -13.10% | -4.02% | 0.63% | 4.83% | 16.39% |
| 2 | 0.91% | 7.13% | -9.84% | -2.87% | 0.83% | 4.37% | 11.38% |
| 3 | 1.01% | 6.03% | -8.86% | -2.23% | 1.04% | 3.95% | 10.09% |
| 4 | 1.11% | 5.38% | -7.74% | -1.62% | 1.39% | 3.77% | 9.33% |
| 5 | 1.16% | 4.99% | -7.04% | -1.36% | 1.40% | 3.65% | 8.52% |
| 6 | 1.21% | 4.77% | -6.54% | -1.29% | 1.51% | 3.66% | 8.27% |
| 7 | 1.27% | 4.77% | -6.46% | -1.26% | 1.67% | 4.01% | 8.15% |
| 8 | 1.35% | 4.97% | -6.72% | -1.27% | 1.76% | 4.41% | 8.37% |
| 9 | 1.47% | 5.51% | -7.59% | -1.36% | 1.79% | 4.93% | 9.24% |
| W | 1.74% | 6.81% | -9.66% | -2.12% | 2.15% | 5.84% | 11.25% |
| W - L | 0.79% | 6.35% | -9.02% | -0.98% | 1.29% | 3.36% | 8.32% |

Table 2: Momentum portfolio returns conditional on business cycles and default shocks

Table 2 documents returns on portfolios formed based upon a sorting procedure conditional on business cycles and aggregate default shocks over the period 1960 - 2009. The returns associated with the momentum strategy (6-1-6) based on equally-weighted portfolios are presented in the columns with t-statistics in parentheses. W and L represent portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio W - L. The sample period is from 1960 to 2009. Panel A presents sorts based on expansions and recessions, Panel B contains results from sorts based on periods of high and low default shocks, and Panel C incorporates sorts based on both business cycles and default shocks.

| | W | L | W - L |
|---|---|---|---|
| *Panel A. Default shocks* | | | |
| Low Default | 2.75% | 3.40% | -0.64% |
| | (7.58) | (5.65) | (-1.55) |
| High Default | 0.62% | -1.32% | 1.93% |
| | (1.79) | (-2.80) | (7.35) |
| *Panel B. State of the business cycle* | | | |
| Expansions | 2.05% | 1.20% | 0.85% |
| | ( 7.00) | ( 3.34) | ( 2.83) |
| Recessions | -0.43% | -0.61% | 0.18% |
| | ( -0.52) | (-0.44) | (0.44) |
| *Panel C. Default shocks and business cycles* | | | |
| Expansions Low Default | 2.81% | 3.09% | -0.28% |
| | ( 7.30) | ( 5.10) | ( -0.63) |
| Expansions High Default | 1.28% | -0.45% | 1.74% |
| | ( 2.97) | (-0.97) | (6.34) |
| Recessions Low Default | 2.39% | 6.14% | -3.75% |
| | ( 2.18) | ( 2.52) | ( -2.14) |
| Recessions High Default | -2.28% | -5.04% | 2.76% |
| | ( -2.10) | (-3.64) | (3.74) |

Table 3: Aggregate default loadings

Table 3 presents loadings of each of the 10 momentum portfolios on the market (MKTRF), default (DEF) and conditional default factors ($CDEF$ measured by the product of $DEF$ and $I$, where $I$ is an indicator function which equals to 1 if the economy is in period of high default shock (above median) and 0 otherwise). The equally-weighted momentum portfolios are based on the 6-1-6 momentum strategy. W and L represent the portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio W - L. The sample period is from 1960 to 2009. The loadings are estimated from the following model: $R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_{i,t}$. The loadings on the market $\beta^{MKTRF}$ , default shocks $\beta^{DEF}$ and conditional default shocks $\beta^{CDEF}$ are estimated for each of the 10 momentum portfolios. The t-statistics from the regressions are based on Huber-White robust standard errors.

| Portfolio | $\beta^{MKTRF}$ | t-stat | $\beta^{DEF}$ | t-stat | $\beta^{CDEF}$ | t-stat |
|---:|---:|---:|---:|---:|---:|---:|
| L | 1.36 | 19.03 | -3.83 | -3.14 | 2.70 | 1.96 |
| 2 | 1.17 | 23.94 | -2.04 | -2.90 | 1.13 | 1.41 |
| 3 | 1.06 | 25.95 | -1.30 | -2.96 | 0.59 | 1.17 |
| 4 | 0.99 | 27.08 | -0.85 | -3.07 | 0.29 | 0.87 |
| 5 | 0.94 | 27.81 | -0.61 | -3.13 | 0.15 | 0.60 |
| 6 | 0.91 | 27.32 | -0.46 | -3.11 | 0.08 | 0.41 |
| 7 | 0.92 | 27.67 | -0.33 | -2.59 | -0.04 | -0.22 |
| 8 | 0.96 | 28.02 | -0.18 | -1.38 | -0.20 | -1.10 |
| 9 | 1.05 | 29.36 | -0.07 | -0.46 | -0.38 | -1.87 |
| W | 1.23 | 28.41 | -0.09 | -0.38 | -0.47 | -1.88 |
| W - L | -0.13 | -1.73 | 3.75 | 3.19 | -3.18 | -2.38 |

Table 4: Cross-sectional analysis of time-varying aggregate default shocks

Table 4 presents estimated monthly premium based on the Fama-MacBeth regressions and using 30 portfolios sorted on momentum, size and book-to-market. $MKTRF$ is the excess return on the market, DEF is aggregate default shocks, $CDEF$ is the conditional aggregate default shocks measured by the product of $DEF$ and $I$, where $I$ is an indicator function which equals to 1 if the economy is in period of high default shock (above median) and 0 otherwise. The t-statistics based on the Shanken (1992) method are reported in parentheses below. The sample period is from 1960 to 2009.

