TWO ESSAYS IN ASSET-PRICING

A Dissertation

by

ALEXEY PETKEVICH

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2011

Major Subject: Finance

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ABSTRACT

Two Essays in Asset-Pricing. (August 2011)

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Past research documents a positive link between momentum and firm-level default risk, yet this anomaly is not connected to default risk at the macro level. Namely, there is no documented momentum during recessions, when default is higher on average. In the first essay, “Momentum and Aggregate Default Risk,” we attempt to resolve this puzzle by analyzing momentum profits over time, conditional on both business cycles and unexpected changes in aggregate default risk. First, we show that momentum is driven by shocks to aggregate default, rather than general economic conditions such as expansions and recessions. Using the Fama and MacBeth procedure, we find that a conditional default shock factor is priced and can explain a large portion of the total momentum returns. Second, we provide a risk-based explanation for this anomaly by linking the returns of momentum portfolios to shareholder recovery during financial distress. We find that losers have higher recovery (i.e., shareholders have high bargaining power) on average, and, as a result, have relatively lower risk in high default states of the world. Therefore, loser stocks have a lower risk premium and lower expected returns in worsening aggregate default conditions, leading to the observed momentum. This effect is more pronounced among stocks of firms with low credit ratings. Our results help to reconcile the seemingly contradictory evidence documented by previous studies and offer a rational explanation for the momentum anomaly.

In the second essay, “Sources of Momentum in Bonds,” we study the relationship between momentum in bond returns and aggregate default. We document that momentum in corporate bonds occurs mainly during periods of high default shocks and is driven by losers. Supporting this result, we find that conditional default risk is priced in the cross-section of corporate bond portfolios. Motivated by these findings, we develop a theoretical model connecting bond momentum returns to the ability of bondholders to recover value in financial distress. Specifically, we find that losers have relatively higher recovery potential and, therefore, become less risky when high default shocks occur. Thus, losers have lower expected returns in high default shocks, leading to the observed conditional momentum. Further, US government bonds, with default risk approaching zero, feature no momentum, however this anomaly prevails in sovereign bonds with positive default risk, consistent with our main results.

To Maryna

ACKNOWLEDGMENTS

First and foremost I offer my sincere gratitude to my supervisor, Arvind Mahajan, who encouraged and challenged me through the whole dissertation process. This dissertation also could not have been written without the help of my dissertation committee Mary Lea McAnally, Ralitsa Petkova, and Sorin Sorescu, who guided me and never accepted less than my best efforts. I have also benefited greatly from the comments and suggestions of faculty members outside of my advisory committee, including Sudheer Chava, Neal Galpin, and Shane Johnson. Their knowledge, feedback and support helped to broaden my horizons and improve my work.

I would like to acknowledge my colleagues in the Finance Ph.D. Program, T. Colin Campbell, Zhanhui Chen, Kershen Huang, and Heungju Park for their friendship and support.

I also want to extend my sincere gratitude to my family, especially my mother, Natalia Goncharova. Finally and most importantly, I thank my wife, Maryna Petkevich for her understanding and patient love through the duration of my studies.

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1. INTRODUCTION

In this dissertation we examine the momentum anomaly in the equity and bond markets. In the first essay, "Momentum and Aggregate Default Risk," we link momentum to aggregate default. Past research documents a positive link between momentum and firm-level default, yet momentum is not connected to default at the macro-level. There is no documented momentum during recessions, when the firm-level default is higher on average. We attempt to resolve this puzzle by examining momentum profits over time, conditional on both business cycles and unexpected changes in aggregate default risk. First, we document that momentum is driven by shocks to aggregate default, rather than general economic states such as expansions and recessions. According to our results a conditional default shock factor is priced and can explain a large portion of the total momentum returns. In particular, we show that momentum produces 1.93% per month during high default shocks and -0.64% per month during low default shocks. Using the Fama and MacBeth (1973) procedure, we find that the conditional default factor is priced can explain 89% of this difference. Moreover, our tests indicate that the conditional default premium remains significant after controlling for exposure to other asset-pricing factors such as size, value and industrial production growth. Second, we provide a risk-based explanation for momentum by linking the returns on momentum portfolios to potential shareholder recovery during financial distress. We find that the shareholders of firms categorized as losers have higher bargaining power on average, and, as a result, have relatively lower risk in high default states of the world. Therefore, losers have a lower risk premium and expected returns in worsening aggregate default conditions, leading to observed momentum returns. This effect is more pronounced among stocks

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This dissertation follows the style of *The Journal of Finance*.

of firms with low credit ratings. Moreover, we provide evidence consistent with reversal: we show that the conditional default loadings between winners and losers converge one year after portfolio formation, potentially explaining the observed reversal effect. Finally, we document that the shareholder recovery of winners (losers) increases (decreases) after portfolio formation yielding a relatively lower (higher) risk and, therefore, lower (higher) expected returns. Our results help to reconcile the seemingly contradictory evidence documented by previous studies and offer a rational explanation for the momentum anomaly.

In the second essay, "Sources of Momentum in Bonds," we ask whether momentum exists in the corporate bond market and attempt to identify major determinants of this anomaly. We document that momentum in corporate bonds occurs mainly during periods of high default shocks and is driven by losers. We then document that conditional default risk is priced in the cross-section of corporate bond portfolios. Motivated by these findings, we develop a theoretical model connecting bond momentum returns to the ability of bondholders to recover value in financial distress. Specifically, we find that losers have relatively higher recovery potential and, therefore, become less risky when high default shocks occur. Thus, losers have lower expected returns during high default shocks, leading to the observed conditional momentum. Further, US government bonds, with default risk approaching zero, feature no momentum; however, this anomaly prevails in sovereign bonds with positive default risk, consistent with our main results. Finally, we present evidence suggesting that reversal also exists in bonds and it takes approximately 20 months to offset cumulative momentum profits.

Overall, we document that momentum in both equity and bond markets is driven by aggregate default shocks. According to our results, macro-level default is also priced in both markets and can explain a large portion of momentum profits. Finally, we document that shareholder (bondholder) recovery can affect equity (bonds) returns.

2. MOMENTUM AND AGGREGATE DEFAULT RISK

Avramov, Chordia, Jostova, and Philipov (2011) find that the momentum strategy is profitable only among stocks with high probability of financial distress. This suggests that momentum profits should be higher during recessions when default risk is expected to be high. However, Chordia and Shivakumar (2002) document that momentum profits are mainly concentrated in periods of economic expansions. In this paper, we attempt to resolve this seeming disagreement between the cross-sectional and time-series findings on momentum profitability. Specifically, we show that in the time-series, momentum profits are mainly observed in periods of high shocks to aggregate default, even after controlling for the general state of the economy. Further, we show that high momentum profits during periods of high default shocks are driven by the low expected returns of losers. Losers are stocks with high shareholder recovery potential in default situations, and therefore, they have lower risk and lower expected returns than winners.

After confirming Chordia and Shivakumar (2002) result that momentum is more pronounced during periods of expansion rather than recession, we document that the returns to momentum are concentrated in periods of high default shocks, both during expansions and recessions. A trading strategy based on buying recent winners and selling recent losers produces 1.93% per month during high default shocks and -0.64% per month during low default shocks. Results from a double sort on business cycles and shocks to aggregate default show that momentum profits are nonexistent or negative during periods of low default shocks, and are positive during periods of high default shocks, irrespective of the economic state. This suggests that momentum is not driven by the general state of the economy, but instead by the state of aggregate default.

Motivated by the above finding, we construct a conditional default shock factor and examine its pricing in the cross-section of momentum portfolios. The conditional default shock factor takes the value of the default factor during periods of high default shocks, and zero otherwise. In particular, it is designed to capture the additional impact of default on returns during periods of increasing aggregate default. Our asset pricing tests show that the premium on the conditional default factor is negative and significant, controlling for the market return, HML, SMB, and industrial production growth. We further document that losers (winners) have positive (negative) 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% the difference between momentum profits in high and low aggregate default states.

Next we examine why the risk exposure of winners to the conditional default factor differs from that of losers. Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) argue that shareholders of certain firms can extract rent using their bargaining power when the firm cannot meet its financial obligations. Further, shareholders with a better ability to recover a portion of the residual firm value face relatively lower risk as the probability of default increases. Similarly, shareholders with a lower or no ability to recover residual firm value face relatively higher risk when bankruptcy risk increases. As a result, firms with high shareholder recovery potential should have lower expected returns than low recovery firms. If the conditional default factor is a common factor capturing firm-level probability of default, then its loadings should be high among stocks with high recovery potential and low among low recovery stocks. If losers in general have high shareholder recovery relative to winners, their shareholders would face a relatively lower risk as default increases and, thus, would 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 (receivables, inventory, capital and cash holdings scaled by total book assets), the Herfindahl index (the concentration of industry sales), and the ratio of R&D expenditures as proxies for shareholder recovery. Firms with highly tangible assets can be more easily liquidated in case of a bankruptcy, while liquidation may lead to a greater loss in value for firms with more intangible assets. When firms lack tangible assets to liquidate, it could be more beneficial for creditors to restructure the debt and other obligations rather than liquidating the firm. Therefore, firms with mainly intangible assets are less likely to be liquidated, giving shareholders a strong bargaining position and allowing them to extract more value in distress negotiations due to the decreased chance of outright liquidation. The firm's Herfindahl index provides a measure of the specificity of the firm's assets, which will impact the market for the firm's assets. Because firms with highly specific assets may also face higher liquidation costs in default, such firms are relatively more valuable as going concerns, giving shareholders higher bargaining power. Finally, we use the ratio of R&D expenditures to total book assets as a proxy for bargaining power. Again, high R&D firms are more difficult to liquidate due to high potential growth options and product specialization. In each case, shareholders with relatively higher bargaining power or recovery potential will have greater ability to avoid liquidation and recover value in financial distress. Therefore, an increase in aggregate default should lead to lower risk and expected equity returns for firms with high shareholder recovery potential. Note that commonly accepted measures of firm-level default do not take into account the potential effect of shareholder bargaining power. Between two firms with the same credit rating, the one with higher bargaining power is less likely to be liquidated, *ceteris paribus*. Given the accepted terminology, we have to emphasize the difference between default and liquidation. The second term is more general and should include the bargaining potential of the firm's shareholders.

Using these three measures, we show that losers have lower tangibility and therefore, they are stocks with high shareholder bargaining power. Thus, losers should have relatively lower expected returns during periods of high aggregate default shocks. As noted earlier, the low expected return of losers in times of high default drives the profitability of the momentum strategy during these periods. Moreover, we provide evidence suggesting that the shareholder recovery of winners (losers) increases (decreases) after portfolio formation yielding a relatively lower (higher) risk and, therefore, lower (higher) expected returns. Similarly, the spread in conditional default loadings between winners and losers disappears approximately one year after portfolio formation. These results are in-line with the findings of Jegadeesh and Titman (2001) that winners only temporarily outperform losers. Further, we uncover the driving forces behind the dynamics of shareholder recovery. According to our results, shareholder bargaining power is driven mostly by the cash holding of the firm. One of the possible explanations of this finding is that poor market performance of losers affects their ability to raise cash. Since the poor performance of loser before portfolio formation might affect their ability to raise cash, losers are stocks with low tangibility at portfolio formation.

Finally, we analyze the subsample of firms with S&P debt ratings, following Avramov, Chordia, Jostova, and Philipov (2011), and confirm that momentum does not exist among high investment grade firms. It 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 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.

Ever since Jegadeesh and Titman (1993) documented the momentum effect,[1] the most widely considered explanation for momentum profits has been behavioral overreaction or underreaction to firm-specific information.[2] Several papers look for risk-

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[1]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.

[2]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.

based evidence to explain momentum profits but are unable to document convincing results.[3] Some papers document significant relation between risk and momentum.[4] These risk-based studies focus 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. Our study suggests that the expected returns of winners and losers change over time because of changing default conditions.

We contribute to the momentum literature on two dimensions. Avramov, Chordia, Jostova, and Philipov (2011) establish a link between credit risk and momentum at the firm level. First, we extend this analysis to the macro level by documenting that momentum returns are related to aggregate economy-wide default risk. Using historical information for the estimation of unexpected shocks to default, we further show that momentum profits are mainly concentrated during periods of positive *shocks* to aggregate default. To our knowledge, aggregate default shocks have not been studied before in the context of the momentum anomaly. 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 rational explanation of

[3]Fama and French (1996) show that their three-factor model cannot explain momentum. 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. Griffin, Ji, and Martin (2003) show that the Chen, Roll, and Ross (1986) model does not explain momentum either.

[4]Pástor and Stambaugh (2003) document that liquidity risk accounts for half of momentum profits. Sadka (2006) finds that shocks to 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) show that winners have higher loadings than losers on the growth rate of industrial production. Chen and Zhang (2009) document that winner-minus-loser portfolios have positive exposures to a low-minus-high investment factor.

the momentum anomaly based on shareholder recovery and time-varying exposure to aggregate default risk. Overall, we provide further evidence that the existence of momentum is consistent with a risk-based explanation. Our results suggest that a large portion of momentum profits can be explained by exposure to conditional default.

2.1 Momentum and Aggregate Default Shocks

2.1.1 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 $t-1$. We skip a month after the formation period since it is not uncommon to observe a short-term return reversal. 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 2.1 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.

Table 2.1 shows that winners outperform losers by 0.79% per month which is consistent with previous studies. The distribution of losers tends to be flatter than

Table 2.1

Summary Statistics of Equity Momentum.

This table 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.

Portfolios	Mean	Std.	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%

that of winners. The standard deviation of winners is 6.81%, while the volatility of losers is 9.65%. The fact that losers are more volatile than winners makes their performance differential even more puzzling.

2.1.2 Sorting on Business Cycles and 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. In particular, 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.

We begin the analysis by examining whether previously documented results hold in our sample. Specifically, we calculate the return of the momentum strategy that buys winners and shorts losers during expansions and recessions.[5] The results of this sorting procedure are presented in Panel A of Table 2.2. 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).

Avramov, Chordia, Jostova, and Philipov (2011) show that the profitability of momentum is driven by companies with high credit risk (low credit ratings). Since

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

Table 2.2

Momentum Portfolio Returns Conditional on Business Cycles and Default Shocks.

This table 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. 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 B. 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 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)

credit risk is likely to be important during recessions, the previous finding that momentum is profitable in expansions presents a puzzle. In this section we attempt to explain this apparent inconsistency. Instead of focusing on the general state of the business cycle, we examine aggregate default shocks. Since momentum is driven by high credit risk firms (likely to have a higher probability of default), it is natural to examine the time series relation between momentum profits and 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:

$$DEF_t = \alpha_0 + \alpha_1 DEF_{t-1} + \alpha_2 DEF_{t-2} + \xi_t, \tag{2.1}$$

where, DEF_t is default spread in month t, and unexpected shocks to default are represented by ξ_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 (2.1) using information up to time $t-1$.[6] First, we estimate model 2.1 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 2.1 shows the time-series of default shocks and levels. Shaded areas of the graph corre-

[6]Using unadjusted shocks yields similar results.

spond to periods of recessions as defined by 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%. However, they did not affect the economy in the long-term and, therefore, these events cannot be captured by the recession dummy.

We use aggregate default shocks to split the sample in two states of nature: high default shock periods and low default shock periods. According to our results default shocks are evenly split and recessions take approximately 20% of the total sample. We then estimate momentum profits for each state of aggregate default. The results presented in Panel B of Table 2.2 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 returns are close to zero during periods of low default shocks.

