Related Securities and the Cross-section of Stock Return Momentum*

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Abstract

We show that related securities – stock and credit default swap (CDS) whose prices are linked through common firm fundamentals – provide important cross-sectional information on which stocks exhibit price momentum or reversal. Using 1,074 U.S. firms during 2003-2014, we find that a joint-market stock momentum strategy that buys (sells) stock/CDS joint-return winners (losers) avoids crashes (Daniel and Moskowitz, 2014) and outperforms traditional stock momentum strategies (Jegadeesh and Titman, 1993) by 122 bps per month with an annualized Sharpe ratio of 0.83. For "disjoint" entities whose past stock returns disagree with past CDS returns, we find greater option-like payoff risks in market downturns (Daniel and Moskowitz, 2014) and that the discrepancy between their stock-implied CDS spreads and market CDS spreads widened, then corrected by subsequent price reversals. We present a new stock trading strategy that 50-50 mixes the joint-market momentum trades with contrarian trades on "disjoint" entities, yielding 135 bps per month with an annualized Sharpe ratio of 1.11. Our findings are consistent with related securities reducing stock price efficiency and causing excess volatility (Goldstein, Li, and Yang, 2013).

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1 Introduction

A long standing empirical investments literature documents significant return momentum effects across a range of assets (Jegadeesh and Titman, 1993, Asness, Moskowitz, and Pedersen, 2013, among others). At the same time, there is an ominous momentum return postscript whereby momentum investment strategies are prone to rare but costly downside risks of sudden and abrupt reversals – termed momentum "crashes" (Daniel and Moskowitz, 2014). Momentum crashes when a bear market with high uncertainty rebounds from its bottom. For example, traditional momentum return strategies recently crashed in 2009, resulting in return losses of -73.42% in three months. In an effort to further understand and hedge these costly momentum crashes, several studies have investigated detecting the timing of the crash (Daniel, Jagannathan, and Kim, 2012), hedging out momentum portfolio time-varying market risks (Grundy and Martin, 2001), or statistically moderating the volatility of the strategy (Barroso and Santa-Clara, 2015; Han, Zhou, and Zhu, 2014).

An additionally important momentum return stylized fact is that momentum profits vary significantly in the cross-section of stocks. Stock momentum profits are shown to be correlated with the cross-sectional variation in expected returns (Conrad and Kaul, 1998), their time-varying exposures on various macro-economic factors (Chordia and Shivakumar, 2002), and their industry components (Moskowitz and Grinblatt, 1999), among others. Lee and Swaminathan (2000) document some additional important findings that different stocks have different momentum cycles, and their trading volume has useful cross-sectional information on individual stock momentum cycles – whether a current stock price is on its early stage of momentum or at the late stage, thereby more likely to reverse subsequently.

In this paper, we link the momentum return crash phenomena with the cross-sectional variation in momentum returns. We argue that momentum profits are enhanced and crashes are avoided by using an ex-ante implementable related securities methodology that systematically captures the part of stock cross-section that is more prone to momentum crashes. Noisy, single stock market pricing signals may not be useful in extracting ex ante reliable momentum signals due in part to differences of opinions and investor psychology (Hong and Stein, 2003; Daniel, Hirshleifer, and Subrahmanyam, 1998). Instead, we introduce an extended valuation signal that comes from a firm's related securities. We posit that stock markets are segmented by different types of investors with different trading opportunities (Goldstein, Li, and Yang, 2013). Capital can be slow-moving (Duffie, 2010), though we assume as a null, a well-integrated pricing system across related securities' markets. Under these assumptions, we decompose the cross-section of each stock momentum portfolio into several sub-groups according to their ex ante probability to attract contrarian stock traders whose trades are motivated by valuation signals from related securities. In particular, we focus on single-name credit default swap (CDS) contracts whose prices are linked to related stock prices through common firm fundamentals.

Using 1,074 U.S. firms during 2003-2014, we find that a joint-market stock momentum strategy that buys (sells) stock/CDS joint-return winners (losers) avoids momentum crashes and outperforms traditional stock momentum strategies (Jegadeesh and Titman, 1993) by 122 bps per month with an annualized Sharpe ratio of 0.83. For "disjoint" momentum strategies whose past stock returns disagree with past CDS returns, we find greater option-like payoff risks in market downturns (Daniel and Moskowitz, 2014) and that the discrepancy between their stock-implied CDS spreads and market CDS spreads widened, followed by quick price reversal. We present results from a new stock trading strategy that equally mixes (50-50) the joint-market momentum trades with contrarian trades on the "disjoint" entities, yielding 135 bps per month with the annualized Sharpe ratio of 1.11. Our findings are consistent with the notion that related securities at times reduce stock price efficiency and cause excess volatility (Goldstein, Li, and Yang, 2013).