| | MODEL (1) | MODEL (2) | MODEL (3) |
|---|---|---|---|
| MKTRF | 0.0010 | 0.0014 | 0.0027 |
| | (0.24) | (0.40) | (0.54) |
| DEF | | 0.0001 | -0.0043 |
| | | (0.05) | (-1.83) |
| CDEF | | | -0.0072 |
| | | | (-2.70) |
| CONST | 0.0011 | 0.0051 | 0.0028 |
| | (1.42) | (1.80) | (0.59) |
| $Adj.R^2$ | 0.24 | 0.39 | 0.58 |

Table 5: Shareholder bargaining power and the probability of financial distress of momentum

Table 5 reports shareholder bargaining power and financial distress of the portfolios of losers (L) and winners (W). Momentum corresponds to the hedge portfolio W - L. Panel A estimates the average probability of financial distress of winners and losers using a modified Z-score and the probability of default based on the Merton (1974) model. The sample period is from 1960 to 2009. The numbers in parentheses represent simple time-series t-statistics for the average monthly measures of financial distress and shareholder bargaining power. Panel B shows the average shareholder bargaining power of winners and losers using the tangibility measure (reflects the expected liquidation value of the firm) and the Herfindahl index based on sales (represents the specificity of the assets) based a 2-digit SIC code industry, and the ratio of R&D expenses to total assets.

| | W | L | W - L |
|---|---|---|---|
| *Panel A. Financial distress* | | | |
| Z-score | 1.63 | 0.61 | 1.02 |
| | | | (12.74) |
| Probability of Fin. Distress | 0.88% | 18.91% | -18.03% |
| | | | (-33.12) |
| *Panel B. Shareholder bargaining power* | | | |
| Tangibility | 0.58 | 0.56 | 0.02 |
| | | | (9.01) |
| Herfindahl index | 9.17% | 10.21% | -1.04% |
| | | | (-5.55) |
| R&D ratio | 6.51% | 7.87% | -1.36% |
| | | | (-5.67) |

Table 6: Beta Loadings Controlling for Other Risk Factors

Panel A of Table 6 presents the loadings for the returns of each of the 10 momentum portfolios on the market $\beta^{MKTRF}$, default shocks $\beta^{DEF}$, conditional default shocks $\beta^{CDEF}$, SMB $\beta^{SMB}$ and HML $\beta^{HML}$ factors. Panel B presents the same analysis, but controlling for the growth rate of industrial production $\beta^{MP}$. The equally-weighted portfolios are based on the 6-1-6 momentum strategy. W and L represent the portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio W - L. The sample period is from 1960 to 2009. The t-statistics from the regressions are based on Huber-White robust standard errors.

| Portfolio | $\beta^{MKTRF}$ | t-stat | $\beta^{DEF}$ | t-stat | $\beta^{CDEF}$ | t-stat | $\beta^{SMB}$ | t-stat | $\beta^{HML}$ | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A. Factor loadings controlling for SMB and HML.* | | | | | | | | | | |
| L | 1.15 | 16.01 | -3.54 | -3.23 | 2.88 | 2.29 | 1.30 | 9.79 | 0.23 | 1.68 |
| 2 | 1.04 | 23.74 | -1.82 | -2.94 | 1.31 | 1.84 | 0.99 | 12.63 | 0.30 | 3.71 |
| 3 | 0.98 | 29.74 | -1.13 | -2.92 | 0.79 | 1.80 | 0.81 | 12.92 | 0.35 | 5.82 |
| 4 | 0.93 | 35.83 | -0.70 | -3.00 | 0.50 | 1.88 | 0.71 | 13.42 | 0.38 | 7.60 |
| 5 | 0.89 | 40.23 | -0.49 | -2.97 | 0.35 | 1.92 | 0.64 | 13.53 | 0.37 | 8.40 |
| 6 | 0.87 | 40.88 | -0.34 | -2.76 | 0.28 | 2.03 | 0.61 | 14.98 | 0.36 | 9.04 |
| 7 | 0.86 | 40.74 | -0.20 | -2.01 | 0.13 | 1.19 | 0.62 | 17.95 | 0.31 | 8.28 |
| 8 | 0.88 | 40.91 | -0.03 | -0.32 | -0.06 | -0.49 | 0.67 | 21.08 | 0.25 | 7.32 |
| 9 | 0.93 | 45.73 | 0.12 | 1.43 | -0.28 | -2.36 | 0.79 | 23.94 | 0.16 | 4.83 |
| W | 0.99 | 33.46 | 0.20 | 1.63 | -0.47 | -2.54 | 1.01 | 19.10 | -0.03 | -0.67 |
| W - L | -0.15 | -1.84 | 3.73 | 3.20 | -3.35 | -2.49 | -0.29 | -1.93 | -0.26 | -1.66 |

| Portfolio | $\beta^{MKTRF}$ | t-stat | $\beta^{DEF}$ | t-stat | $\beta^{CDEF}$ | t-stat | $\beta^{MP}$ | t-stat |
|---|---|---|---|---|---|---|---|---|
| *Panel B. Factor loadings controlling for MP.* | | | | | | | | |
| L | 1.36 | 18.94 | -3.86 | -3.16 | 2.76 | 1.99 | 0.18 | 0.21 |
| 2 | 1.17 | 23.91 | -2.05 | -2.91 | 1.15 | 1.43 | 0.15 | 0.25 |
| 3 | 1.06 | 25.90 | -1.31 | -2.97 | 0.62 | 1.22 | 0.20 | 0.41 |
| 4 | 0.99 | 27.10 | -0.85 | -3.05 | 0.29 | 0.85 | -0.02 | -0.05 |
| 5 | 0.94 | 27.83 | -0.61 | -3.10 | 0.14 | 0.57 | -0.04 | -0.10 |
| 6 | 0.91 | 27.38 | -0.46 | -3.04 | 0.07 | 0.32 | -0.11 | -0.33 |
| 7 | 0.92 | 27.74 | -0.32 | -2.52 | -0.06 | -0.32 | -0.13 | -0.40 |
| 8 | 0.96 | 28.07 | -0.17 | -1.31 | -0.22 | -1.18 | -0.13 | -0.41 |
| 9 | 1.05 | 29.38 | -0.06 | -0.41 | -0.40 | -1.93 | -0.11 | -0.34 |
| W | 1.20 | 27.93 | -0.07 | -0.31 | -0.48 | -1.87 | 0.03 | 0.08 |
| W - L | -0.15 | -2.08 | 3.79 | 3.19 | -3.23 | -2.37 | -0.15 | -0.10 |