Since the correlation between the NBER recession dummy and shocks to aggregate default is not perfect (it is only 5% in our sample), the relation between momentum profitability and aggregate default that we document does not contradict previous findings. We use independent sorts to separate the sample into recessions and expansions and positive and negative shocks to aggregate default. The results of this procedure are presented in Panel C of Table 2.2. Clearly, default shocks occur during expansions as well as during contractions. Panel C of Table 2.2 documents

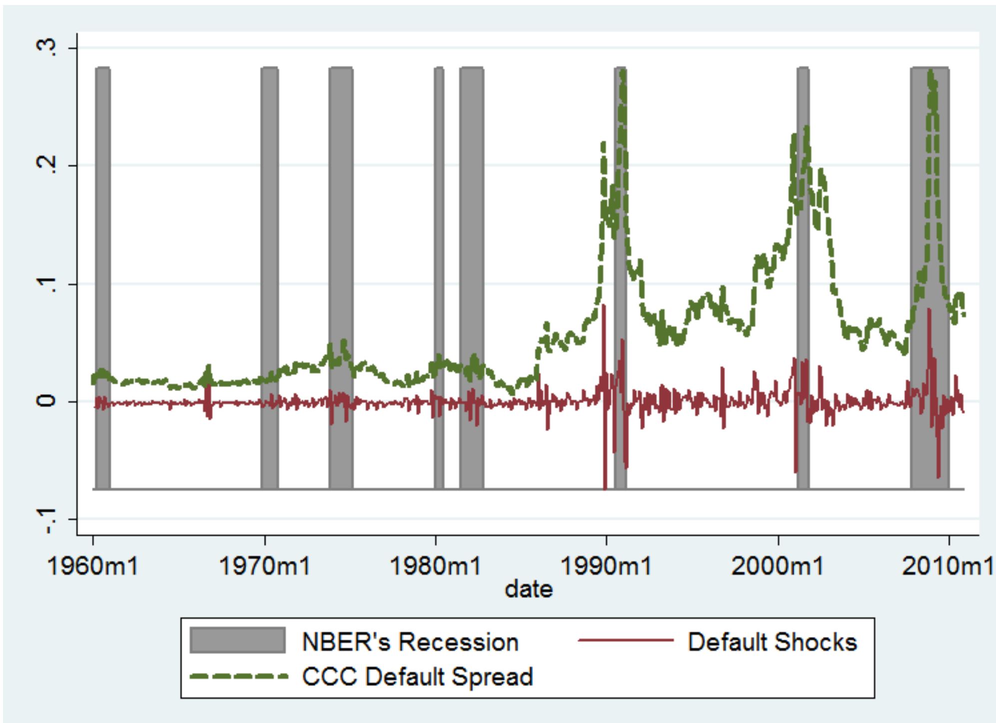

Fig. 2.1. Default Spread and Default Shocks.

This figure shows the time-series of default shocks as defined by residuals of (2.1) 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.

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 in 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 among stocks that are likely to be more sensitive to aggregate default conditions (stocks of low credit rating 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 aggregate default has the ability to explain the cross-sectional behavior of momentum portfolios. 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?

2.1.3 Conditional Default Shocks

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

$$E[r_i] = \gamma_0 + \beta_1' \gamma_i, \tag{2.2}$$

where, $E[r_i]$ represents the expected excess return on asset i, γ_i is a vector of factor prices of risk, β_1' is a vector of factor loadings, and γ_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 depends on the nature of the default 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:[7]

$$C\xi_t = I_t \xi_t, \tag{2.3}$$

where ξ_t denotes a non-traded default factor measured by default shock at time t (the residual from (2.1), and I_t is an indicator function that equals 1 if the economy is in a period of high default shock and 0 otherwise.[8] Therefore, the conditional default variable takes a non-zero value only during periods of positive default shocks.

The return-generating process can be written as:

$$R_{i,t}^{e} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_{i,t}, \tag{2.4}$$

[7] Watanabe and Watanabe (2011) apply a similar approach for the analysis of time-varying liquidity.

[8] The indicator function is estimated using the cumulative recursive procedure explained in section 2.1.2

where, $MKTRF_t$ is the excess return of the CRSP value-weighted portfolio. Given the previous evidence that momentum profits only occur during states of high unexpected default, we are particularly interested in the β_i^{CDEF} coefficients of winners and losers. The β_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 β_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 (2.4). 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 (2.4), we use 30 test assets. These assets include 10 momentum portfolios, 10 size portfolios, and 10 book-to-market portfolios.[9]

Table 2.3 presents the loadings of the momentum portfolios with respect to the market return (β^{MKTRF}), unexpected default (β^{DEF}), and conditional default (β^{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 default is significant with a t-statistic of -2.38.

[9] 10 size and 10 book-to-market portfolios are obtained from Kenneth R. French's web site. Liu and Zhang (2008) also uses 10 size, 10 book-to-market, and 10 momentum portfolios for momentum analysis. Adding 10 industry portfolios to the sample will yield similar results.

Table 2.3

Aggregate Default Loadings.

This table 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 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 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 β^{MKTRF} , default shocks β^{DEF} and conditional default shocks β^{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	β^{MKTRF}	t-stat	β^{DEF}	t-stat	β^{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

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 2.3 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 2.4 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 2.2, the momentum profit in

Table 2.4

Cross-sectional Analysis of Time-varying Aggregate Default Shocks.

This table 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. 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

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 2.4) multiplied by the spread in conditional default betas between winners and losers (-3.18, Table 2.3), 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 explore one possible explanation for the hedging ability of losers in periods of high unexpected default.

2.2 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 default. The question is: why do stocks with a high probability of default do better than expected when the aggregate risk of defaulting increases? We rely on a model by Garlappi and Yan (2011) to explore this.

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 shareholder bargaining power that depends on characteristics of the firms. The authors demonstrate that the expected equity returns of high bargaining power firms decrease as bankruptcy risk increases, because the shareholders have a strong bargaining position and, therefore, lower risk when the firm is in financial distress. Therefore, if the probability of financial distress should increase, the shareholders with high bargaining power will relatively benefit in this economic environment, because of high recovery possibility. On the other hand, the shareholders of firms with low recovery potential will have a weak bargaining position in distress negotiations. Therefore, if the probability of financial distress increases, the equity of these types of firms will become riskier and generate higher expected returns.

We hypothesize that losers are high bankruptcy risk and high shareholder recovery stocks. Then, they possibly have low expected returns in high default states because their shareholders do not require additional premium for holding equity in high default states of the world. In the next section we examine whether losers indeed posses these characteristics.

2.2.1 Firm-level Default 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 default measure can be defined as:

$$DD_{naive} = \frac{ln[(E+F)/F] + (r_{it-1} - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}, \tag{2.5}$$

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

The naive probability of default is

$$\pi_{naive} = N(-DD_{naive}). \tag{2.6}$$

The distance to default 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 (3.17)). 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 default 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:

$$\text{Z-score} = \frac{1.2 \times WC + 1.4 \times RE + 3.3 \times EBIT + SALES}{TA}, \tag{2.7}$$

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 compute each of these two measures of financial distress for losers and winners portfolios as equally-weighted averages of the individual measures for the stocks in each portfolio. Panel A of Table 2.5 presents the results. Specifically, we find that the probability of default 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.

Table 2.5

Shareholder Bargaining Power and the Probability of Financial Distress of Momentum.

This table 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 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. Panel B 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.

	W	L	W - L
Panel A. Financial distress			
Z-score	1.63	0.61	1.02
			(12.74)
Probability of Default	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)

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.

2.2.2 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 shareholder 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 potentially 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 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 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

$$Tng = \frac{(0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times PPE + Cash)}{TotalAssets}. \quad (2.8)$$

Low tangibility implies low expected liquidation value and higher 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 assets 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:

$$HI_{j,t} = \sum_{i=1}^{N_{j,t}} s_{i,t}^2, \quad (2.9)$$

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, hence, 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 2.5 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 suggest 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 provide a plausible explanation for the low expected returns of losers observed in periods of high aggregate default shocks.

2.3 Analysis by Credit Risk Groups

This section presents further evidence on the relation between momentum and aggregate default. In Section 2.3.1 we examine the relation between aggregate default shocks and momentum returns conditional on different credit risk groups. The purpose of this analysis is to test whether high credit risk stocks, which drive the momentum anomaly, are also sensitive to aggregate default shocks. Besides, this test will ascertain the previous findings are not unique to our specific sample and test-period.

Section 2.3.2 explores how the conditional default betas of the momentum portfolios change depending on credit risk. We conjecture that financially distressed firms are sensitive to worsening default conditions and, therefore, the largest difference between the CDEF loadings of losers and winners should be observed for high credit risk group. Moreover, if our conjecture is correct, the conditional default factor should not be priced for low credit risk stocks.

Section 2.3.3 reports the difference in shareholder recovery and probability of financial distress between winners and losers for each of the credit risk groups. A central prediction of Garlappi and Yan (2011) is an inverse U-shaped relation between expected returns and the probability of financial distress for high recovery stocks. That is, the expected returns of high recovery stocks should decrease in bankruptcy risk for speculative grade firms (those with low credit rated bonds, or speculative grade firms). This relation does not necessarily hold for stocks in the low credit risk group (firms with high credit rated bonds, or investment grade firms). Even though the investment grade firms have high shareholder recovery, they also have lower probability of financial distress and, therefore, they are less likely to be affected by shareholder recovery.

2.3.1 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. 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 argue 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 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 within different credit risk groups separately, 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 2.6 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 2.6 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

Table 2.6

Momentum Portfolio Returns by Credit Risk Groups.

This table 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 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)

shock states. It is interesting that in times of high default, 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 cross-sectional and time-series default.

2.3.2 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 (2.4). Table 2.7 reports the results of this analysis. Columns β_{SG}^{CDEF}, β_{MG}^{CDEF}, and β_{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 (β^{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.

Table 2.7

Conditional Default Loadings by Credit Risk Groups.

This table 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 - $R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF}\xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_{i,t}$. β_{SG}^{CDEF} represent the loadings of the momentum portfolios based on speculative grade firms, β_{MG}^{CDEF} the loadings based on middle grade and β_{IG}^{CDEF} based on investment grade firms. The t-statistics from the regressions are based on Huber-White robust standard errors.

Portfolio	β_{SG}^{CDEF}	t-stat	β_{MG}^{CDEF}	t-stat	β_{IG}^{CDEF}	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

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 2.8 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.

Table 2.8

Conditional Default Premium by Credit Risk Groups.

This table presents estimated monthly premiums 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

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 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 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.

2.3.3 Shareholder Recovery and Financial Distress by Credit Risk Group

In Section 2.2 we showed that losers have higher shareholder bargaining power and higher probability of financial distress on average. However, one could argue that this result does not need to hold for high credit risk group that essentially drives the profitability of momentum. Possibly, losers of investment grade and middle grade groups may have much higher shareholder recovery and, therefore, drive the observed results. To address this we extend 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 2.9 presents the results of this analysis. Panel A shows that speculative grade losers have a lower Z-score and a higher probability of default than winners. In particular, Z-scores of losers is lower by 1.17 and their probability of default 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 default 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 produce positive momentum profits, because of the smaller difference in probability of financial distress between winners and losers for this credit risk group.

Table 2.9

The Probability of Financial Distress by Credit Risk Group.

This table 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 Default	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 Default	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 Default	0.49%	9.51%	-9.02%
			(-13.37)

Table 2.10 reports the estimates of tangibility, the Herfindahl index, and the R&D ratio for speculative, middle grade and investment grade stocks. As before, these are three separate measures of shareholder recovery. The table shows that losers have higher recovery 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.

Table 2.10

Shareholder Bargaining Power by Credit Risk Group.

This table 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 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)

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.

In this section we obtain results based on the sample of firms which are credit rated by S&P.[10] Since these firms are a subset of our total sample, consistency of this results with our hypotheses enhance confidence in our larger sample results. Furthermore, these results allow us to extend the findings of Avramov, Chordia, Jostova, and Philipov (2011) - momentum exists in high credit risk firms but only in high default states of nature.

2.4 Time-series Evolution of Conditional Default Loadings, Shareholder Recovery, and Financial Distress

2.4.1 Time-series Dynamics of Conditional Default Loadings

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

[10] Avramov, Chordia, Jostova, and Philipov (2011) results are based on this sample as well

that the difference in investors' risk perception between losers and winners is 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 (2.4) for portfolios of losers and winners across calendar months and present CDEF loadings for event month $t + k$.

Figure 2.2 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, 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. It appears that the CDEF loadings spread between losers and winners is temporary which is consistent with the findings of Jegadeesh and Titman (2001) and Griffin, Ji, and Martin (2003). Furthermore, this result provides additional support to our risk-based explanation of the momentum anomaly.

2.4.2 Time-series Dynamics of Shareholder Recovery and Financial Distress

This section examines how shareholder recovery and financial distress evolve before and after the portfolio formation period. We document thus far that the difference in the exposure to the conditional default factor for losers and winners is driven by shareholder recovery and financial distress. 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 for-

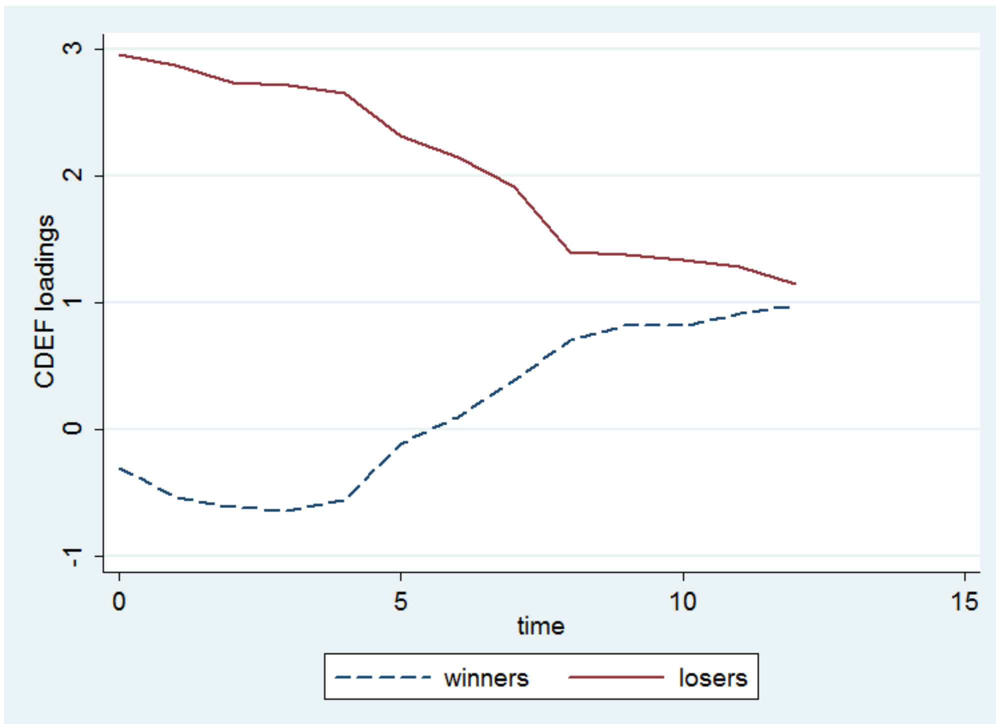

Fig. 2.2. CDEF Loading of Losers and Winners Over Time.

This figure presents the dynamics of the β^{CDEF} loadings from equation (2.4) 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.

mation period making them relatively safer (riskier). That is, momentum profits decreases 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.

To test this hypothesis, we adapt tangibility as a proxy for shareholder recovery. A firm with a low concentration of tangible assets should have higher recovery, because the shareholders of this firm are less sensitive by bankruptcy risk, since expected liquidation value is low (high liquidation costs). As a result, creditors can create more value by restructuring obligations of the firm. Similarly, higher tangibility represents lower shareholder recovery.

Figure 2.3 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.

We confirm the findings of Jegadeesh and Titman (2001) by documenting 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 recovery 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 per month, which is 76% of the total momentum performance. Moreover, Figure 2.3 documents that the duration of the tangibility spread is about 12 months which is close to the duration of momentum.