We focus on cross-market pricing information in stock and CDS markets for several reasons. First, several papers document potential information flows on credit related events from CDS to stock markets (Acharya and Johnson, 2007; Ni and Pan, 2010; Qiu and Yu, 2012). Distinct information in the two markets could also provide a more precise signal on firm prospects than a single market signal because related security prices often reveal signals that are relevant to their common firm fundamentals.[1] They also often reveal such information non-synchronously with different frequencies, speeds, and content. Second, stock and CDS prices are structurally linked through the firm's capital structure (Merton, 1974)[2],

[1]For example, CDS at-market spreads are shown to predict upcoming credit rating changes (Hull, Predescu, and White, 2004; Flannery, Houston, and Partnoy, 2010; Chava, Ganduri, and Ornthanalai, 2012; Lee, Naranjo, and Sirmans, 2014) and earnings surprises (Batta, Qiu, and Yu, 2014) in consistent directions.

[2]Schaefer and Strebulaev (2008) also show that the elasticity between stock and corporate bond returns

and therefore, CDS returns could guide future stock returns. For example, if a current stock price is significantly underpriced (overpriced) relative to the level implied by its CDS counterpart, one can infer that the future price of the stock is less likely to fall below (rise above) its current level because of potential convergence trades by active and sophisticated arbitrageurs who would buy (sell) stocks while buying (selling) CDS protection (Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012).[3] Third, we focus on the CDS market rather than corporate bond market or credit rating information because the CDS market is shown to have richer, faster information on credit risks that are consistently priced in the stock cross-section. Studies that measure credit risk through corporate bond returns or credit ratings document a "distress risk puzzle" whereby they find a negative relation between credit risk and stock returns (Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008; Avramov, Chordia, Jostova, and Philipov, 2009). Using CDS market information, Friewald, Wagner, and Zechner (2014) show that the puzzle is resolved. Han and Zhou (2011) also find that the term structure of CDS spreads contains useful information on future stock returns.[4]

We identify 1,074 US entities that have actively trading stocks and five-year CDS contracts during 2003-2014.[5] We compute CDS holding period excess returns (net of risk-free rate) as the profit and loss (P&L) of a CDS trading with a unit \$1-notional using an International Swaps and Derivatives Association (ISDA) CDS standard pricing model. We independently double-sort stocks into five by five portfolios based on their past 12-month return (skipping the most recent month) as well as various horizon past CDS returns. We then go long (sell short) the joint stock/CDS-market winners (losers) for a month and rebalance the portfolio every month.

We find that our joint stock/CDS-market momentum strategy (joint-market momentum, hereafter) significantly outperforms traditional momentum strategies (Jegadeesh and Titman, 1993) for almost all formation horizons of past CDS returns, ranging from three- to 12-months. The relative outperformance is peaked at the past four-month CDS signal,

is accurately estimated using structural credit models. Bai and Wu (2010) find that the link between stock and CDS prices is tight particularly in their cross-section.

[3]This could be viewed as stock trades for hedging, which is motivated by speculation in CDS markets (Goldstein, Li, and Yang, 2013).

[4]CDS spreads are also updated faster than credit ratings due in part to rating agencies' practice of weighting accuracy and stability (Moodys, September 2006, "Analyzing the Tradeoff Between Rating Accuracy and Stability). Moreover, continuous CDS spreads are more granular than discrete credit rating notches.

[5] The five-year CDS contracts are the most liquidly traded corporate CDS contracts.

yielding an extra 122 bps per month with an annualized Sharpe ratio of 0.83. Our results are robust to risk-adjustments, including the market, Fama and French (1993) SMB and HML, Carhart (1997) UMD, and Novy-Marx (2015) earnings momentum factors (SUE and CAR3). We further show that combining various horizons of past stock returns (Novy-Marx, 2012) does not yield the same results, which sharply identifies that it is the CDS market information that drives the performance enhancement of our joint-market momentum strategy. The two markets' joint signals also appear to more precisely predict upcoming corporate events in anticipated directions than traditional stock only signals — joint-market winners (losers) are more likely to exhibit faster (slower) earnings growth and undergo rating upgrades (downgrades) than traditional stock winners (losers). This relative CDS market information advantage is profound among distressed entities as well as during high credit risk periods.