Table 7: Conditional default premium controlling for other risk factors

Table 7 presents estimated monthly premiums based on the Fama-MacBeth regressions and using 30 portfolios sorted on momentum, size and book-to-market. $MKTRF$ is the excess return on the market, DEF is aggregate default shocks, $CDEF$ is the conditional aggregate default shocks measured by the product of $DEF$ and $I$, where $I$ is an indicator function which equals to 1 if the economy is in period of high default shock (above median) and 0 otherwise. SMB, HML and MP represent the size, value, and growth rate of industrial production factors, respectively. The t-statistics based on the Shanken (1992) method are reported in parentheses below. The sample period is from 1960 to 2009.

| | MODEL (1) | MODEL (2) | MODEL (3) |
|---|---|---|---|
| MKTRF | 0.0009 | 0.0014 | 0.0008 |
| | ( 0.26) | ( 0.29) | ( 0.21) |
| DEF | -0.0019 | -0.0047 | -0.0024 |
| | ( -1.15) | ( -1.79) | ( -1.34) |
| CDEF | -0.0045 | -0.0075 | -0.0048 |
| | (-2.56) | (-2.56) | (-2.67) |
| SMB | 0.0026 | | 0.0026 |
| | (2.00) | | (1.99) |
| HML | 0.0027 | | 0.0028 |
| | (2.20) | | (2.22) |
| MP | | -0.0006 | -0.0002 |
| | | (-0.48) | (-0.15) |
| CONST | 0.0042 | 0.0039 | 0.0043 |
| | (1.34) | (0.83) | (1.32) |
| $Adj.R^2$ | 0.66 | 0.54 | 0.68 |

Table 8: Momentum portfolio returns by credit risk groups

Table 8 presents returns of momentum portfolios formed based upon a sorting procedure using aggregate default shocks over the period from 1985 to 2009. The returns generated using the momentum strategy (6-1-6) based on equally-weighted portfolios are presented in three columns. W and L represent the portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio W - L. Panel A, Panel B and Panel C contain results obtained from sorting based on speculative grade, middle grade and investment grade firms. The stocks are categorized in groups based on their publication rated debt. The numbers in parentheses represent simple time-series t-statistics for the average monthly returns.

| | W | L | W - L |
|---|---|---|---|
| *Panel A. Speculative grade stocks* | | | |
| Low Default | 3.27% | 4.80% | -1.52% |
| | (5.54) | (3.42) | (-1.25) |
| High Default | 0.60% | -3.73% | 4.33% |
| | (0.89) | (-4.64) | (6.83) |
| *Panel B. Middle grade stocks* | | | |
| Low Default | 2.27% | 3.17% | -0.90% |
| | (6.00) | (4.21) | (-1.39) |
| High Default | 0.70% | -0.71% | 1.41% |
| | (1.36) | (-1.17) | (3.82) |
| *Panel C. Investment grade stocks* | | | |
| Low Default | 1.82% | 2.06% | -0.24% |
| | (4.93) | (3.15) | (-0.42) |
| High Default | 0.91% | 0.29% | 0.62% |
| | (2.12) | (0.60) | (1.44) |

Table 9: Conditional default loadings by credit risk groups

Table 9 reports loadings for the returns of each of the 10 momentum portfolios on the conditional default factor ($CDEF$ measured by the product of $DEF$ and $I$, where $I$ is an indicator function which equals to 1 if the economy is in period of high default shock (above median) and 0 otherwise) by credit risk groups. The equally-weighted portfolios momentum portfolios are based on the 6-1-6 momentum strategy. W and L represent the portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio W - L. The sample period is from 1985 to 2009. The conditional default loading are estimated from the following model: $R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF}\xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_{i,t}$. $\beta^{CDEF}_{SG}$ represent the loadings of the momentum portfolios based on speculative grade firms, $\beta^{CDEF}_{MG}$ the loadings based on middle grade and $\beta^{CDEF}_{IG}$ based on investment grade firms. The t-statistics from the regressions are based on Huber-White robust standard errors.

| Portfolio | $\beta^{CDEF}_{SG}$ | t-stat | $\beta^{CDEF}_{MG}$ | t-stat | $\beta^{CDEF}_{IG}$ | t-stat |
|---|---|---|---|---|---|---|
| L | 4.48 | 4.71 | 1.50 | 3.10 | 1.25 | 3.18 |
| 2 | 2.64 | 4.37 | 0.66 | 1.98 | 0.62 | 2.27 |
| 3 | 2.22 | 4.46 | 0.31 | 1.08 | 0.37 | 1.62 |
| 4 | 1.34 | 2.89 | 0.33 | 1.23 | 0.29 | 1.40 |
| 5 | 1.12 | 2.72 | 0.20 | 0.83 | 0.10 | 0.53 |
| 6 | 0.58 | 1.64 | 0.02 | 0.09 | 0.05 | 0.29 |
| 7 | 0.34 | 1.00 | -0.14 | -0.63 | -0.12 | -0.63 |
| 8 | 0.05 | 0.17 | -0.30 | -1.37 | -0.19 | -1.08 |
| 9 | -0.23 | -0.66 | -0.48 | -2.07 | -0.42 | -2.32 |
| W | -0.87 | -2.01 | -0.78 | -2.80 | -0.74 | -3.38 |
| W - L | -5.36 | -4.39 | -2.28 | -2.13 | -1.99 | -1.79 |

Table 10: Conditional default premium by credit risk groups

Table 10 presents estimated monthly premium based on the Fama-MacBeth regressions for speculative grade, middle grade and investment grade stocks (SG, MG, IG, respectively). MKTRF is the excess return on the market, DEF is aggregate default shocks, CDEF is the conditional default factor measured by the product of DEF and $I$, where $I$ is an indicator function which equals to 1 if the economy is in period of high default shock (above median) and 0 otherwise. The coefficients are presented in columns for each of the three credit risk groups. The Fama-MacBeth t-statistics, calculated based on the Shanken (1992) method, are reported in parentheses. The sample period is from 1986 to 2009.