Further, we find that the probability of default (based on Merton (1974)) follows a similar pattern. Figure 2.4 presents the dynamics of the probability of default for

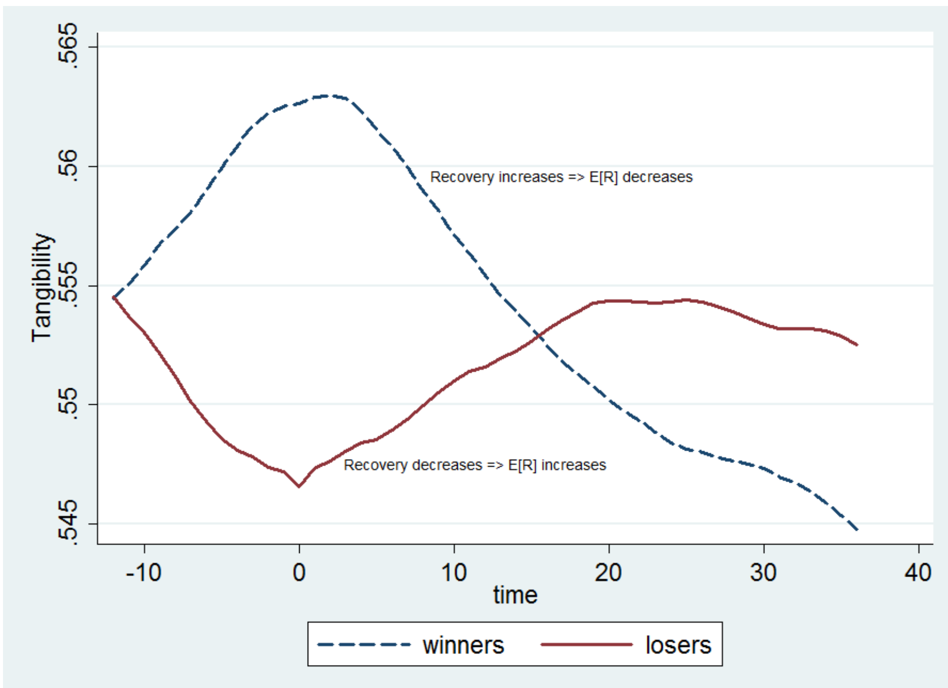

Fig. 2.3. Tangibility of Losers and Winners Over Time.

This figure 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.

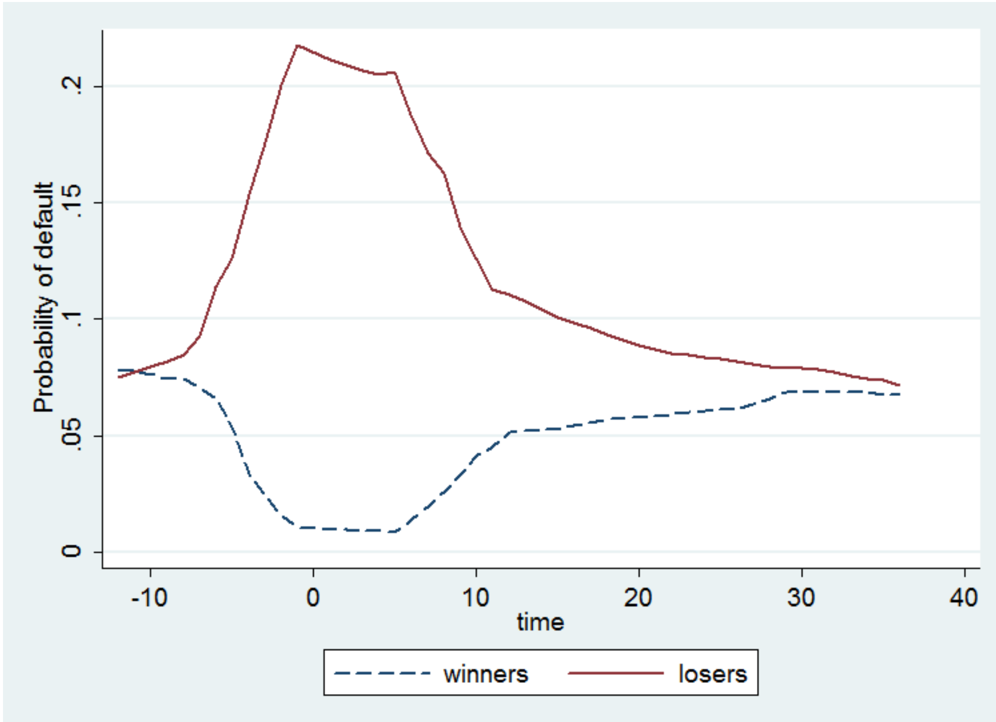

Fig. 2.4. Probability of Default of Losers and Winners Over Time.

This figure 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.

winners and losers before and after the formation period. Specifically, we document that probability of default spread between losers and winners is temporary. Winners (losers) experience a drop (increase) in the probability of default before the formation period and an increase (decline) afterwards.

2.4.3 Tangibility Discussion

In Section 2.2.2 we document that winners have higher tangibility of than losers. In this section we attempt to answer the question why we observe this behavior. Also, according to Figure 2.3, tangibility of winners (losers) increases (decreases) before and decreases (increases) after the formation period. This result is particular

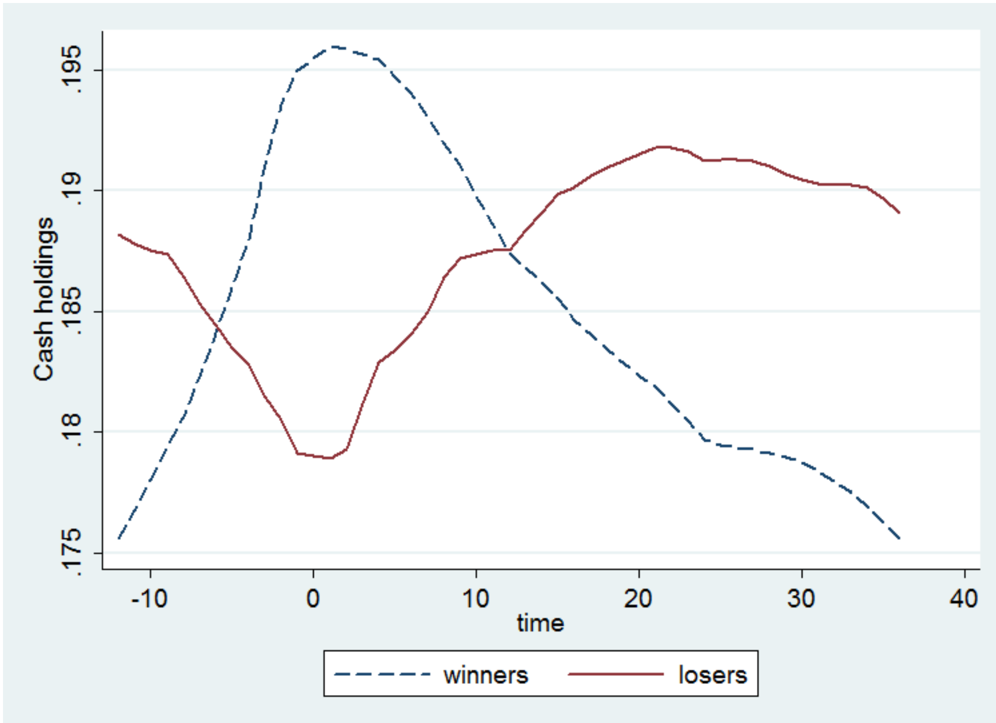

Fig. 2.5. Cash Holdings of Losers and Winners Over Time.

This figure presents the dynamics of the cash holding component (defined as the ratio of cash holdings to total book assets) for winners and losers before and after the formation period. For every month t from January 1960 to December 2009, we calculate average cash holdings of losers and winners for month $t+k$, where $k = -12, \ldots, +36$. We then average cash holdings for $t+k$ across portfolio formation months.

interesting, because the structure of the real assets of the firm tends to be stable overtime. One of the possible explanations of this result is that the cash component is the major determinant of the "tangibility effect." Indeed, it is much easier to change the cash holdings of the firm rather than its plant property and equipment.

First, we hypothesize that losers have lower tangibility, because they have relatively lower cash holdings. Second, we propose that losers are likely to be more cash-constrained, than winners because of poor previous equity performance. By definition, losers have experienced a decline in price and, therefore, market value over the previous 6 months. Thus, it is potentially more difficult for them to raise cash, because in periods of high default shocks their bankruptcy probability increases and credibility decreases. On the other hand, winners should have easier time raising cash due to their superior market performance. Therefore, short-term default shocks are not likely to affect their credibility. In other words, current equity performance could affect the future cash holdings of the firm.

We examine the importance of the cash component in tangibility dynamics using the previously described procedure. Figure 2.5 presents the dynamics of the cash component (defined as the ratio of cash holdings to total book assets) for winners and losers before and after portfolio formation. For every month t from January 1960 to December 2009, we calculate average cash holdings of losers and winners for month $t+k$, where $k = -12, \ldots, +36$. We then average cash holdings for $t+k$ across portfolio formation months.

According to our results the cash component is a major determinant of the "tangibility effect." Figure 2.5 supports our hypothesis that losers are likely to be cash-constrained firms. Moreover, the time-series dynamics of cash holding closely follows the dynamics of tangibility. We document a sharp decline in the cash holdings of losers during the portfolio formation period and an increase afterwards.[11]

[11]The dynamics of other components is similar, however less pronounced.

Table 2.11

Cross-section Regressions of Cash Holding on Lagged Equity Returns.

This table presents the cross-sectional firm fixed-effects regressions of the cash holding of the firms (defined as the ratio of cash holdings to total book assets) on lagged equity returns (RET_{t-i}). We matched quarterly cash holdings with monthly return data. The t-statistics from the regressions are presented in the parenthesis below. The sample period is from 1960 to 2009.

	MODEL (1)	MODEL (2)	MODEL (3)	MODEL (4)	MODEL (5)	MODEL (6)	MODEL (7)
RET_{t-4}	0.01593						0.01535
	(37.53)						(37.12)
RET_{t-5}		0.01574					0.01599
		(37.36)					(37.88)
RET_{t-6}			0.01582				0.01729
			(37.90)				(41.28)
RET_{t-7}				0.01536			0.01670
				(36.78)			(39.86)
RET_{t-8}					0.01472		0.01605
					(35.02)		(38.07)
RET_{t-9}						0.01493	0.01616
						(35.28)	(38.12)

We then further investigate the relation between previous equity performance and future cash holdings. Table 2.11 presents firm fixed-effect regressions of the cash holdings of the firm on previous stock returns. Models 1 through 7 document that lagged returns have consistently positive coefficients. In other words, historical stock returns can affect current cash holdings. Therefore, it is likely that poorly (well) performing firms will have lower (higher) cash holdings in the future. This result provides additional support to the conjecture that losers are cash-constrained firms that are likely to have a hard time raising cash in periods of high default.

2.5 Robustness Tests

2.5.1 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 (2.4) with SMB and HML. Therefore, we examine the model of the following form

$$R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \epsilon_{i,t}, \tag{2.10}$$

where, SMB and HML stand for the size and value factors, respectively.[12] To estimate factor risk premia, we follow the procedure described in Section 2.1.3 and use 30 test assets: 10 momentum, 10 size, and 10 book-to-market portfolios.

Panel A of Table 2.12 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 β^{CDEF} spread between losers and winners is still negative and significant (-3.35 with a t-statistics of -2.49). Model 1 of Table 2.13 presents the second stage of the Fama and MacBeth (1973) estimation. The magnitude of the conditional default premium declines from -72 to -45 basis points, however, the factor remains statistically significant.

Further, Liu and Zhang (2008) link the growth rate of industrial production MP[13] 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 by augmenting the MP factor to the model (2.4)

$$R^e_{i,t} = \beta_i + \beta_i^{MKTRF} MKTRF_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \beta_i^{MP} MP_t + \epsilon_{i,t}, \quad (2.11)$$

---

[12]The SMB and HML factors are obtained from Kenneth R. French's web site.

[13]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.

Table 2.12

Beta Loadings Controlling for Other Risk Factors.

Panel A of this table presents the loadings for the returns of each of the 10 momentum portfolios on the market β^{MKTRF} , default shocks β^{DEF}, conditional default shocks β^{CDEF}, SMB (β^{SMB}) and HML (β^{HML}) factors. Panel B presents the same analysis, but controlling for the growth rate of industrial production (β^{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	β^{MKTRF}	t-stat	β^{DEF}	t-stat	β^{CDEF}	t-stat	β^{SMB}	t-stat	β^{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	β^{MKTRF}	t-stat	β^{DEF}	t-stat	β^{CDEF}	t-stat	β^{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

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

Panel B of Table 2.12 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 2.13 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 are correlated. Finally, in Model 3 of Table 2.13, 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 2.2, 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 in this section suggest 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.

Table 2.13

Conditional Default Premium Controlling for Other Risk Factors.

This table 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. 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

2.5.2 Alternative Momentum Strategies

We have showed thus far that 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 2.14 reports the CDEF loadings of momentum portfolios controlling for the market and unconditional default shocks variables in equation (2.4). 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 2.14 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 2.14

Alternative Momentum Strategies.

Panel A of this table 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 (β^{CDEF}_{6-1-12} and β^{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 calculated from the Shanken (1992) method.

Portfolio	β^{CDEF}_{6-1-12}	t-stat	β^{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

2.6 Concluding Remarks

There are two main findings in this paper. First, we show that momentum profitability is concentrated in periods of high default shocks. Specifically, losers have low expected returns in states of high aggregate default. Since high default shocks occur both in expansions and recessions, it is not the general state of economic conditions that drives momentum profitability. This result is in contrast with previous studies that document that momentum profits are more pronounced during expansions. In addition, this finding is in line with previously documented results that momentum exists only among high credit risk stocks. Since high credit risk stocks are more sensitive to high default states of nature, the time-series and cross-sectional results on the relation between momentum and default are in line with each other.

Then we 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. The conditional default factor is negatively priced and has high economic significance. Furthermore, losers have a positive conditional default loading, while winners have a negative conditional default loading. These results suggest that losers (winners) perform better (worse) than the CAPM predicts during periods of high default shocks. The combined effect of a negative 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. Such studies include Jegadeesh and Titman (1993), Fama and French (1996), Grundy and Martin (2001), Griffin, Ji, and Martin (2003), and Moskowitz (2003), among others. Our results suggest that behavioral arguments are not necessary to explain momentum. Momentum profits are consistent with a risk-based explanation.

3. SOURCES OF MOMENTUM IN BONDS

In this section, we study the relation between momentum in bond returns and aggregate default risk. We find that positive momentum profits in the corporate bond market is primarily documented during worsening aggregate default conditions (high default shocks), and the observed momentum profits are primarily driven by losers. Because bankruptcy concerns increase at the firm-level during periods of high default shocks, this is reminiscent of a conditional factor model that depends on aggregate default risks. Indeed, we find that a conditional default factor is priced, accounting for a large amount of the cross-sectional variation in corporate bond portfolios. To explain this, we develop a simple theoretical model of "default-risky" bonds with a no-arbitrage condition and show that the seemingly puzzling behavior of bond momentum can be explained in a rational expectation framework. We predict that expected bond returns will depend on default risk and the ability of bondholders to recover firm value in default, and provide empirical support for this proposition. Winners (losers) have relatively lower (higher) recovery potential and therefore, become riskier (less risky) in high default states of the world. This leads to the documented *conditional* momentum profits. Because our prediction is based on "default-risky" bonds, we would only expect to find these results for bonds with nonzero default risk. Consistent with our expectations, we find that U.S. government bonds feature no momentum, while sovereign bonds exhibit positive momentum.