Motivated by our stronger price momentum among joint-market winners and losers ("joint" entities), we further investigate the cross-section of stock momentum by sub-sampling trading entities into (1) "joint" entities and (2) "disjoint" entities whose past stock returns strongly disagree with past CDS returns, and (3) others. We then implement a stock momentum strategy for each of the first two extreme groups and compare their performance to traditional momentum strategies. We focus on the best performing strategy based on past 12-month stock and four-month CDS return signals. We first find that momentum crashes are closely related to the poor performance of momentum strategy on "disjoint" entities. The worst performance of the traditional stock momentum strategy (-42.56% per month) is driven by the "disjoint" entities. In contrast, performance of the "joint" group momentum is substantially less left-skewed (-0.783% versus -2.315%, monthly basis), less volatile (5.068% versus 6.415%), and has smaller Kurtosis (8.303 versus 16.316) than traditional momentum strategies.

Why are the "disjoint" entities associated with momentum return crashes? We provide two explanations. First, the option-like payoff risks in traditional momentum portfolios (Daniel and Moskowitz, 2014) are found only in the "disjoint" entity momentum portfolio. Daniel and Moskowitz (2014) show that momentum crashes are due to the significantly more negative down-and-up market beta of the momentum portfolio than its down-market beta. When a bear market rebounds from its bottom, the excessive negative beta exposure of traditional stock momentum portfolios quickly loses its cumulative profits. We show that only the "disjoint" momentum portfolio shows such asymmetry in time-varying beta. For our joint momentum portfolio, we do not find any significant asymmetry between its down-and-up market beta and its down-market beta. Consistent with these results, we also find that when a bear market rebounds from its bottom, the net beta of the joint momentum portfolio quickly becomes positive, leading the net beta of a traditional momentum portfolio. However, our "disjoint" momentum portfolio shows the most lagged reaction of its net beta to rebounding market conditions. Put together, our results suggest more timely updated market risk information when a sharper combined signal is extracted from related security signals.

Second, we show that "disjoint" winner (loser) stocks substantially under-estimate (over-estimate) firm credit risks relative to their levels implied by CDS prices. When stock/CDS cross-market arbitrage is unlimited, mispriced credit risk, if any, would be quickly corrected. This implies that stocks that misprice the underlying credit risk relative to CDS prices tend to show price reversal rather than momentum. We find that for "disjoint" entities, over past four months prior to the formation of momentum portfolio, the discrepancy between their stock-implied CDS spreads by the Merton (1974) model and their observed at-market CDS spreads significantly widened to nearly 40% of their initial divergence level. We then find that the two spreads converge. Importantly, we do not find any mispriced credit for "joint" entities. To show the relevance of cross-market arbitrage to the reversing stock price pattern, we implement a cross-market convergence trade for "disjoint" entities (Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012) and find significant profits. The profits range from 121 bps to 158 bps per month depending on the approach we use to get Stock-CDS delta-hedge ratios.

Building on our cross-section of stock return momentum intuition, we propose a more powerful stock trading strategy that mixes joint-market momentum trades with contrarian trades on "disjoint" entities. When we mix these momentum-contrarian trades with equal-capital allocations (i.e., 50-50 combo), this stock trading strategy yields 135 bps per month with the annualized Sharpe ratio of 1.11. This Sharpe ratio is net 34% higher than that of the joint-market momentum strategy (0.83). When we use a value-weighting scheme, the strategy yields an even higher annualized Sharpe ratio of 1.18. Overall, this last set of results confirms the notion that stock market efficiency could deteriorate when the market is segmented with different types of traders who might have different trading motives due to related securities (Goldstein, Li, and Yang, 2013; Boehmer, Chava, and Tookes, 2013).

Our paper contributes to three important research streams: (1) momentum crashes (Daniel and Moskowitz, 2014; Daniel, Jagannathan, and Kim, 2012; Grundy and Martin, 2001; Barroso and Santa-Clara, 2015; Han, Zhou, and Zhu, 2014), (2) the cross-section of stock return momentum (Lee and Swaminathan, 2000) and (3) related securities' valuations and capital market efficiency (Schaefer and Strebulaev, 2008; Friewald, Wagner, and Zechner, 2014; Bai and Wu, 2010; Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012; Goldstein, Li, and Yang, 2013; Boehmer, Chava, and Tookes, 2013). We provide a novel cross-sectional approach to tame momentum crashes. Importantly, we show that related securities' prices are informative about individual momentum cycles. Specifically, we show that "joint" and "disjoint" entities exhibit early and late stage momentum cycles, respectively. For the former, price momentum continues, whereas for the latter, price tends to reverse quickly, causing momentum crashes. We highlight the role played by informed, sophisticated cross-market arbitrageurs in inducing hedge-motivated trades in equities (Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012; Goldstein, Li, and Yang, 2013). Our finding of a large stock market momentum return anomaly that fully integrates cross-asset and cross-sectional signals, therefore, contributes to the literature on the potential interplay between stock market efficiency and stock market segmentation due to related securities' signals (Goldstein, Li, and Yang, 2013; Boehmer, Chava, and Tookes, 2013).