| | SG | MG | IG |
|---|---|---|---|
| MKTRF | 0.0088 | 0.0011 | -0.0021 |
| | (1.27) | (0.20) | (-0.38) |
| DEF | -0.0014 | -0.0019 | 0.0004 |
| | (-0.57) | (-0.74) | (0.14) |
| CDEF | -0.0057 | -0.0029 | -0.0000 |
| | (-1.83) | (-1.15) | (-0.01) |
| CONST | -0.0006 | 0.0053 | 0.0087 |
| | (-0.15) | (1.05) | (1.80) |
| $Adj.R^2$ | 0.65 | 0.37 | 0.35 |

Table 11: Aggregate default loadings from 1928 to 1960

Table 11 presents loadings of each of the 10 momentum portfolios on the market (MKTRF), default (DEF) and conditional default factors ($CDEF$ measured by the product of $DEF$ and $I$, where $I$ is an indicator function which equals to 1 if the economy is in period of high default shock (above median) and 0 otherwise). The equally-weighted momentum portfolios are based on the 6-1-6 momentum strategy. W and L represent the portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio W - L. The sample period is from 1928 to 1960. The loadings are estimated from the following model: $R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_{i,t}$. The loadings on the market $\beta^{MKTRF}$ , default shocks $\beta^{DEF}$ and conditional default shocks $\beta^{CDEF}$ are estimated for the returns of each of the 10 momentum portfolios. The t-statistics from the regressions are based on Huber-White robust standard errors.

| Portfolio | $\beta^{MKTRF}$ | t-stat | $\beta^{DEF}$ | t-stat | $\beta^{CDEF}$ | t-stat |
|---|---|---|---|---|---|---|
| L | 1.45 | 11.21 | -7.10 | -2.99 | 7.11 | 2.94 |
| 2 | 1.37 | 16.46 | -5.18 | -3.21 | 5.32 | 2.75 |
| 3 | 1.31 | 18.57 | -4.55 | -3.28 | 4.68 | 2.91 |
| 4 | 1.26 | 20.79 | -4.16 | -3.30 | 4.45 | 2.98 |
| 5 | 1.23 | 25.23 | -3.11 | -3.24 | 3.14 | 2.82 |
| 6 | 1.20 | 28.00 | -2.51 | -3.02 | 2.72 | 2.83 |
| 7 | 1.16 | 27.82 | -1.62 | -2.11 | 1.78 | 1.84 |
| 8 | 1.14 | 28.54 | -1.29 | -1.71 | 1.52 | 1.57 |
| 9 | 1.12 | 24.20 | -0.89 | -1.13 | 1.08 | 0.99 |
| W | 1.22 | 18.72 | -0.65 | -0.71 | 1.60 | 1.06 |
| W - L | -0.23 | -1.59 | 6.45 | 2.88 | -5.51 | -2.24 |

Table 12: International momentum portfolio returns conditional on aggregate default shocks

Table 12 documents returns on portfolios formed based upon a sorting procedure conditional on the US aggregate default shocks over the period 1985 - 2010. The returns associated with the momentum strategy (6-1-6) based on equally-weighted portfolios are presented in the columns with t-statistics in parentheses. W and L represent portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio W - L. The sample is based on the DataStream data. Panels A, B, C, and D present sorts based on the UK, German, French, and Netherlands data, respectively.

| | W | L | W - L |
|---|---|---|---|
| *Panel A. UK* | | | |
| Low Default | 2.63% | 2.28% | 0.35% |
| | (7.49) | (3.63) | (0.80) |
| High Default | 1.00% | -1.29% | 2.29% |
| | (2.14) | (-2.51) | (8.95) |
| *Panel B. Germany* | | | |
| Low Default | 2.24% | 2.02% | 0.22% |
| | (6.07) | (3.06) | (0.43) |
| High Default | 0.59% | -0.41% | 1.00% |
| | (1.66) | (-0.74) | (2.58) |
| *Panel C. France* | | | |
| Low Default | 2.95% | 3.44% | -0.49% |
| | (7.08) | (5.42) | (-0.99) |
| High Default | 1.41% | -0.14% | 1.55% |
| | (3.37) | (-0.26) | (4.25) |
| *Panel D. Netherlands* | | | |
| Low Default | 2.77% | 1.95% | 0.82% |
| | (7.03) | (2.59) | (1.84) |
| High Default | 0.88% | -1.21% | 2.09% |
| | (2.00) | (-2.25) | (5.50) |

Table 13: Shareholder bargaining power and momentum: international evidence

Table 13 reports shareholder bargaining power for the portfolios of losers (L) and winners (W) for the UK, German, French and Netherlands markets from 1985 to 2010. Momentum corresponds to the hedge portfolio W - L. We measure shareholder bargaining power of winners and losers using the tangibility measure (reflects the expected liquidation value of the firm). The sample is based on the DataStream data. The numbers in parentheses represent simple time-series t-statistics for the average monthly tangibility.

| | W | L | W - L |
|---|---|---|---|
| Tangibility in UK | 0.526 | 0.511 | 0.015 |
| | | | (5.32) |
| Tangibility in Germany | 0.495 | 0.483 | 0.012 |
| | | | (3.01) |
| Tangibility in France | 0.469 | 0.455 | 0.014 |
| | | | (3.38) |
| Tangibility in Netherlands | 0.519 | 0.502 | 0.017 |
| | | | (4.53) |