Following a standard momentum methodology (Jegadeesh and Titman (1993)), we create momentum portfolios based on corporate bond returns. Consistent with much of the previous literature (Khang and King (2004), Gebhardt, Hvidkjaer, and Swaminathan (2005b)), we do not find statistically significant momentum in the corporate bond market in general. However, in their recent work Jostova, Nikolova, Philipov, and Stahel (2011) report that the momentum effect exists in corporate bond returns. They find that, similar to equity momentum (Avramov, Chordia, Jostova, and Philipov (2011)), bond momentum is primarily driven by firms with low credit ratings (speculative grade bonds). Further, Mahajan, Petkevich, and Petkova (2011) show that equity momentum is strongly related to aggregate default. After controlling for unexpected default shocks, we discover that momentum does in fact exist for bond returns, but only when high default shocks occur. We also confirm the finding of Jostova, Nikolova, Philipov, and Stahel (2011) that the momentum anomaly is primarily found in corporate bonds with high credit risk. This suggests that the impact of aggregate default on bond momentum is conditional on the state of the economy.

Indeed, our tests indicate that the response of corporate bond prices to default shocks varies over time in a systematic way. Specifically, to explain the performance of the momentum portfolios of corporate bonds, we augment the model that typically incorporates the market and term-structure premia with default and conditional default factors (conditional on being a high default shock state). According to our results, the conditional default loadings of bond winners (losers) is positive (negative) implying that they should have relatively higher (lower) risk and expected returns. Moreover, the conditional default factor is priced in the cross-section of momentum bond portfolios and can explain a large portion of the "anomalous" performance.

Motivated by these findings and the results from a companion paper of this work examining stock return momentum (Mahajan, Petkevich, and Petkova (2011)), we theoretically explain bond momentum based on bondholder recovery using a simple model of risky debt valuation with a no-arbitrage restriction. The model predicts that bondholders' ability to recover value in default should become more important than the default premium during periods of high default shocks. In addition, the model predicts that if winners (losers) are on average less (more) risky, but have lower (higher) recovery value for bondholders. Therefore, momentum profits will prevail in periods of high aggregate default risk, and become ambiguous in low default periods.

Thus, this simple model provides an explanation for bond return momentum in a rational expectation framework.

A key assumption for our theoretical explanation of bond momentum is a negative relationship between expected bond returns and bondholder recovery. To verify this link empirically, we follow Garlappi and Yan (2011) and proxy for recovery using estimates of the tangibility, the specificity of the assets held by the bond issuing firms, and R&D expenditures. Garlappi and Yan (2011) find that shareholders have differing ability to recover residual value from the firm should the firm default on its debt obligations depending on firm characteristics, such as the tangibility and specificity of the particular firm's assets. We argue that, because recovery of value through liquidation in default constitutes a zero-sum game between bond and stock owners, bondholders' ability to recover value in default will vary by firm as well. Based on Garlappi and Yan (2011), we introduce three measures of bondholder recovery: the firm's tangibility of assets, industry Herfindahl index, and ratio of R&D expenditures to total assets. Tangibility is calculated as the ratio of inventory, equipment, receivables and cash to the total book value of assets and represents the expected liquidation value of the firm. Bondholders of low tangibility firms should expect lower liquidation value in default, and thus lower ability to recover value through liquidation. Therefore, the bondholders of low tangibility firms should face higher risk during periods of high default shocks and require higher expected returns. On the other hand, bondholders of high tangibility firms should have higher recovery and, therefore, lower risk and returns. The second measure of bondholder recovery is based on the industry's Herfindahl index (the concentration of industry sales), representing the specificity of the firm's assets and, essentially, liquidation costs. High (low) Herfindahl index firms should have relatively higher (lower) asset specificity and, as a result, are more difficult (easier) to liquidate, yielding higher (lower) risk and required returns. In either case, bondholders of low recovery firms should face higher risk, especially in periods of high default shocks, and should require higher returns. Finally, as we discuss in detail later, the ratio of R&D expenditures to (book) total assets represents product specialization and growth options. Again, bondholders of high R&D firms will have lower potential recovery and, therefore, should require a premium in periods of high aggregate default.

Using these measures of bondholder recovery, we show that bonds in the "loser" portfolio have relatively higher recovery potential in general. As a result, these bonds should have relatively lower risk in periods of high default shocks and, therefore, produce lower returns. We further document that winners tend to have lower recovery on average and, thus, bondholders of these securities should face higher risk during high default states of the world, leading to higher returns. This result supports the prediction from our theoretical model that, in high default states of the world, recoverability plays a key role in driving the observed momentum anomaly in the corporate bond market. Moreover, we present evidence suggesting that in the corporate bond market the recovery premium primarily exists in high default states, and the default premium is more pronounced during low default shocks. Taken together these results provide a strong support to the prediction of the theoretical model.

Our interpretation of the results is based on the proposition that corporate bonds face nonzero default risk, making bondholder recovery in default an important underlying driver of momentum in bond returns. If this is in fact the driving force behind observed momentum returns, we would expect no momentum in a market where bonds have (nearly) zero default risk. Thus, we extend this study to examine the momentum effect in the U.S. government and sovereign bond markets. According to our proposition, the momentum effect is driven by the difference in sensitivities between winners and losers to the conditional default factor. Using this argument, we should not observe any momentum in securities that have little sensitivity to default shocks. Indeed, we document that US government bonds are not sensitive to default shocks and, as a result, there is virtually no momentum in these bonds. On the other hand, many sovereign bonds have potential default concerns (for example, the Russian government defaulted on obligations in 1998) and, therefore, we expect to observe momentum in the sovereign market. Consistent with this prediction, we find that sovereign bonds exhibit positive momentum in times of high default and negative momentum in times of low default. Taken together, these results help to support our proposition that momentum is liked to aggregate default risk.

Our work contributes to a large literature on momentum returns and a growing literature focusing on momentum in bond markets. Jegadeesh and Titman (1993) first discover that momentum strategies produce positive returns that commonly accepted asset-pricing models cannot explain. The majority of subsequent studies of momentum returns focus on equity momentum, but a number of recent works examine momentum in other markets. Khang and King (2004) analyze bond momentum, but do not find statistically significant momentum in the corporate bond market in general. Gebhardt, Hvidkjaer, and Swaminathan (2005b) reconfirm that momentum in corporate bonds is insignificant; however, the authors find that equity momentum spills over to the bond market. In other words, bonds of equity winners continue to do well, and bonds of equity losers tend to underperform. However, the evidence of momentum in bond returns is mixed. Jostova, Nikolova, Philipov, and Stahel (2011) observe momentum in bonds, and find that this anomaly is more pronounced after 1994. And, despite a litany of empirical evidence, commonly accepted asset-pricing models generally fail to explain the momentum puzzle.[14]

We provide a number of contributions to the momentum literature. First, this paper adds to the newly developing literature on bond momentum, which has shown rather mixed results regarding the existence of momentum in bond returns. We report evidence suggesting that, in the time-series, momentum in corporate bonds ex-

[14]Fama and French (1996) show that the market, SMB and HML factors cannot capture momentum profitability. Griffin, Ji, and Martin (2003), testing the theoretical model of Chen, Roll, and Ross (1986), incorporates innovations in macro-economic variables and shows this also cannot explain momentum.

ists and depends on the state of economy-wide default shocks. This result allows us to reconcile the mixed findings from the existing empirical literature (Gebhardt, Hvidkjaer, and Swaminathan (2005b), Jostova, Nikolova, Philipov, and Stahel (2011)). Second, we show that bond momentum can be explained by a conditional default factor. Third, in the cross-section, we find that corporate bond losers have relatively lower bondholder recovery than winners and, thus, have lower risk and returns during high default shocks. Finally, we extend the analysis to the US government and sovereign bond markets. Consistent with our risk-based explanation, we find that momentum is observed in sovereign bonds, which are more likely to have default concerns, but not in US government bonds. Together, this evidence provides support for a risk-based explanation for momentum returns, driven by the risk faced by bondholders in default. To best of our knowledge no other work has provided a risk-based explanation to this puzzle consistent with rational expectations, empirically or theoretically.

3.1 Corporate Bonds Momentum and Aggregate Default Shocks

3.1.1 Data and Portfolio Construction

We begin by obtaining bond returns, the number of bonds in the issue, and prices from DataStream. We include all US corporate bonds that are traded in the US market and have all necessary information available in DataStream. Because of thin coverage of the bond market in the early 1990s, we restrict the sample period to begin in January of 1995 and include all data through December of 2010. To estimate measures of bondholder recovery, we also include firm financial data from Compustat.

We exclude from the sample all convertible bonds and asset-backed securities. The sample contains information from 5123 individual corporate bonds. To correct for potential data errors and to make sure that the results are not driven by outliers, we follow Jostova, Nikolova, Philipov, and Stahel (2011) and exclude all observations with returns above 50% per month. In addition, to ensure that the results are not driven by small and non-liquid bonds, we exclude securities with market capitalizations that would place them below 5th percentile of the total bond market capitalization. We then follow Gebhardt, Hvidkjaer, and Swaminathan (2005a) and estimate corporate bond returns using the following approach.

$$r_{i,t} = \frac{(P_{i,t} + AC_{i,t} + C_{i,t}) - (P_{i,t-1} + AC_{i,t-1})}{P_{i,t-1} + AC_{i,t-1}}, \tag{3.1}$$

where, $r_{i,t}$ is return on bond i at time t; $P_{i,t}$ is the price of the bond; AC is the accrued interest at the end of the month t; and C represents any coupon payments that have been made between t and $t-1$.

To create bond momentum portfolios, we follow Jegadeesh and Titman (1993) and sort bonds into deciles based on the cumulative performance over the formation period ($t-7$ to $t-1$). The bonds are equally-weighted within each decile. The top decile is comprised of recent winners and the bottom decile contains recent losers. We skip a month after the formation periods to avoid short-term reversals. The momentum strategy assumes buying recent winners and selling recent losers. The portfolios are rebalanced every month and then held for 6 months (we refer to this strategy as 6-1-6).

Table 3.1 presents simple summary statistics for the portfolios from January 1995 to December 2010. The first impression from the data is that the bond momentum strategy does not appear to be profitable in our sample on average (the return to the bond momentum strategy is 17 basis points per month and not statistically significant). We also find that the distributions of the bond momentum portfolios do not differ substantially. The standard deviation of losers appears to be only slightly higher than winners (2.80% vs. 1.71%, respectively). This provides little evidence of momentum in the bond market on average.

Table 3.1
Summary Statistics of Bond Momentum.

This table presents descriptive statistics for equally-weighted momentum portfolios over the period from 1995 to 2010. The bond momentum portfolios are based on the 6-1-6 strategy. Portfolios L and W are comprised of loser and winner bonds, respectively. Basic descriptive statistics, such as mean, median, standard deviation and percentiles are presented in the subsequent columns.

Portfolios	Mean	Std.	5%	25%	Median	75%	95%
L	0.79%	2.80%	-2.72%	-0.27%	0.77%	1.76%	4.89%
Portfolio 2	0.71%	2.00%	-2.18%	-0.31%	0.76%	1.68%	3.74%
Portfolio 3	0.69%	1.96%	-2.38%	-0.42%	0.72%	1.80%	3.54%
Portfolio 4	0.67%	1.94%	-2.48%	-0.36%	0.81%	1.74%	3.51%
Portfolio 5	0.69%	1.84%	-2.19%	-0.39%	0.84%	1.74%	3.51%
Portfolio 6	0.68%	1.84%	-2.17%	-0.46%	0.80%	1.80%	3.34%
Portfolio 7	0.64%	1.82%	-2.34%	-0.52%	0.76%	1.79%	3.08%
Portfolio 8	0.67%	1.86%	-2.34%	-0.43%	0.84%	1.76%	3.37%
Portfolio 9	0.72%	1.74%	-2.41%	-0.27%	0.89%	1.82%	3.15%
W	0.96%	1.71%	-2.06%	-0.03%	0.99%	2.01%	3.61%
W - L	0.17%	2.12%	-2.42%	-0.46%	0.26%	1.06%	3.05%

3.1.2 Bond Momentum Conditional on Shocks to Default

The existing empirical evidence of bond momentum is mixed. Khang and King (2004) do not find statistically significant momentum in corporate bonds returns. Gebhardt, Hvidkjaer, and Swaminathan (2005b) report that past winners tend to underperform past losers in the corporate bond market, but also find that equity momentum spills over to bonds, suggesting that corporate bond momentum may be security specific. On the other hand, Jostova, Nikolova, Philipov, and Stahel (2011) show that the momentum anomaly exists among corporate bonds. They argue that there is a link between bond momentum and credit risk by documenting that this anomaly is more pronounced among speculative grade bonds (low credit ratings).

We attempt to reconcile these seemingly contradictory results by exploring the profitability of the momentum strategy in bonds conditional on shocks to aggregate economy-wide default. Mahajan, Petkevich, and Petkova (2011) present evidence suggesting that equity momentum is sensitive to default shocks. Motivated by their results, as well as the previous literature, we conjecture that the bond momentum premium exists in a state dependent fashion.

To better understand the behavior of the corporate bond momentum premium in the time-series, we compose a measure that captures unexpected changes in aggregate default. We use unexpected default because it is potentially better suited for describing default risk exposure, as it is less likely to be predicted by the market. Following Mahajan, Petkevich, and Petkova (2011), we first define the aggregate default premium as the yield spread between Moody's CCC corporate bond index and the 10-year Treasury bond. Default shocks are then estimated as the residual of the following AR(2) model:

$$DEF_t = \alpha_0 + \alpha_1 DEF_{t-1} + \alpha_2 DEF_{t-2} + \xi_t, \tag{3.2}$$

where, DEF_t is the default premium at month t. Aggregate default shocks are captured by ξ_t. An increase (decrease) in the residuals corresponds to higher (lower) shocks to aggregate default.[15] However, this approach employs the data that is not available during the period being analyzed. To avoid the potential look-ahead bias we estimate model (3.2) using a recursive cumulative procedure.[16] Specifically, we estimate the model using the pre-sample period (from January of 1954 to December of 1959). We then add one observation to the sample and re-estimate the model using the updated time-series. We repeat this procedure (keep adding one observation) until we obtain the estimates for every observation in the sample. Therefore, the residual at any time t is conditional on the data from January 1954 to $t-1$.

An alternative interpretation of ξ_t is that the minus default shock $(-\xi_t)$ can be viewed as an approximated holding period return of a long CCC and a short Treasury bond portfolio, provided that DEF_t is persistent.[17] This facilitates a risk-based explanation of our empirical results.

We now document momentum in corporate bond returns conditional on default shocks. Based on the current momentum literature, we hypothesize that corporate bond momentum is likely to be observed during periods of high default shocks. Table 3.2 presents the performance of bond momentum conditional on high and low default states of the world. Panel A documents the returns of winners and losers for the entire sample period (1995-2010). Panels B and C, presents the results of the earlier (1995-2002) and later (2003-2010) periods.

[15]In this paper we use the median of the distribution to split the sample.

[16]The results based on the unadjusted shocks are similar and available upon request.

[17]Specifically, the following approximation holds if n is sufficiently larger than 1: $DEF_t - DEF_{t-1} \approx -\frac{1}{n}(R_t^{CCC} - R_t^{Tr})$, where $R_t = -\ln P_t/n$, and P_t is the price of this asset and n is the remaining maturity. In addition, the sum of estimated α_1 and α_2 is indeed close to 1, confirming the persistence of DEF_t. Then $-\xi_t \approx \frac{1}{n}(R_t^{CCC} - R_t^{Tr})$.

Table 3.2

Bond Momentum Portfolio Returns Conditional on Default Shocks.

This table documents returns on the bond portfolios formed based upon a sorting procedure conditional on aggregate default shocks (residuals from (3.2)) over the period from 1995 to 2010.The returns to 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 of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). Panel A presents results from the whole sample. Panel B and Panel C present analysis of earlier (1995-2002) and later (2003-2010) periods.

	W	L	W - L
Panel A. Total sample			
High Default	0.80%	0.19%	0.61%
	(4.56)	(0.71)	(3.35)
Low Default	1.19%	1.45%	-0.26%
	(6.99)	(4.99)	(-1.05)
Total	0.98%	0.79%	0.19%
	(8.01)	(3.90)	(1.28)
Panel B. Period from 1995 to 2002			
High Default	0.96%	0.54%	0.42%
	(4.25)	(2.24)	(2.79)
Low Default	0.75%	1.13%	-0.38%
	(2.73)	(3.37)	(-1.79)
Total	0.87%	0.84%	0.02%
	(4.98)	(3.97)	(0.18)
Panel C. Period from 2003 to 2010			
High Default	0.62%	-0.21%	0.84%
	(2.25)	(-0.34)	(2.51)
Low Default	1.57%	1.61%	-0.04%
	(7.85)	(3.65)	(-0.28)
Total	1.11%	0.74%	0.37%
	(6.34)	(2.13)	(1.33)

Consistent with the results of Khang and King (2004), we do not find a significant difference between the performance of losers and winners in corporate bonds in the sample. In particular, Panel A shows that the momentum strategy (W - L) produces 19 basis points (not statistically different from zero). However, after conditioning on high and low default states of the world, we observe positive momentum returns during high default shocks (61 basis point with a t-statistic of 3.35), and almost identical performance of losers and winners in low default states. The difference is -26 basis points with a t-statistic of -1.25. Thus, it appears that momentum does occur in bond returns, but is state-dependent. This finding extends the result of Jostova, Nikolova, Philipov, and Stahel (2011) by showing that corporate bond momentum is related to both firm-level and aggregate-level default.

However, one might argue that this result is primarily observed in early periods of the sample when temporary mispricing is more likely to occur. Moreover, if bond momentum is driven by mispricing or market inefficiency, it should decline over time. Therefore, we also test whether positive momentum profits in high default states decline over time. For this test, we split the sample into two subperiods: 1995-2002 and 2003-2010. As shown in Panels B and C of Table 3.2, the performance of momentum increases during the latter period (42 and 84 basis points for the 1995-2002 and 2003-2010 periods, respectively). While the magnitude of the momentum effect in the later part of our sample appears larger, we find that the difference between the two subsamples is not statistically significant. Hence, this result suggests that momentum is directly affected by aggregate default conditions rather than temporary mispricing.

Chordia and Shivakumar (2002) and Stivers and Sun (2010) argue that equity momentum is likely to be observed during "good times"[18] We further investigate the relation between the profitability of bond momentum and general economic conditions by presenting a double sorting procedure on both business cycles and aggregate default shocks. Figure 3.1 presents the results of this analysis. We document that the majority of the momentum performance is documented under very specific circumstances, namely, at the intersection of recessions and high default shocks. The total performance of momentum during these periods is 1.77% per month. Note that momentum is also positive in periods of high default shocks (49% per month). Finally, during periods of expansions and low default states, there is virtually no difference between the returns of winners and losers. This suggests that the momentum premium is strongly correlated with aggregate default shocks in the time-series.

To summarize, we document that the overall profitability of momentum in corporate bonds is essentially zero (based on the Data Stream sample). However, after conditioning on high states of default, we observe that momentum is positive and significant during these periods and zero otherwise. This finding suggests that the state-dependent nature of the corporate bond risk premium may generate the seemingly contradictory evidence about the existence of momentum in corporate bonds. This also suggests that the conditional aggregate default risk should be priced, and that the returns of winners and losers will have different sensitivities to this conditional risk factor. We verify these in the following sections.

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[18]Chordia and Shivakumar (2002) define the periods of expansions (as defined by the National Bureau of Economic Research) as "good times". Stivers and Sun (2010) suggest that low cross-sectional dispersion in recent stock returns correspond to "good times."

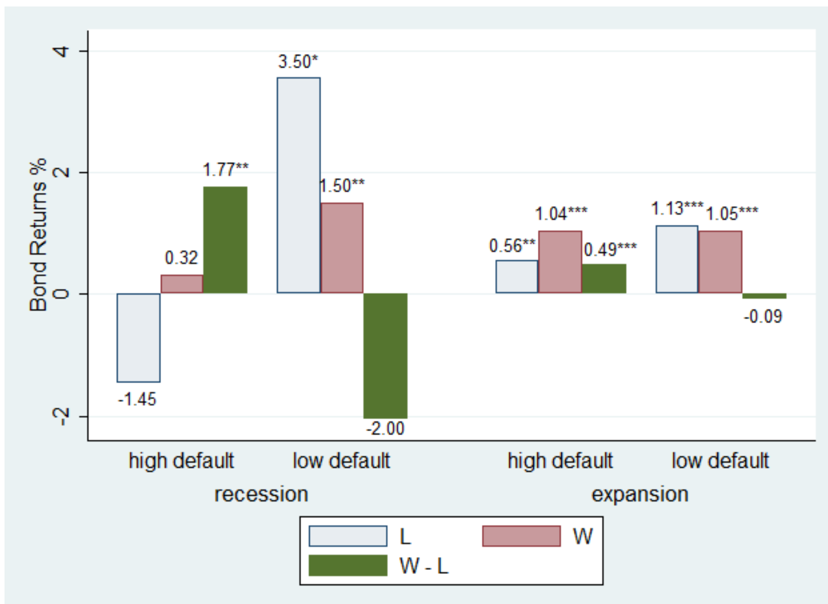

Fig. 3.1. Bond Momentum Portfolio Returns Conditional on Default Shocks and on Business Cycles.

This figure documents returns on portfolios formed based upon a sorting procedure conditional on both business cycles and aggregate default shocks (residuals from (3.2)) over the period 1995 - 2010.

3.1.3 Pricing the Conditional Default Risk Factor

This section presents evidence suggesting that momentum portfolios have different exposure to unexpected default shocks in the corporate bond market. To capture this result, we present an empirical asset pricing model that incorporates the commonly accepted factors of bond returns and a factor depicting unexpected default shocks. Fama and French (1993) argue that besides the standard market, SMB, and HML factors, the default (DEF) and term (TERM) premia should be included in the model to capture the cross-sectional variation of bond returns. Further, Gebhardt, Hvidkjaer, and Swaminathan (2005a) suggest that DEF and TERM are major determinants of bond returns and should be examined separately. We begin with a general model that includes the main drivers that appear in both models:

$$R^e_{i,t} = \beta_i + \beta_i^{MKT} MKT_t + \beta_i^{TERM} TERM_t + \beta_i^{DEF} DEF_t + \epsilon_t, \tag{3.3}$$

where, $R^e_{i,t}$ corresponds to the excess return on portfolio i; MKT, TERM[19] and DEF stand for the market, term structure and default premiums, respectively. However, our hypothesis is based on the assumption that the bond momentum portfolios are sensitive to unexpected shocks to aggregate default rather than the simple default premium. To test this proposition, we substitute shocks to default ξ_t (as defined in (3.2)) into the model in place of DEF.

The majority of the current bond empirical literature focuses on unconditional models. We argue that the momentum premium in corporate bonds is conditional on high unexpected default risks. Therefore, we follow Mahajan, Petkevich, and

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[19]Following Gebhardt, Hvidkjaer, and Swaminathan (2005a), we estimate TERM as the difference in the thirty-year government bond returns (from the DataStream database) and one month treasury bill returns (from CRSP).

Petkova (2011) and introduce a conditional default factor that allows the default betas to be time-dependent.

$$C\xi_t = I_t\xi_t, \tag{3.4}$$

where, ξ_t represents the shock to aggregate default in month t as defined in (3.2).[20] I_t is an indicator that takes a value of 1 during high default shocks and 0 otherwise. As a result, the conditional default factor ($C\xi_t$) captures the additional default exposure when the economy is in a high default state. Hence, the model can be written as:

$$R^e_{i,t} = \beta_i + \beta_i^{MKT} MKT_t + \beta_i^{TERM} TERM_t + \beta_i^{DEF}\xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_t. \tag{3.5}$$

Specifically, we are interested in the default β_i^{DEF} and conditional default β_i^{CDEF} factors. While β_i^{DEF} measures the sensitivity of momentum portfolios to default shocks, β_i^{CDEF} estimates the additional effect of default shocks during high default states. As a result, the total effect of high default shocks is captured by the sum of two coefficients ($\beta_i^{DEF} + \beta_i^{CDEF}$). In addition, as discussed in the previous section, $-\xi_t$ can be regarded as the risk premium related to aggregate default. Thus, $-\beta_i^{DEF}$ and $-\beta_i^{CDEF}$ will be comparable to conventional betas in linear factor models of asset prices.

Since the loadings in the model (3.5) are not directly observable, we estimate these for every asset separately in the time-series using the entire sample. Rolling window estimators are not appropriate in this case, because the time-variability of default betas should be efficiently captured by the conditional default factor. We follow a standard Fama and MacBeth (1973) procedure to estimate the risk premiums for each of the factors. To control for the errors-in-variables problem, we apply the correction for standard errors proposed by Shanken (1992).

[20] Note that shocks are estimated using a cumulative recursive procedure described in section 3.1.2.

The beta loadings of (3.5) are presented in Table 3.3. We find that the difference in the market loadings (β^{MKT}) of winner and loser portfolios is negative and statistically significant. This implies that corporate bond losers are more sensitive and riskier, which makes the reversal anomaly, rather than the momentum anomaly, a more likely result. Consistent with Acharya, Amihud, and Bharath (2011), we observe a positive β_i^{TERM}; however, the spread in term loadings of losers and winners is not significant. Thus, we can infer that both the stock and Treasury market factors matter in explaining corporate bond returns, yet cross-sectional variations from the momentum strategies are not well accounted for by these conventional factors. We now turn to the default factors. As discussed earlier, to interpret the default betas in a consistent manner with the market betas, we report $-\beta_i^{DEF}$ and $-\beta_i^{CDEF}$. We show that losers are riskier ($-\beta_L^{DEF}$ is 1.07) than winners ($-\beta_W^{DEF}$ is 0.34) on average, but losers are safer ($-\beta_L^{CDEF}$ is -0.33) than winners ($-\beta_W^{DEF}$ is 0.28) in high default states of the world. The total effect of default risks on losers is 0.74 ($1.07 - 0.33$), while the total effect for winner is 0.62 ($0.34 + 0.28$). More importantly, the spread of conditional default loadings between losers and winners is 61 basis points with a t-statistic of 2.13.

Taken together, these results suggest that corporate bond losers are on average riskier, as suggested by the market and unconditional default betas, yet become relatively safer than winners in high default states of world and, as a result, have lower expected returns. Further, whether bond momentum prevails is a quantitative concern, depending on which effect dominates. Our findings allow us to reconcile the mixed results on corporate bond momentum. Because default shocks generate the opposite directions of risk exposures between losers and winners, the overall effect can be ambiguous.

To estimate factor premiums in the cross-section, we follow the Fama and MacBeth (1973) procedure and use 30 momentum-based portfolios in equation (3.5). Table 3.4 reports the time-series means of these premiums. Even though the MKT

Table 3.3
Factor Loadings Estimates.

This table presents the time-series estimates the loadings for the returns of each of the 10 bond momentum portfolios on the market β^{MKTRF}, term structure β^{TERM}, default risks $-\beta^{DEF}$ and conditional default risks $-\beta^{CDEF}$. W and L represent the portfolios of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). The equally-weighted portfolios are based on the 6-1-6 strategy. The sample period is from 1995 to 2010. The t-statistics from the regressions are based on Huber-White standard errors.

Portfolio	β^{MKTRF}	t-stat	β^{TERM}	t-stat	$-\beta^{DEF}$	t-stat	$-\beta^{CDEF}$	t-stat
L	0.23	3.69	0.29	5.30	1.07	2.73	-0.33	-1.88
2	0.12	2.31	0.40	8.02	0.64	2.47	-0.29	-1.74
3	0.09	2.34	0.46	10.01	0.48	1.46	-0.16	-0.92
4	0.08	1.92	0.47	9.58	0.44	1.63	-0.06	-0.27
5	0.06	1.83	0.47	10.11	0.37	1.17	0.00	0.01
6	0.05	1.62	0.46	8.57	0.30	1.43	0.11	0.68
7	0.05	1.49	0.45	8.42	0.28	1.13	0.18	1.25
8	0.04	1.23	0.45	8.11	0.28	1.22	0.21	1.68
9	0.03	1.04	0.41	7.96	0.27	1.23	0.26	1.69
W	0.06	2.04	0.33	7.13	0.34	1.36	0.28	1.89
W - L	-0.17	-3.81	0.04	0.91	-0.73	-1.64	0.61	2.13

premium is positive and significant in Model (1), the adjusted R^2 is low (0.29), suggesting that missing factors are needed in the model. Augmenting the model with the term and default factors improves the R^2; however, only the term premium is significant in this specification. Moreover, our previous results in Table 3.3 suggest that the term loadings of winners and losers do not differ significantly and, therefore, cannot explain momentum profits. Finally, in Model (4) we augment the model with the conditional default factor. Consistent with Mahajan, Petkevich, and Petkova (2011), the conditional default premium (-CDEF) is positive and significant (0.0060 with a t-statistic of 2.21).

Table 3.4

Pricing Time-varying Aggregate Default Risks in the Cross-section.

This table presents estimated monthly risk premiums based on the Fama-MacBeth proceedure and using 30 bond momentum portfolios. MKT is the excess return on the market, TERM represents the term structure premiums and defined as the difference in the thirty-year government bond returns and one month treasury bill returns. DEF is aggregate default shocks estimated proxies by the residual of (3.2), $CDEF$ is the conditional default aggregate 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. T-statistics based on the Shanken (1992) method are reported in parentheses below. The sample period is from 1995 to 2010. To be consistent with Table 3 and the conventional return-only factor pricing model, $-DEF$ and $-CDEF$ are reported.

	MODEL (1)	MODEL (2)	MODEL (3)	MODEL (4)
MKT	0.0177	0.0048	0.0050	0.0252
	(1.95)	(0.49)	(0.50)	(1.59)
TERM		-0.0142	-0.0147	-0.0100
		(-2.25)	(-2.41)	(-1.75)
-DEF			0.0018	0.0035
			(0.51)	(0.79)
-CDEF				0.0060
				(2.21)
CONST	0.0034	0.0094	0.0098	0.0062
	(2.26)	(4.07)	(3.31)	(1.91)
$Adj.R^2$	0.29	0.54	0.57	0.63

One interpretation of these results is that winners do not necessarily outperform losers. The results suggest that winners become riskier during high default states of the world, and, thus, are rewarded with higher returns. This result also suggests that the conditional default factor can explain a large portion of momentum profits in periods of high default shocks. In particular, the -CDEF beta spread between losers and winners ($-(\beta_W^{CDEF} - \beta_L^{CDEF}) = 0.61$) multiplied by the premium ($-CDEF = 0.0060$) explains approximately 36.6 basis points of momentum profits. The difference between momentum performance in high and low default states is 87 basis points, implying that the conditional default factor explains approximately 42% of momentum profits in corporate bonds. To summarize, these results provide additional evidence in support of a risk-based explanation of momentum. We find that momentum profits in corporate bonds are only positive in high default states of the world and the conditional default factor can explain a large part of these profits.

3.2 Sources of Momentum in Bonds

The empirical results thus far point to the claim that bond losers may be relatively safer than bond winners in high default states of the world. One possible explanation for this result is based on differences in potential bondholder recovery in financial distress. This section provides a theoretical framework that incorporates bondholder recovery into a bond pricing model to show that explanation is theoretically reasonable. Following our theoretical framework, we present empirical results using proxies for bondholder recovery that support our theoretical predictions.