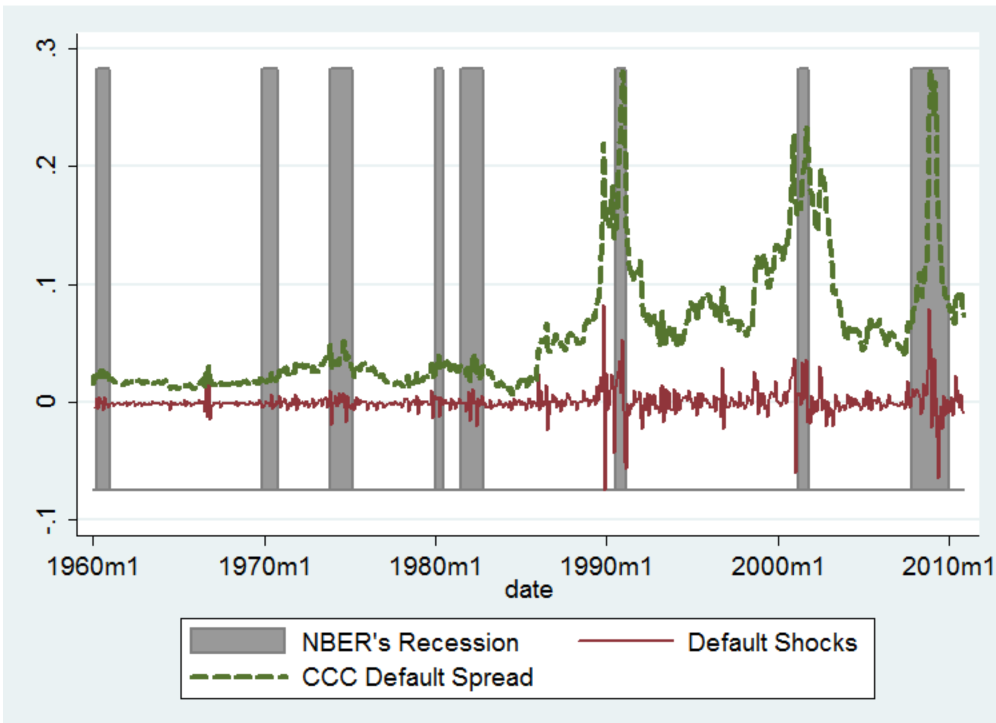


Figure 1: Default Spread and Default Shocks.

Figure 1 shows the time-series of default shocks as defined by residuals of (1) and the yield spread between Moody's CCC corporate bond index and the 10-year Treasury bond. Shaded areas of the graph correspond to periods of recessions as defined by NBER.

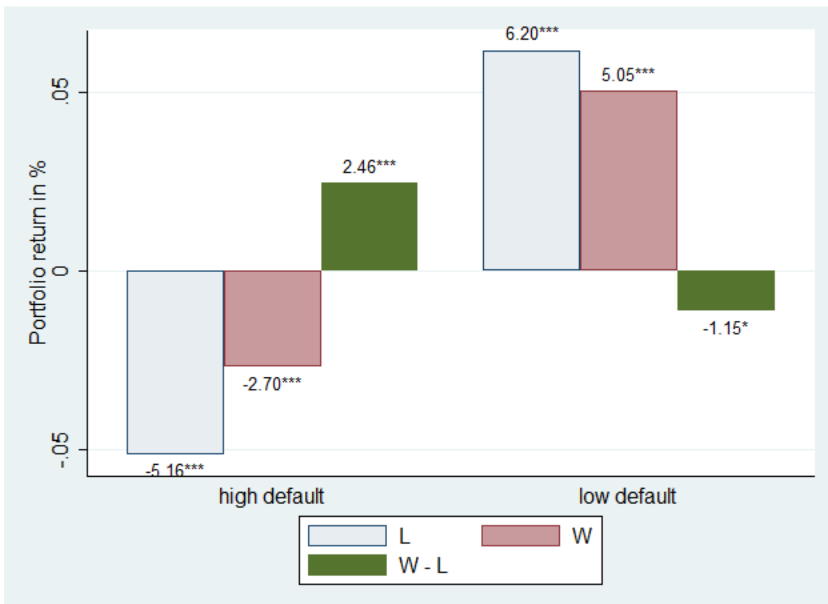


Figure 2: Momentum conditional on default shocks prior to 1960

Figure 2 documents the equally-weighted returns of portfolios sorted on momentum (6-1-6 strategy) during periods of high and low default shocks. W and L represent portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). The sample period is from 1928 to 1960.

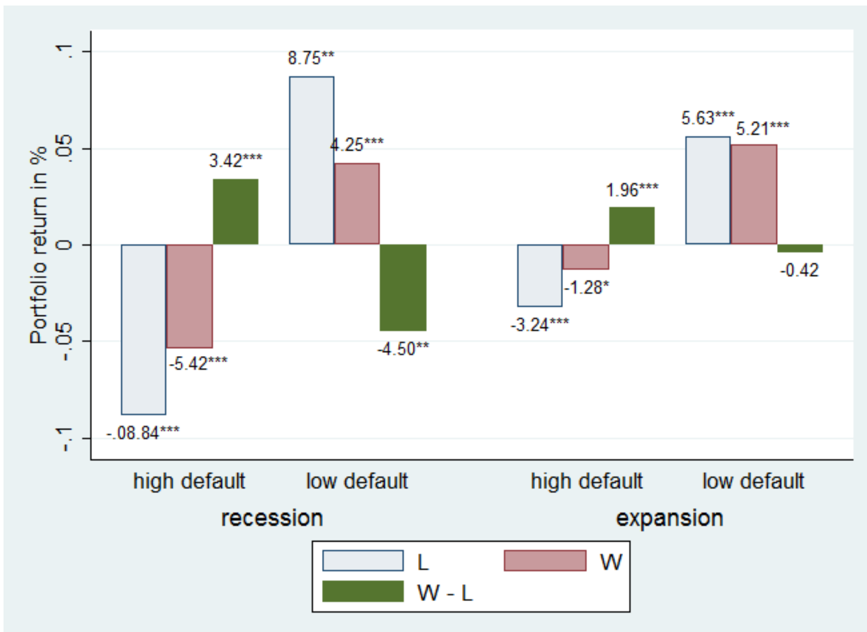


Figure 3: Momentum conditional on default shocks and business cycles prior to 1960

Figure 3 documents the performance of equally-weighted portfolios sorted on momentum (6-1-6 strategy) conditional on both default shocks and business cycles. W and L represent portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). The sample period is from 1928 to 1960.

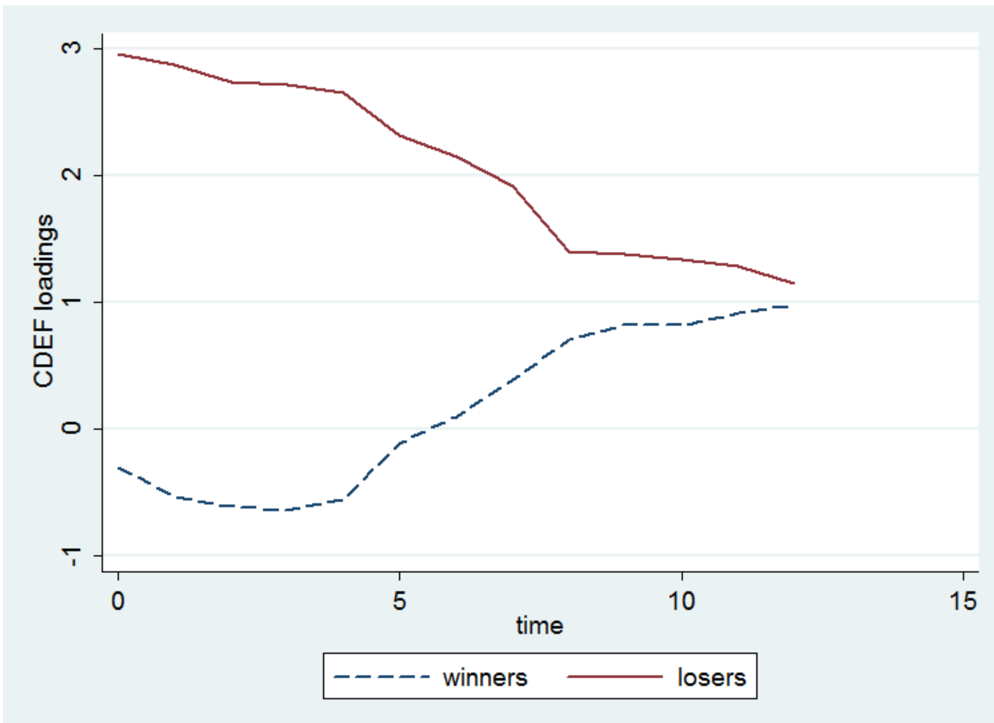


Figure 4: CDEF loading of losers and winners over time

Figure 4 presents the dynamics of the $\beta^{CDEF}$ loadings from equation (5) for winners and losers after the portfolio formation period. The equally weighted portfolios of winners and losers are based on the 6-1-6 strategy. The period of the analysis is 1960 - 2009.

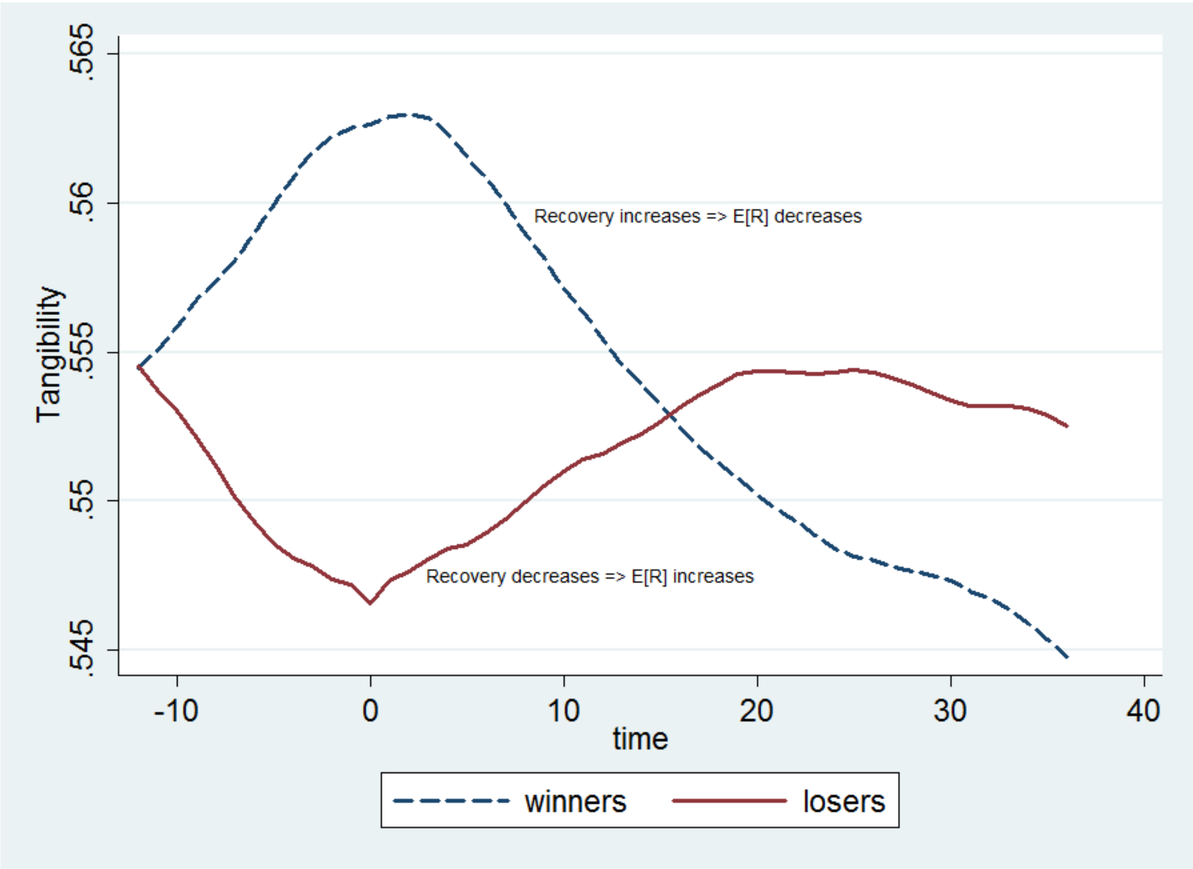


Figure 5: Tangibility of losers and winners over time

Figure 5 presents shareholder recovery (measured by tangibility) of the losers and winners portfolios over a 36-month post-formation period. For every month $t$ from January 1960 to December 2009, we calculate average tangibility of losers and winners for month $t+k$, where $k = -12, \ldots, +36$. We then average tangibility for $t+k$ across portfolio formation months.