3.2.1 Theoretical Framework

In this section, we offer a theoretical explanation for our empirical findings based on a no-arbitrage bond pricing model. In particular, we use a reduced-form valuation model to derive corporate bond returns. Denote the price of a zero-coupon corporate debt with maturity n at time t by $D_t^{(n)}$. Then, with a no-arbitrage condition, we can write the pricing formula of $D_t^{(n)}$ as

$$D_t^{(n)} = \phi_{t,t+1} E_t \left[M_{t+1} D_{t+1}^{(n-1)} \right] + (1 - \phi_{t,t+1}) E_t \left[M_{t+1} X_{t+1} \right], \tag{3.6}$$

where M_{t+1} is the stochastic discount factor, $(1-\phi_{t,t+1})$ is the risk-neutral conditional probability of default at $t+1$ conditional on the fact that this bond has not filed for bankruptcy before t, and X_{t+1} is the recovery value if default (or an event of financial distress) occurs. $\phi_{t,t+1}$ is assumed to be adapted at t. We suppress the notation for issuer for the time being. If we further assume that X is a fraction η of total firm value (denoted as V), say $X_t = \eta_t V_t$. Then,

$$D_t^{(n)} = E_t \left[M_{t+1} \left(\phi_{t,t+1} D_{t+1}^{(n-1)} + (1 - \phi_{t,t+1}) \eta_{t+1} V_{t+1} \right) \right], \tag{3.7}$$

or alternatively

$$1 = E_t \left[M_{t+1} \left\{ \phi_{t,t+1} + (1 - \phi_{t,t+1}) \frac{\eta_{t+1} V_{t+1}}{D_{t+1}^{(n-1)}} \right\} \frac{D_{t+1}^{(n-1)}}{D_t^{(n)}} \right]. \tag{3.8}$$

Then, taking logs of both sides, we obtain

$$0 = \log E_t \left[M_{t+1} \Pi_{t+1} \frac{D_{t+1}^{(n-1)}}{D_t^{(n)}} \right], \tag{3.9}$$

where,

$$\Pi_{t+1} \equiv \phi_{t,t+1} + (1 - \phi_{t,t+1}) \frac{\eta_{t+1} V_{t+1}}{D_{t+1}^{(n-1)}}. \tag{3.10}$$

Thus, corporate bond returns will depend on the default-related discount factor (3.10) as well as the conventional discount factor M_{t+1}. To gain more insight from this pricing equation, define $\log D_{t+1}^{(n-1)}/D_t^{(n)}$ as the holding period return (r_{t+1}) on this corporate bond, and approximate it as follows:

$$
\begin{aligned}
E_t(r_{t+1} - r_t^f) \approx & - Cov_t\left(m_{t+1}, r_{t+1}\right) - Cov_t(\pi_{t+1}, r_{t+1}) \\
& - E_t\left(\pi_{t+1}\right) - \frac{1}{2} Var_t\left(\pi_{t+1}\right) - Cov_t\left(m_{t+1}, \pi_{t+1}\right),
\end{aligned}
\tag{3.11}
$$

where, m and π are the logarithms of M and Π respectively. Focusing on the first two terms related to the risk premium, we can rewrite the above return-beta relationship (3.11) as

$$
\begin{aligned}
& E_t(r_{t+1}^i - r_t^f) \approx -Cov_t(m_{t+1}, r_{t+1}^i) \\
& - \left(1 - \phi_{t,t+1}^i\right) \left[Cov_t\left(\log \eta_{t+1}^i, r_{t+1}^i\right) + Cov_t\left(\log \frac{V_{t+1}^i}{D_{t+1}^i}, r_{t+1}^i\right)\right],
\end{aligned}
\tag{3.12}
$$

where, the superscript i refers to an issuer. The equation states that the risk premium for holding a corporate bond comes from the covariations of returns with the aggregate wealth (m_{t+1}), and those with the default risk. The former is important in describing the risk premium of all risky assets. However, according to our empirical results, this term does not appear to account for the momentum profits. Thus, our main interest centers on the latter term. The default premium for a corporate bond consists of two terms. The first covariance is related to the recoverability of the bond in case of the bankruptcy. A higher value of η means that this bond is safer when the issuer declares default, hence the sign of this covariance is negative so that the risk premium is positive. The second term for the default risk premium refers to the covariations between bond returns and the logarithm of the ratio of the firm value to debt. Intuitively, the firm value will become lower and closer to the value of debt if default is more likely.[21] Thus, it is natural to view that this covariance is also negative such that the default risk premium is positive. This risk premium

[21]This argument implicitly assumes that $D^{(n)}$ is a constant fraction of the total amount of debt.

decomposition turns out to be useful in understanding the conditional momentum in corporate bonds.

Suppose that there are two bond issuers w (winner) and l (loser). We assume that w has more intangible capital such as human capital and organizational skills, while l has more tangible and recoverable capital which is easier to liquidate in case of bankruptcy. Now, the momentum strategy yields

$$\begin{aligned} E_t(r^w_{t+1} - r^l_{t+1}) \approx Cov_t\left(-m_{t+1}, r^w_{t+1} - r^l_{t+1}\right) - \left(1 - \phi^w_{t,t+1}\right) Cov_t(\log \eta^w_{t+1}, r^w_{t+1}) \\ + (1 - \phi^l_{t,t+1}) Cov_t(\log \eta^l_{t+1}, r^l_{t+1}) - \left(1 - \phi^w_{t,t+1}\right) Cov_t(\log \frac{V^w_{t+1}}{D^w_{t+1}}, r^w_{t+1}) \\ + (1 - \phi^l_{t,t+1}) Cov_t(\log \frac{V^l_{t+1}}{D^l_{t+1}}, r^l_{t+1}). \end{aligned} \tag{3.13}$$

Logically, if default is indeed a serious concern for both issuers, the second and the third terms in the right hand side of (3.13) become important, because the cash flow in the event of bankruptcy becomes a highly probable outcome.[22] Given the assumption that winners (losers) have lower (higher) recoverability in case of default, $|Cov_t(\log \eta_{t+1}, r_{t+1})|$ is higher for the winner, because the issuer w is more sensitive to random changes in bond recoverability especially when default is more likely. This produces positive a risk premium from the momentum strategy as default is near.

For the covariance between $\log(V/D)$ and bond returns, since the distance to default is short in this case, we can infer that the firm value V is approaching D such that $\log V/D$ converges to zero. Thus, these covariances can approach a zero

[22]It is possible to build a model that establishes this link, but to focus on the asset pricing implications, we do not pursue this further. In a somewhat different setting, Garlappi and Yan (2011) provide a similar theory. To make our exposition easy, assume that $1 - \phi$ is the same between w and l.

value. In addition, if default shocks are highly systematic in that both winners and losers show similar covariations, these terms can be cancelled out.[23] Therefore, in the states of high aggregate default risks, winners become riskier mainly due to the lower recoverability for bondholders. Put differently, when default becomes a probable event, larger weights are given to post-default cash flows in determining the corporate bond risk premium.

In the case of low aggregate default states, the conditional default likelihood $(1-\phi_{t,t+1})$, the absolute values of $Cov_t(\log \eta_{t+1}, r_{t+1})$ and $Cov_t(\log V_{t+1}/D_{t+1}, r_{t+1})$ tend to be small, hence the bond risk premium are similar to those of default-free bonds. Having said that, our empirical result documents that losers are riskier on average than winners. Given that $\left|Cov_t(\log \eta^w_{t+1}, r^w_{t+1})\right| > \left|Cov_t(\log \eta^l_{t+1}, r^l_{t+1})\right|$, $\left|Cov_t(\log V^l_{t+1}/D^l_{t+1}, r^l_{t+1})\right|$ is greater than $\left|Cov_t(\log V^w_{t+1}/D^w_{t+1}, r^w_{t+1})\right|$ because, otherwise, the issuer w should be unconditionally riskier contrary to the empirical finding. This makes the sign of (3.13) in the low default states ambiguous, and the momentum strategy does not generate significantly positive profits during the regime of low aggregate default shocks due to the offsetting effects. Thus, our empirical results are consistent with a risk-based model of asset prices, provided that winners (losers) have low (higher) recoverability in the event of bankruptcy.

To summarize, we make several predictions from the model. First, expected bond returns contain a recovery component. Second, there is a risk premium for securities with low bondholder recovery in high default states, and, therefore, buying high recovery and selling low recovery bonds should generate a positive premium. Finally, according to our model the recovery premium should be mainly observed in high default states, which amplifies the risk premium due to the bond recoverability.

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[23] A related implication is that the bonds which are subject to higher default risks will show more pronounced effects. For instance, this conditional nature of momentum should prevail more conspicuously among junk bonds, if the theory is true. This is indeed verified in the next section.

This premium does not necessary exist in low default states because of the additional covariance terms between the distance to default and bond returns. In the next sections we empirically examine these predictions.

3.3 Bondholder Recovery, Default Risk, and Conditional Premia

Our empirical results so far indicate that winners are relatively riskier during periods of high default shocks, while losers are riskier on average, and we derived a theoretical framework that explains this phenomenon using the recoverability of corporate bonds. In this section, we uncover fundamental characteristics of bond issuing companies that can justify the difference in the expected returns of losers and winners in periods of high default shocks.

3.3.1 Bondholder Recovery

Motivated by the predictions of our theoretical model, we attempt to confirm empirically that the different exposure to the conditional default factor for winners and losers is driven by bondholder recovery. We hypothesize that the ability to recover value in default plays an important role in determining the risk of bonds in high and low default states of the world. Our predictions are reminiscent of the results of Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011), who examine the relation between bankruptcy risk and expected equity returns conditional on shareholder recovery. Specifically, the authors show that for high shareholder recovery firms, expected returns to equity should be low when bankruptcy risk is high. This occurs because the shareholders of these firms will have high bargaining power in the process of distress negotiations, reducing the risk of the firm's equity when default risk is high. We use this logic to argue that the same should hold in the corporate bond market. First, it is important to note that recovery in default should be a zero-sum game between bond and equity holders, holding constant the value of the firm's assets in default. High bargaining power for shareholders stems from a lower amount of value that bondholders would claim through liquidation, i.e. high shareholder recovery corresponds to low bondholder recovery. To capture this aspect we introduce three different measures of bondholder recovery based on the firm's tangibility, asset specificity, and potential growth options.

The tangibility measure of bondholder recovery is based on the expected liquidation value of the firm. Bondholders of firms with high asset tangibility should recover a relatively larger portion of value in cases of financial distress. Therefore, the bondholders of high tangibility firms should face relatively lower risk in high default states of the world, and, as a result, should require lower expected returns. Using the same logic, the bondholders of a firm with low tangibility should recover less and, thus, become relatively riskier during high default periods. We measure tangibility using the proxies of recovery per dollar from the previous empirical literature. Berger, Ofek, and Swary (1996) argue that more general assets produce higher liquidation value. In particular, they find that claim holders will recover 71.5 cents on the dollar for receivables, 54.7 cents per dollar of inventory, and 53.5 cents per dollar of property plant and equipment. Additionally, claim holders should recover 100% of cash holdings. We calculate tangibility as

$$Tng = \frac{(0.715 \times Receivables + 0.547 \times Inventory + 0.535 \times PPE + Cash)}{TotalAssets}. \tag{3.14}$$

All else equal, the bondholders' ability to recover value in default will be high if the tangibility of the firm's assets is high.

The second proxy of bondholder recovery is based on the specificity of the firm's assets. Shleifer and Vishny (1992) argue that redeployable assets[24] should have

[24] In the context of this paper, redeployable assets can have other alternative usage that is not specific to a particular industry.

higher liquidation value, because they can be successfully used for production in other industries. This is especially important during periods of high default states of the world, when firms are likely to experience more problems leading to asset sales below their potential value. All else equal, assets should be more readily redeployed when there are numerous firms in the same industry that could make use of the assets. In other words, firms in highly concentrated industries should have a smaller market in which to sell their assets in liquidation (more specific assets) and, hence, should have higher liquidation costs and lower liquidation value in bankruptcy. We measure the specificity of assets using the firm's two-digit SIC industry Herfindahl index based on sales. This is calculated as:

$$HI_{j,t} = \sum_{i=1}^{N_{j,t}} s_{i,t}^2, \tag{3.15}$$

where, $s_{i,t}$ represents sales of firm i at time t as a proportion of total sales of its' industry j. Firms with a high (low) Herfindahl index should have relatively higher (lower) asset specificity and, therefore, should have higher (lower) liquidation costs and lower (higher) bondholder recovery.

Finally, the last measure of bondholder recovery is measured by the ratio of R&D expenditures to book total assets. Opler and Titman (1994) suggest that high R&D firms should have higher product specialization. Additionally, such firms are also more likely to have potential growth options. Thus, it will be more difficult to liquidate these firms, leading to lower bondholder recovery and higher risk and returns in periods of high default shocks.

Using each measure of bondholder recovery, we find that winners have relatively lower bondholder recovery in general. Panel A of Table 3.5 shows that the average tangibility of winners is lower than the tangibility of losers (0.44 vs. 0.46 for winners and losers respectively), and the difference is statistically significant (t-statistics of -4.48). We also observe that losers are more likely to be found in less concentrated industries, suggesting that these firms have more redeployable assets and, as a result, lower liquidation costs in default. On the other hand, winners are more likely to belong to high concentration industries, implying more specific assets and lower liquidation value. We find the difference in Herfindahl's index between winners and losers is significant (1.17% with a t-statistic of 6.56). Finally, we show that the R&D ratio of winners is higher (3.95% vs. 3.39%, respectively). In sum, all measures of bondholder recovery suggest that winners have lower recovery on average and, therefore, should have higher risk and higher expected returns during periods of high aggregate default shocks.

Table 3.5

Bondholder Recovery and the Probability of Financial Distress of Winners and Losers.

This table documents the bondholder recovery and financial distress of losers (L) and winners (W) . Panel A presents the average bondholder recovery of winners and losers using the tangibility measure reflecting the expected liquidation value of the firm, 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. Panel B 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 1995 to 2010. The numbers in parentheses represent simple time-series t-statistics for the average monthly measures financial distress and shareholder recovery.

	W	L	W - L
Panel A. Bondholder recovery			
Tangibility	0.44	0.46	-0.02
			(-4.48)
Herfindahl index	8.18%	7.01%	1.17%
			(6.56)
R&D ratio	3.95%	3.39%	0.56%
			(3.27)
Panel B. Financial distress			
Z-score	1.65	1.38	0.27
			(6.35)
Probability of Default	2.65%	9.70%	-7.05%
			(-7.40)

Overall, our analysis suggests that winners can be characterized by lower expected liquidation value and higher asset specificity. In either case, bondholders of winners should be more affected by higher liquidation costs and require higher returns. These concerns should be especially relevant in high default states of the world when default risk is higher and firms are "cheap."

3.3.2 Default Risk

Our results indicate that losers are more sensitive to unexpected changes in aggregate default. Thus, we can hypothesize that losers have higher risk of financial distress on average and, thus, are more affected by unexpected increases in aggregate default, but become less risky when the economy is in a high default risk state. The purpose of this section is to test this proposition.

We use two measures to document the relation between momentum portfolios and firm level default risk. The first measure is based on Bharath and Shumway (2008).[25] The authors start with the assumption that equity is valued as a European call option on the total value of the firm. However, to calculate this measure of firm distance to default, one needs to estimate unobservable parameters. Bharath and Shumway (2008) argue that 1) the market value of debt can be approximated by 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.[26] Then, "naive" distance to default can be defined as:

$$DD_{naive} = \frac{ln[(E+F)/F] + (r_{i,t-1} - 0.5\sigma_V^2)T}{\sigma_V\sqrt{T}}, \tag{3.16}$$

[25] A similar approach was introduced by Vassalou and Xing (2004) and Campbell, Hilscher, and Szilagyi (2008).