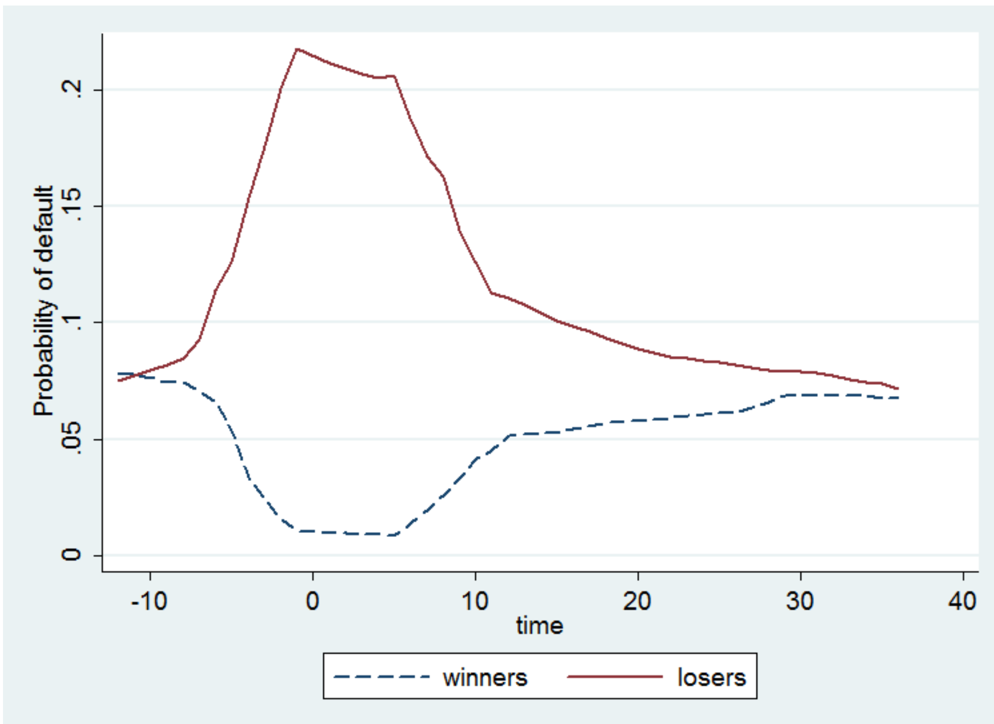


Figure 6: Probability of default of losers and winners over time

Figure 6 presents the dynamics of the probability of default for winners and losers before and after the formation period. For every month $t$ from January 1960 to December 2009, we calculate average probability of default (based on the Merton (1974) model) of losers and winners for $t+k$, where $k = -12, \ldots, +36$. We then average probability of default for $t+k$ across portfolio formation months.

## A. Internet Appendix

### *A.1. Shareholder Recovery and Financial Distress by Credit Risk Group*

We showed that losers have higher shareholder bargaining power and higher probability of financial distress on average. However, one could argue that losers of investment and middle grade groups have much higher shareholder recovery and, therefore, drive the observed results. We address this concern by extending our previous analysis and estimate the bargaining power and probability of financial distress of winners and losers in each of the three credit risk groups separately.

Table A.1 presents the results of this analysis. Panel A shows that speculative grade losers have a lower Z-score and a higher probability of financial distress than winners. In particular, Z-scores of losers is lower by 1.17 and their probability of financial distress is higher by 28.32% (both of them statistically different from zero). Similar results hold for middle and investment grade stocks (Panels B and C). While the difference between winners and losers in terms of Z-scores and probability of distress decreases as we move from speculative to investment grade portfolios, it remains statistically significant across all three groups. According to our previous results momentum is driven by the difference in exposure to the conditional default factor between losers and winners. Thus, investment grade stocks do not generate positive momentum, because of the smaller difference in probability of financial distress between winners and losers for this credit risk group.

Table A.2 reports the estimates of tangibility, the Herfindahl index, and the R&D ratio for speculative, middle grade and investment grade stocks. The table shows that losers have higher shareholder bargaining power than winners across all credit risk categories. For example, the tangibility of winners is higher than the tangibility of losers by 0.029 for speculative grade stocks. Also, within the same credit risk category, the Herfindahl index the R&D ratio of losers is significantly higher than that for winners. We observe similar results for the other two credit risk groups as well. Note, that the difference in the R&D ratio between winners and losers becomes insignificant for investment grade stocks.

In summary, our results show that losers tend to have higher shareholder recovery and probability of financial distress across all credit risk groups. Thus, it is possible the shareholders of losers face lower risk in high default states of nature because of higher bargaining power. Note that the shareholders of investment grade losers do not necessarily face lower risk due to the fact that the conditional default factor is not priced for this credit risk category and, therefore, recovery is not likely to affect these stocks.

*A.2. Alternative Momentum Strategies*

According to our results losers have higher loadings on the conditional default factor than winners using the 6-1-6 momentum strategy. This section presents further evidence that this result is robust to alternative momentum strategies. Namely, we show that our finding also hold for the strategy based on holding stocks for 12 months after the formation period (rather than 6, referred to as 6-1-12) and the strategy based on the returns over the previous 12 months (rather than 6, referred to as 12-1-6). Following our previous methodology, we skip a month after the formation period for both of these strategies.

Panel A of Table A.3 reports the CDEF loadings of momentum portfolios controlling for the market and unconditional default shocks variables in equation (5). The results presented in this panel reveal a familiar pattern. The loadings of losers are positive (2.19 and 2.61 for the 6-1-12 and 12-1-6 strategies, respectively). However, they gradually decline and become negative as we move to winners (-0.02 and -0.38 for the 6-1-12 and 12-1-6 strategies, respectively). Similarly to the previously documented results, the difference in the loadings of winners and losers is significant for both alternative strategies. Note that on average the 12-1-6 strategy produces higher returns than 6-1-12. Then it is not surprising that the 12-1-6 momentum strategy has a higher CDEF spread between winners and losers (-2.21 and -2.99 for the 6-1-12 and 12-1-6 strategies, respectively). Our results suggest that the economic and statistical significance of portfolios loadings on conditional default increases as the profitability of the momentum strategy increases.