[26] This is essentially an extension of the Merton (1974) model.

where E and F stand for the market value of equity and the face value of debt, respectively, σ_V is the standard deviation of the firm's value, and T is the estimation period. Therefore, the naive *probability* of default is

$$\pi_{naive} = N(-DD_{naive}). \tag{3.17}$$

However, one potential concern is that this measure of default risk incorporates historical returns, and consequently, could be related to momentum. To address this issue, we incorporate the modified Altman Z-score as an alternative measure. This measure of individual distress risk is based solely on financial statement data and should not be directly related to momentum. We follow Graham, Lemmon, and Schallheim (1998) and calculate this measure as:

$$\text{Z-score} = \frac{1.2 \times WC + 1.4 \times RE + 3.3 \times EBIT + SALES}{TA}, \tag{3.18}$$

where WC, RE, $EBIT$, and $SALES$ represent working capital, retained earnings, earnings before interest and taxes, and sales, respectively. TA stands for the book value of total assets.

Our previous findings indicate that losers have higher sensitivities to unexpected shocks to aggregate default. We hypothesize that this is observed due to the fact that losers have higher bankruptcy risk on average. Panel B of Table 3.5 presents the results of this analysis. Indeed, it appears that losers have lower Z-scores than winners (the difference is 0.27 and statistically significant with a t-statistics of 6.35). Similarly, we find that the probability of default for losers is 7.05% higher than for winners. This difference is statistically significant from zero (t-tatistics is 7.40).

In summary, our results suggest that losers are more sensitive to default and are also likely to have higher bondholder recovery. Therefore, the difference in conditional default betas between losers and winners is potentially driven by the difference in bondholder recovery. More importantly, the recovery argument comes into play under certain conditions. Namely, it should mainly happen during periods of high default shocks, which makes default risk conditional on high shocks.

3.3.3 Conditional Default and Recovery Premia

In this part of the paper we examine two important implications of the theoretical framework presented in this paper. The first prediction suggests that the default premium should be less important during high default states of the world. We argue that in these extreme economic conditions the performance of winners and losers is similar; therefore, the potential default premium of losers becomes less important. Second, our model predict that recovery premium of winners should become more important during high default shocks, leading to higher winner performance and, therefore, momentum.

To test these predictions we sort bonds in high and low bondholder recovery portfolios using the median values of tangibility. Similarity, we split the sample in high and low default portfolios using credit ratings. Then we estimate the recovery (default) premium as a difference between low and high tangibility (credit rating) portfolios for every month of sample.

The results of this analysis are presented in Table 3.6. According to Panel A of the table, there is almost no difference between performance of low and high tangibility (recovery) bonds during periods of low default shocks (-0.04% not statistically different from zero). However, when economy experience unexpected increase in aggregate default, low tangibility tend to outperform high tangibility bonds. The difference is 21 basis points with a t-statistics of 3.76. One of the possible explanations of this result is that bondholders of low tangibility bonds face higher risk during periods of high default, because of lower potential recovery in case of forced liquidation. On the other hand, in periods of low aggregate default the "recovery effect" is less important, because of unexpectedly low likelihood of outright liquidation. Thus, there is no difference in returns of low and high tangibility portfolios.

Table 3.6

Conditional Recovery and Default Premia.

This table documents the bondholder recovery and financial distress premia conditional on aggregate default shocks (residuals from (3.2)) over the period from 1995 to 2010. Panel A show conditional performance of low, high, and low minus high (bondholder recovery premium) tangibility portfolios. Panel B documents conditional performance of low, high, and low minus high (default premium) credit rating portfolios. The numbers in parentheses represent simple time-series t-statistics.

	High Default Shocks	Low Default Shocks	High - Low Shocks
Panel A. Conditional recovery premium			
Low Tng	0.82%	0.71%	0.11%
	(4.20)	(4.81)	(0.44)
High Tng	0.62%	0.75%	-0.21%
	(3.11)	(4.09)	(-0.75)
Low - High Tng	0.21%	-0.04%	0.24%
	(3.76)	(-0.67)	(3.05)
Panel B. Conditional default premium			
Low Rating	0.74%	0.94%	-0.20%
	(3.51)	(4.85)	(-1.68)
High Rating	0.75%	0.57%	0.18%
	(3.80)	(3.02)	(0.66)
Low - High Rating	-0.01%	0.37%	-0.38%
	(-0.10)	(3.14)	(-2.14)

Panel B of Table 3.6 documents the conditional default premium. We find that in this case the performance of low and high rated bonds is essentially the same during periods of high default shocks. The difference is -0.01% and it is not statistically different from zero. However, in high default states of the world low rated bonds outperform high rated bonds by 37 basis points with a t-statistics of 3.14. This evidence provides additional support to our hypothesis that default premium is likely to be more pronounced in low aggregate default states.

Overall, we confirm the predictions of our theoretical model. Specifically, we show that the recovery "effect" is mainly observed in periods of high default shocks and the default premium is more pronounced during low default shocks. Therefore, bonds winners outperform losers during high default shocks, because they have low recovery and higher risk during these economic conditions, which leads to observed conditional momentum in high default states.

3.4 Robustness Checks

In this section we present robustness checks. First, we confirm the previous evidence of Jostova, Nikolova, Philipov, and Stahel (2011) and link bond momentum to firm-level default. We expect that bond momentum will be primarily observed at the intersection of high firm and aggregate level defaults. Second, taking into account that low credit risk bonds drive momentum returns, we examine whether the difference in the conditional default loadings between winners and losers remains for different credit risk groups. Third, we extend our analysis to the sovereign bond and US government bond markets. Since sovereign bonds are likely to contain a default component and US government default risk should approach to zero (at least in theory), we expect to find some weak evidence of momentum among sovereign bonds and no momentum in US government bonds. Finally, we explore the wealth transfer effect between equity and bondholders of the same firm.

3.4.1 Bond Momentum and Conditional Default Shocks by Credit Risk Group

Jostova, Nikolova, Philipov, and Stahel (2011) document that momentum in the bond market is primarily driven by high credit risk bonds. Specifically, they show that non-investment grade bonds are more likely to be concentrated in winner and loser portfolios, and, therefore, they argue that excluding non-investment grade bonds from the sample leads to zero momentum profits.

Given our results thus far, we propose that high credit risk bonds (low rated) are more sensitive to aggregate default than low credit risk (high rated). Thus, momentum in the corporate bond market is driven by high credit risk bonds during periods of high default. This would also help to explain why bond momentum is difficult to observe. The majority of studies have concentrated on investment grade bonds (Gebhardt, Hvidkjaer, and Swaminathan (2005b)) without conditioning on states of the world. Under our framework, we would expect that it will be difficult to observe momentum among investment grade bonds, because they are less likely to be affected by recovery.

To test this proposition, we estimate the performance of the momentum strategy conditional on default shocks for subsamples with different credit risk. We follow Avramov, Chordia, Jostova, and Philipov (2011) and assign numeric values to each credit rating[27] (1 represents AAA rating and 22 corresponds to D). We then drop high credit risk bonds (D and lower) from the total sample and repeat our previous analysis for this subsample. Additionally, we exclude bonds with ratings below CCC+ from the sample and, finally, we exclude bonds rated below BBB.

The result of this approach is presented in Table 3.7. The equally-weighted returns of the momentum strategy (based on a 6-1-6 strategy) are estimated conditionally on default shocks (as defined by residuals of (3.2)). Panel A of Table 3.7

[27]The credit ratings of bonds are obtained from DataStream.

presents the results for the subsample of bonds with credit ratings from AAA to C. Consistent with our previous results, momentum in the corporate bonds market is only significant in periods of high default shocks (41 basis points with a t-statistic of 2.49). Furthermore, after excluding bonds with ratings below CCC+, momentum performance declines, but remain positive and significant (27 basis points with a t-statistics of 1.71). Finally, in Panel C, we exclude all bonds with ratings below BBB, and the returns to the bond momentum strategy become negative for both high and low default shock periods. First, these results support the conclusion of Jostova, Nikolova, Philipov, and Stahel (2011) that momentum is primarily driven by high credit risk bonds. Moreover, we extend this result by documenting a link between momentum profits and aggregate default shocks. Note that high default shocks are necessary for positive momentum; Panel A of Table 3.7 shows that even including high credit risk bonds in the sample does not generate positive momentum during periods of low default shocks.

3.4.2 CDEF Loadings by Credit Risk Group

This section continues the analysis of different credit risk groups. Jostova, Nikolova, Philipov, and Stahel (2011) find that momentum in bonds is primarily driven by high credit risk bonds. Therefore, we hypothesize that the spread of CDEF loadings should disappear for the subsample of low credit risk bonds. We argue that bonds with lower credit ratings are more sensitive to unexpected changes in aggregate default. As we discussed in Section 3.3.1, one possible explanation of the momentum anomaly is based on bondholder recovery. However, the bondholder recovery argument is likely to be more important for high credit risk firms and in high default states of the world. In other words, we suggest that bondholder recovery affects performance through the aggregate and firm-level default risks.

To test this proposition, we follow the previously described methodology (Section 3.1.3). We estimate equally-weighted returns of the momentum portfolios based the

Table 3.7

Momentum in Corporate Bonds by Credit Risk Group.

This table presents returns of momentum portfolios formed based upon a sorting procedure using aggregate default shocks (residuals from (3.2)) over the period from 1995 to 2010. 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 the sample based on bonds with ratings from AAA to C, AAA to CCC+, and AAA to BBB, respectively. The numbers in parentheses represent simple time-series t-statistics for the average monthly returns.

	W	L	W - L
Panel A. AAA to C			
High Default	0.76%	0.35%	0.41%
	(4.14)	(1.60)	(2.49)
Low Default	0.99%	1.29%	-0.30%
	(6.00)	(4.64)	(-1.39)
Panel B. AAA to CCC+			
High Default	0.71%	0.45%	0.27%
	(3.96)	(1.78)	(1.70)
Low Default	0.92%	1.31%	-0.39%
	(5.46)	(5.34)	(-1.98)
Panel C. AAA to BBB			
High Default	0.78%	0.68%	0.10%
	(4.32)	(3.42)	(0.72)
Low Default	0.66%	1.05%	-0.38%
	(3.63)	(4.98)	(-2.31)

6-1-6 momentum strategy. We then estimate the CDEF loadings (β^{CDEF}) for every portfolio using (3.5) using different credit risk groups. The results of this approach are presented in Panel A of Table 3.8. First, we estimate (3.5) for the subsample of bonds with ratings C and higher. The CDEF loadings (β^{CDEF}_{AAA-C}) of losers and winners are 0.29 and -0.41, respectively. More importantly, the difference in the CDEF loadings between losers and winners is significant (t-statistics 2.02). This result is consistent with our previous finding that losers are relatively safer than winners in high default states of the world. We then repeat this analysis for the subsample of bonds with credit ratings CCC+ and higher. In this case, the CDEF spread between winners and losers decreases and becomes insignificant (0.48 with a t-statistics of 1.55). Finally, we exclude from the sample bonds rated below BBB, and the spread becomes even smaller (0.39 with a t-statistics of 1.12). Further, we continue with the estimation of the price of conditional default risk using the Fama and MacBeth (1973) procedure and the Shanken (1992) adjustments of standard errors. The results are consistent with our prediction that after excluding low rated bonds from the sample, the price of conditional default risk is no longer significant.

Taken together, our results indicate that momentum in the corporate bond market is primarily driven by high credit risk bonds during unexpected increases in aggregate default. Specifically, after excluding bonds with high credit ratings, the momentum returns disappear in both high and low default periods. Moreover, the difference between the CDEF loadings between losers and winners becomes insignificant.

3.4.3 Momentum in Government and Sovereign Bonds

Our results thus far indicate that momentum exists in corporate bonds and it is driven by bondholder recovery in high default states of the world. We assume that default risk of the US government bonds should approach zero. Therefore, there is should be no difference between the CDEF factor loadings of winners and losers, and, hence, no difference in expected returns, and no momentum.

Table 3.8

Fama-MacBeth by Credit Group.

Panel A of this table reports loadings for the returns of each of the 10 bond 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 1995 to 2010. The conditional default loading are estimated from the following model - $R^e_{i,t} = \beta_i + \beta_i^{MKT} MKT_t + \beta_i^{TERM} TERM_t + \beta_i^{DEF} \xi_t + \beta_i^{CDEF} C\xi_t + \epsilon_t$. β^{CDEF}_{AAA-C}, $\beta^{CDEF}_{AAA-CCC+}$, and $\beta^{CDEF}_{AAA-BBB}$ represent the CDEF loadings of the momentum portfolios based on samples with different credit risk. The t-statistics from the regressions are based on Huber-White standard errors. Panel B presents estimated monthly premiums of the conditional default factor based on the Fama-MacBeth procedure and using 30 portfolios sorted on momentum. The Fama-MacBeth t-statistics calculated from the Shanken (1992) method. To be consistent with Table 3, Table 4 and the convention of return-only factor pricing models, $-\beta$'s and $-CDEF$ are displayed.

Portfolio	$-\beta^{CDEF}_{AAA-C}$	t-stat	$-\beta^{CDEF}_{AAA-CCC+}$	t-stat	$-\beta^{CDEF}_{AAA-BBB}$	t-stat
Panel A. CDEF loadings						
L	-0.41	-1.71	-0.32	-1.24	-0.33	-1.25
2	-0.31	-1.14	-0.31	-1.17	-0.31	-1.60
3	-0.21	-0.96	-0.23	-1.06	-0.19	-1.04
4	-0.06	-0.29	-0.06	-0.27	-0.13	-0.68
5	-0.01	-0.07	-0.02	-0.11	-0.10	-0.53
6	0.07	0.35	0.08	0.37	0.05	0.22
7	0.12	0.48	0.11	0.45	0.03	0.14
8	0.20	0.82	0.15	0.65	0.04	0.20
9	0.22	1.16	0.17	0.66	0.10	0.44
W	0.29	1.63	0.17	0.72	0.06	0.27
W-L	0.69	2.02	0.48	1.55	0.39	1.12
Panel B. Price of conditional default risk						
-CDEF	0.0037	1.98	0.0027	1.71	-.0008	-0.28

On the other hand, sovereign bonds may have some default component, and, as a result, different recovery rates. One of the most famous examples is the Russian default of 1998. Similar events also unfolded in Argentina in late 2001. There is also empirical evidence implying that sovereign bonds can be affected by default. For example, Pan and Singleton (2008) use the data from Mexico, Turkey, and Korea to document that the sovereign CDS spreads reflect default risk and it is related to unpredictable future variation in credit-event arrival intensity. Hence, we argue that momentum can exist in sovereign bond markets, because such bonds have some default component by definition. However, we do not expect the momentum anomaly to be large in magnitude, because the default component in sovereign bonds is rather small. Finally, we do not expect to observe any momentum in US government bonds due to insignificant default risk.

To test this proposition, we estimate the performance of the 6-1-6 momentum strategy for US government and sovereign bonds. The data is obtained from the DataStream database. We include all government bonds traded in the US market. Following Jostova, Nikolova, Philipov, and Stahel (2011), we drop observations with returns above 50% per month. The period of the sample is from 1995 to 2010.

Panel A of Table 3.9 documents the performance of the momentum strategy based on US government bonds conditional on high and low default shocks. We observe that aggregate default shocks do not affect the momentum based on US government bonds based on the entire sample. While losers tend to outperform winners on average, the difference is not significant (-12 basis points with a t-statistics of -1.34). Further, it appears that in high default states the performance of winners and losers increases; however, it increases at the same rate, and, as a result, there is no significant momentum.

In Panel B of Table 3.9, we document the returns of losers and winners in sovereign bonds traded in the US market, conditional on default shocks. First, we note that the momentum anomaly does not exist for the full sample (-3 basis points with a t-statistics of -0.23). However, after conditioning on aggregate default, we document positive (negative) momentum in periods of high (low) default states of the world. Note that the difference in performance of losers and winners is only weakly significant.

Table 3.9

US Government and Sovereign Bond Momentum Portfolio Returns Conditional on Default Shocks.

This table documents returns on the bond portfolios formed based upon a sorting procedure conditional on aggregate default shocks (residuals from (3.2)) over the period from 1995 to 2010.The returns to 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 of winners and losers, respectively. Momentum corresponds to the hedge portfolio (W - L). Panel A presents results using US government bonds. Panel B document documents this relation for sovereign bonds that traded on the US market.

	W	L	W - L
Panel A. US government bonds			
High Default	0.68%	0.73%	-0.05%
	(2.72)	(-0.44)	(-0.41)
Low Default	-0.36%	-0.17%	-0.20%
	(-1.29)	(2.21)	(-1.48)
Total	0.18%	0.30%	-0.12%
	(1.06)	(1.58)	(-1.34)
Panel B. Sovereign bonds			
High Default	0.31%	0.04%	0.27%
	(1.76)	(0.11)	(1.69)
Low Default	-0.01%	0.37%	-0.38%
	(-0.06)	(1.72)	(-1.73)
Total	0.19%	0.22%	-0.03%
	(1.08)	(0.99)	(-0.23)

Overall, these results suggest that momentum is indeed related to the credit risk characteristics of bonds. We show that there is no momentum in US government bonds, consistent with the limited exposure of this type of asset to credit risk. On the other hand, sovereign bonds likely incorporate some nonzero default risk, and as a result we find weak evidence of momentum in this type of security.

3.4.4 Wealth Transfers between Bonds and Equity Holders

This section presents evidence suggesting that recovery affects the performance of bonds and equity of the same firm differently. Mahajan, Petkevich, and Petkova (2011) argue that shareholders of equity losers have high bargaining power (low tangibility) and, therefore, become relatively safer during high default states. Using the same intuition, we propose that bond losers should have high bondholder recovery (high tangibility), which should lead to lower expected returns during periods of high default shocks.

First, we test the prediction of the theoretical model suggesting that recovery effects are more pronounced during high default states of the world. The probability of bankruptcy in these states is higher on average and, therefore, potential recovery concerns become important. Second, we examine the wealth transfer hypothesis. We propose that an increase in tangibility leads to higher risk and expected stock returns because of decreasing shareholder bargaining power in periods of high default shocks. On the other hand, we expect that bond returns decline in tangibility, because lower tangibility is equivalent to lower bondholder recovery (given that these are debt and equity holders of the same firms, low bondholder recovery also means high shareholder bargaining power), leading to higher risk and expected bond returns. In other words, during periods of high default shocks, we should observe a wealth transfer from equity (bond) to bond (equity) holders if tangibility is low (high).

To test these propositions, we match the returns of bonds and equity for firms in the sample. We then sort firms into quintiles based on their tangibility (as defined in (3.14)) and estimate equally-weighted returns of bonds and equity for these portfolios. Using (3.2), we split the sample into periods of low and high default shocks using previously described cumulative recursive procedure and calculate the returns of the portfolios conditional on default shocks.

Table 3.10 presents the results of this analysis. We find the evidence supporting the theoretical prediction that both equity and debt returns of low and high tangibility portfolios do not differ significantly during periods of low default shocks. Specifically, we show that the difference in stock returns between high and low tangibility companies is -34 basis points with a t-statistic of -0.69. Similarly, we find that tangibility does not affect the bond returns of the firms in low default states (the difference is -3 basis points with a t-statistics of -0.31). In other words, recovery does not affect firms' performance if the economy experiences unexpected declines in aggregate default.

On the other hand, during the high default states of the world, we observe that bond returns decrease and stock returns increase as tangibility increases. In particular, Panel B of Table 3.10 shows that the bonds of low tangibility firms outperform the bonds of high tangibility firms by 23 basis points on average. Furthermore, equity performance of high tangibility firms is 93 basis points higher than of low tangibility firms. The difference between performance of high and low tangibility firms is statistically significant in both cases. This result supports our proposition that tangibility drives the returns of both bonds and equity, and in the opposite direction, in periods of high default shocks. As we already discussed in Section 3.3.1, bond losers have higher bondholder recovery (higher tangibility) than winners. Therefore, bond losers become safer during the periods of high default states of the world partially due to risk shifting from bond to equity holders. Similarly, bond winners become relatively riskier due to risk transfer from equity and bond holders.

More importantly, these results provide evidence of wealth transfers between bond and equity holders that are concentrated in periods of high default shocks. Figure 3.2 documents that bondholders have positive returns and shareholders have negative returns for low tangibility firms (high shareholder recovery and low bondholder recovery). Given that these are matched by company, shareholders appear to earn lower returns while the return to bondholders increases. This implies that low expected liquidation value in periods of high default shifts risk from equity to bond holders. It is likely that bondholders of firms with a low concentration of tangible

Table 3.10

Tangibility and Performance of Bond and Equity Conditional on Default Shocks.

This table documents the performance of equity and bonds conditional on default shocks. To comprise the sample we matched bonds and equity of the same firms and sorted them based on tangibility (as defined in (3.14)). Low (high) tangibility portfolio is based on the firms with bottom (top) 20% of tangibility. High and low aggregate default shocks are defined based on residuals from (3.2)). Panel A presents the equally-weighted equity and bond returns of high and low tangibility firms during periods of low default shocks. Panel B present a similar analysis for high default shocks. The sample period is from 1995 to 2010. The numbers in parentheses represent simple time-series t-statistics.

	Low Tng	High Tng	Low - High Tng
Panel A. Low default shocks			
Bond returns	0.81%	0.84%	-0.03%
			(-0.31)
Equity returns	2.13%	2.47%	-0.34%
			(-0.69)
Panel B. High default shocks			
Bond returns	0.70%	0.48%	0.23%
			(2.68)
Equity returns	-0.28%	0.65%	-0.93%
			(-1.99)

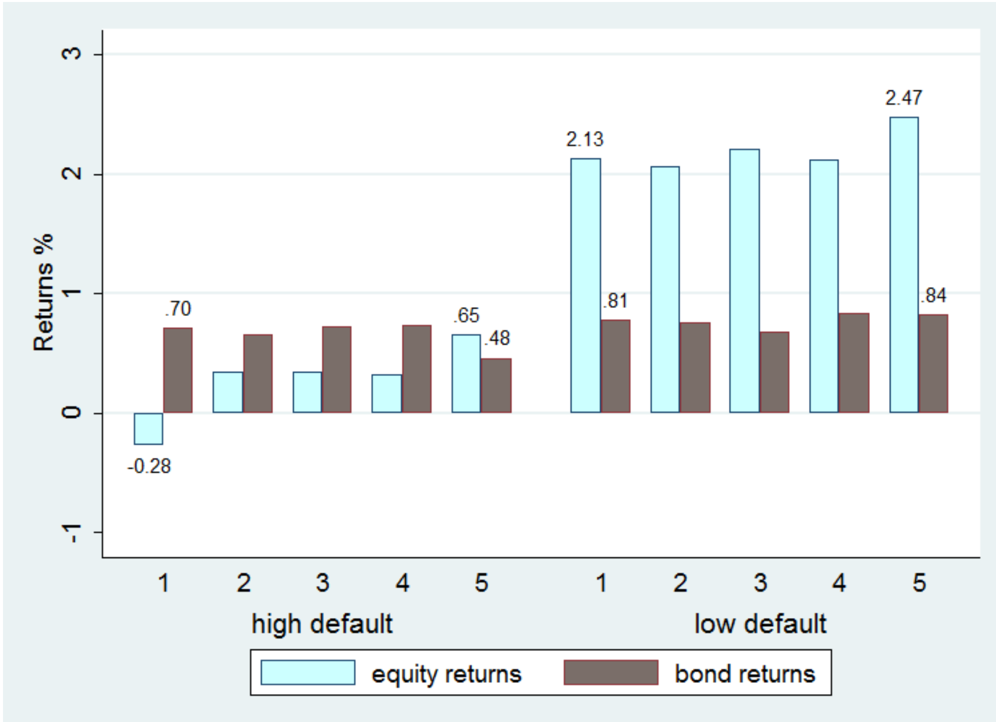

Fig. 3.2. Performance of Bonds and Equity Conditional on Tangibility and Default Shocks.

This figure documents returns on tangibility portfolios (1 corresponds to lowest quintile and 5 represent the highest quintile of tangibility) conditional on aggregate default shocks over the period 1995 - 2010.

assets have higher risk due to lower bondholder recovery and, therefore, claim higher returns in periods of high default shocks. To summarize, we show that the recovery effect is asymmetric in that it is more important in high default states of the worlds. More importantly, we document that one of the possible reasons of momentum in the corporate bond market is risk shifting from equity to bondholders.

3.4.5 Reversal

The previous empirical literature shows that equity losers keep outperform equity winners for nearly one year after the formation period. For example, Jegadeesh and

Titman (2001) document a momentum reversal after the first year.[28] This evidence implies that equity winners only temporary outperform losers. If momentum exists in equity, it is possible that the same effect persist in the corporate bond market. To best of our knowledge no other work analyzed long-term reversal in corporate bond returns.

Figure 3.3 presents cumulative momentum performance over a 20-month post formation period. First, we estimate performance every month t from January 1960 to December 2010, we calculate the difference between average returns of losers and winners for month $t + k$, where $k = +1, \dots, +20$. We then estimate cumulative momentum profits starting from month 1.

According to Figure 3.3, cumulative momentum performance keeps increasing for the first 10 months after the formation period. However, from month 11 through 19, it consistently decline and at month 20 it becomes negative. Even though, the magnitude of the observed reversal is not high (almost 2% at the 10th month), the pattern is similar to the equity reversal effect documented by Jegadeesh and Titman (2001) and Griffin, Ji, and Martin (2003).

To summarize, we find long-term reversal in the corporate bond market. However, we have to admit that our analysis is based on the limited sample of bonds available from the DataStream database. It is possible that extending the time-series and including more observations in the sample can change this result.

3.5 Concluding Remarks

Does momentum exist in bond markets? A recent paper by Jostova, Nikolova, Philipov, and Stahel (2011) shows momentum in corporate bonds exists and is primarily driven by high credit risk bonds. However, Khang and King (2004) and

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[28] Griffin, Ji, and Martin (2003) document similar findings.

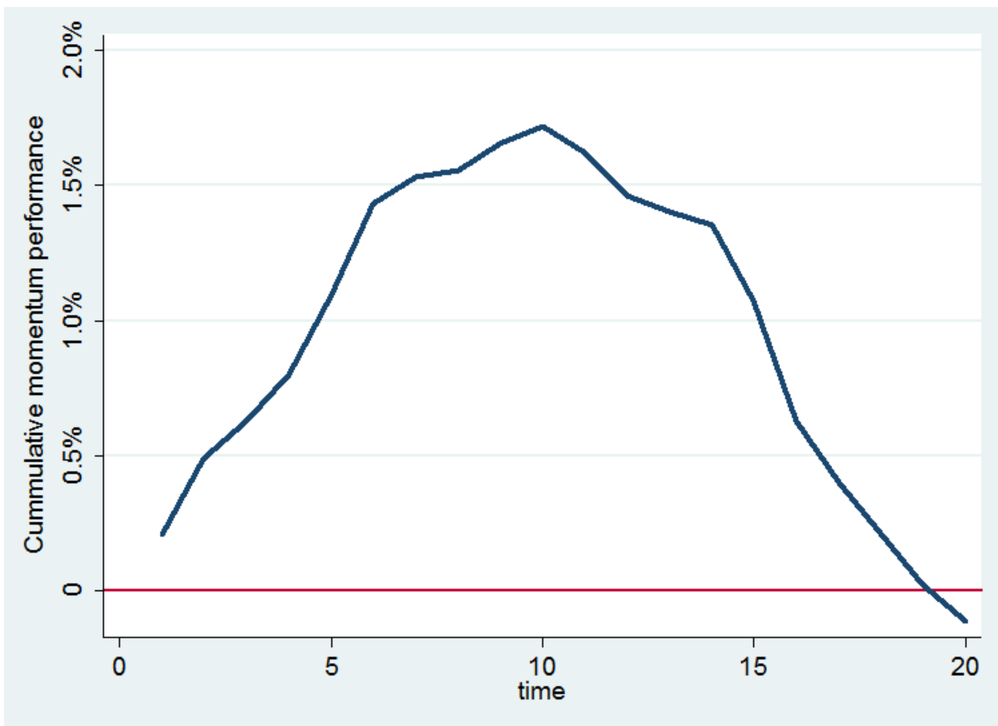

Fig. 3.3. Long-term Reversal in Corporate Bond Returns.

This figure documents cumulative returns of the momentum portfolio 20 months after the formation period.

Gebhardt, Hvidkjaer, and Swaminathan (2005b) do not find significant momentum in the bond market. We reconcile this conflicting evidence by showing that momentum does exist in bond markets, but is only found in financially distressed bonds during high default states of the world. Our results indicate that momentum in the corporate bond market is related to aggregate default risks, and we show that momentum returns are primarily observed in periods of high default shocks and are essentially non-existent otherwise.

A central prediction of the paper is that bonds losers and winners have different exposures to unexpected changes in aggregate economy-wide default shocks. Indeed, we show that the CDEF spread between winners and losers is positive and significant. Furthermore, it appears that the conditional default factor is priced in the cross-section of bond momentum portfolios and has a positive premium. Taken together, these results suggest that winners are relatively riskier than losers in periods of high default shocks, and, therefore, the bondholders of winners face higher risk and require higher returns during these periods.

Mahajan, Petkevich, and Petkova (2011) provide a risk-based explanation of the momentum anomaly in the equity market by documenting that this phenomenon is driven by shareholder recovery and financial distress. We extend this empirical analysis to the corporate bond market, and our results suggest that momentum in bonds is driven by bondholder recovery. In addition, we offer a theoretical explanation to our findings. Specifically, we find that winners have lower bondholder recovery than losers, and, therefore, become relatively riskier in high default states of the world, leading to higher expected returns, while the opposite is true for losers. Using the same argument, we propose that bondholders of winners require a higher recovery premium during periods of high default shocks when the risk of actual liquidation increases across the board. On the other hand, during low default shocks recovery become less important, because of lower threat of liquidation. Motivated by these results, we analyze the potential wealth transfer between bond and equity holders due to recovery. Our results support the hypothesis that bonds winners become riskier in periods of high default, due in part to the risk transfer from equity to bondholders.

One possible direction of future research is to explore whether recovery is correlated among different types of assets. Further, it would be interesting to examine whether the conditional default factor affects the expected returns of securities in the commodities and currencies markets.

4. CONCLUSIONS

In this dissertation, we address two research questions. First, we study the relation between aggregate-level default and momentum. Second, we investigate whether momentum exits in the corporate bond market.

There are two main findings in the first essay. First, we document that momentum profitability is concentrated in periods of high default shocks. Specifically, losers have low expected returns in states of high aggregate default. Since high default shocks occur both in expansions and recessions, it is not the general state of economic conditions that drives momentum profitability. This result is in contrast with previous studies that document that momentum profits are more pronounced during expansions. Second, we provide a possible risk-based explanation to this behavior based on shareholder bargaining power. 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. According to our results, losers are 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 during those periods.

In the second essay we present evidence suggesting that momentum exists in the corporate bond market. We document that momentum returns are primarily observed in periods of high default shocks and are essentially non-existent otherwise. Further, we show that the CDEF spread between winners and losers is positive and significant. Furthermore, it appears that the conditional default factor is priced in the cross-section of bond momentum portfolios and has a positive premium. Taken together, these results suggest that winners are relatively riskier than losers in periods of high default shocks, and, therefore, the bondholders of winners face higher risk and require higher returns during these periods. We also provide a risk-based explanation to this finding using bondholder recovery. According to our findings, winners have lower bondholder recovery than losers. Therefore, bondholders of winners require a higher recovery premium during periods of high default shocks when the risk of actual liquidation increases across the board. On the other hand, during low default shocks recovery becomes less important, due to lower threat of liquidation. Finally, we present evidence suggesting that reversals also exist in bonds.

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