Panel B of Table A.3 presents the estimates of the risk premium of the conditional default factor from the Fama-MacBeth procedure. Again, to obtain consistent estimates we use 30 test assets: 10 momentum (using 2 alternative momentum strategies), 10 size, and 10 book-to-market portfolios. We find that the CDEF premium does not change substantially (-64 and -67 basis points for the 6-1-12 and 12-1-6 strategies, respectively) depending on the set of momentum portfolios used for the estimation. Therefore, the conditional default factor is consistently priced for different momentum specifications.

Table A.1: The probability of financial distress by credit risk group

Table A.1 documents the financial distress of portfolios comprised of winners (W) and losers (L) for each of the three credit risk categories. Momentum corresponds to the hedge portfolio W - L. The average probability of financial distress of winners and losers is measured by a modified Z-score and the probability of default is based on the Merton (1974) model. The sample period is from 1985 to 2009. Panel A, Panel B and Panel C, present the measures of financial distress of winers and losers for speculative grade, middle grade and investment grade stocks, respectively. The numbers in parentheses represent simple time-series t-statistics for the average monthly measures of distress.

| | W | L | W - L |
|---|---|---|---|
| *Panel A. Speculative grade stocks* | | | |
| Z-score | 1.35 | 0.18 | 1.17 |
| | | | (16.05) |
| Probability of Fin. Distress | 3.74% | 32.06% | -28.32% |
| | | | (-42.79) |
| *Panel B. Middle grade stocks* | | | |
| Z-score | 1.98 | 1.43 | 0.55 |
| | | | (14.74) |
| Probability of Fin. Distress | 0.74% | 15.38% | -14.64% |
| | | | (-17.12) |
| *Panel C. Investment grade stocks* | | | |
| Z-score | 2.22 | 1.82 | 0.40 |
| | | | (10.02) |
| Probability of Fin. Distress | 0.49% | 9.51% | -9.02% |
| | | | (-13.37) |

Table A.2: Shareholder bargaining power by credit risk group

Table A.2 reports the shareholder bargaining power of the portfolios of losers (L) and winners (W) for each of the three credit risk categories. Momentum corresponds to the hedge portfolio W - L. The average shareholder bargaining power of winners and losers is estimated using the tangibility measure (reflects the expected liquidation value of the firm) and the Herfindahl index based on sales (represents the specificity of the assets) within a 2-digit SIC code industry, and the ratio of R&D expenses to total assets. The sample period is from 1985 to 2009. Panel A, Panel B and Panel C, present the shareholder bargaining power of winners and losers for speculative grade, middle grade and investment grade firms, respectively. The stocks are categorized in groups based on their publication rated debt. The numbers in parentheses represent simple time-series t-statistics for the average monthly measures of shareholder bargaining power.

| | W | L | W - L |
|---|---|---|---|
| *Panel A. Speculative grade stocks* | | | |
| Tangibility | 0.494 | 0.465 | 0.029 |
| | | | (5.71) |
| Herfindahl index | 6.80% | 7.29% | -0.51% |
| | | | (-3.57) |
| R&D ratio | 4.44% | 4.97% | -0.57% |
| | | | (-3.82) |
| *Panel B. Mid grade stocks* | | | |
| Tangibility | 0.470 | 0.450 | 0.020 |
| | | | (5.07) |
| Herfindahl index | 6.47% | 6.75% | -0.28% |
| | | | (-2.66) |
| R&D ratio | 3.58% | 3.87% | 0.29% |
| | | | (3.67) |
| *Panel C. Investment grade stocks* | | | |
| Tangibility | 0.475 | 0.453 | 0.022 |
| | | | (5.31) |
| Herfindahl index | 5.39% | 5.64% | -0.25% |
| | | | (-2.76) |
| R&D ratio | 3.66% | 3.76% | -0.10% |
| | | | (-1.54) |

Table A.3: Alternative momentum strategies

Panel A of Table A.3 presents the loadings for the returns of each of the 10 momentum portfolios on the conditional default factors for the 6-1-12 and 12-1-6 momentum strategies ($\beta^{CDEF}_{6-1-12}$ and $\beta^{CDEF}_{12-1-6}$, respectively) from the following model: $R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF}\xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_{i,t}$. W and L represent the portfolios comprised of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). The sample period is from 1960 to 2009. The t-statistics from the regressions are based on Huber-White robust standard errors. Panel B presents estimated monthly premiums of the conditional default factor ($CDEF$) based on the Fama-MacBeth procedure and using 30 portfolios sorted on momentum, size and book-to-market. The Fama-MacBeth t-statistics is estimated using the Shanken (1992) error-in-variables correction.

| Portfolio | $\beta^{CDEF}_{6-1-12}$ | t-stat | $\beta^{CDEF}_{12-1-6}$ | t-stat |
|---|---|---|---|---|
| *Panel A. Conditional default loadings* | | | | |
| L | 2.19 | 2.09 | 2.61 | 2.21 |
| 2 | 0.87 | 1.46 | 0.99 | 1.55 |
| 3 | 0.41 | 1.03 | 0.47 | 1.11 |
| 4 | 0.20 | 0.67 | 0.24 | 0.77 |
| 5 | 0.11 | 0.47 | 0.11 | 0.44 |
| 6 | 0.08 | 0.39 | 0.02 | 0.10 |
| 7 | 0.02 | 0.08 | 0.02 | 0.12 |
| 8 | -0.03 | -0.10 | -0.09 | -0.36 |
| 9 | -0.02 | -0.07 | -0.23 | -0.78 |
| W | -0.02 | -0.05 | -0.38 | -0.98 |
| W - L | -2.21 | -2.86 | -2.99 | 2.93 |
| *Panel B. Conditional default premium* | | | | |
| CDEF | -0.0064 | -2.61 | -0.0067 | -2.67 |