The remainder of this paper is organized as follows: Section 2 summaries our data and CDS return construction process. In Section 3 we provide our main results. In Section 4, we conclude.

2 Data

Our dataset consists of 1,074 firms from January 2003 to April 2014 for which there is an actively traded stock and an active single-name CDS contract.[6] We obtain equity data from the Center for Research in Security Prices (CRSP). We require the firm's equity to have a share code equal to 10 or 11 and be traded on the NYSE, AMEX or Nasdaq. CDS data are acquired from the Markit Group, a leading financial information services company. All CDS contracts we consider are denominated in U.S. dollars and have five-year maturities. The "Big Bang" protocol of April 2009 changed the standard for CDS contracts on a number of dimensions, including a move from Modified Restructuring (MR) to No Restructuring (XR) for North American corporate CDS contracts.[7] As such, our database consists of MR contracts prior to the "Big Bang" and XR contracts afterward. Markit constructs a composite CDS spread using input from a variety of market makers and ensures each daily observation passes a rigorous cleaning test to ensure accuracy and reliability. Table 1 provides summary statistics and a correlation matrix of variables used in this study. The average firm in our sample has an equity market capitalization of $18.23 billion, a BBB S&P credit rating, and a CDS spread of 183 basis points (bps). As a measure of liquidity, Markit reports on a daily basis each firm's CDS market "depth," or the number of distinct contributors providing quotes used to construct the composite spread. Markit requires a minimum of two contributors. The mean CDS depth of our sample is 5.42.

2.1 CDS Returns

To compute the CDS holding period (excess) return, we compute the profit or loss (P&L) of a CDS over a given holding interval. We use an ISDA CDS standard pricing model to compute the P&L. The P&L of a CDS trading with a unit $1-notional is what we term the CDS holding period excess return. This notion of CDS return is consistent with Berndt and Obreja (2010), who view the protection seller's position in a CDS as a long asset swap position in the risky par-bonds issued by the same reference entity. Hence, the protection seller's position in a CDS could be viewed as a 100% levered risky par-bond position that is

[6] The size of our stock/CDS joint cross-section is similar to that of Boehmer, Chava, and Tookes (2013) who use 1,091 unique firms during the 2003-2007 period.

[7] For more details, visit www.markit.com/cds/announcements/resource/cds_big_bang.pdf.

financed at the default-free riskless rate, which serves as the basis for the notion of "excess" return. We interchangeably use the terms – CDS holding period excess return, CDS holding period return, and CDS return – throughout this manuscript. For more details regarding CDS return computation, see Appendix C.

The summary statistics of Table 1 show that the mean (median) monthly CDS return of our sample is 0.23% (0.51%) with a standard deviation of 2.17%. The simple correlation between the stock return and CDS return is 0.041.

3 Main Results

3.1 Joint Stock/CDS Momentum

In this section, we provide evidence that past CDS returns, when combined with past stock returns, significantly improve the performance of the traditional stock momentum strategy (Jegadeesh and Titman, 1993) by sharpening signals in two related security prices on future firm fundamentals.

Our joint stock/CDS momentum strategy that trades stocks is constructed in the spirit of Jegadeesh and Titman (1993). We conduct two independent sorts at the end of each month. First, firms are sorted into five equally-sized portfolios based on their stock return over the past 12 months, skipping the most recent month. Second, firms are sorted into five equally-sized portfolios based on their CDS return over the past J months.[8] The joint winner portfolio (JW) is defined as the overlap between the stock momentum winner portfolio (W_S) and the CDS momentum winner portfolio (W_C). The joint loser portfolio (JL) is defined similarly as the overlap between the stock momentum loser portfolio (L_S) and the CDS momentum loser portfolio (L_C). We purchase firm stocks in JW and sell short firm stocks in JL. The position is held and rebalanced after K-month. We focus on the baseline case $K = 1m$ in this paper.

Table 2 summarizes performance of our joint stock/CDS momentum strategies over the period January 2003 to April 2014. The joint momentum strategy is computed using various

[8] Stock price and CDS spread data prior to January 2003 are further used in the formation of momentum portfolios in 2003.

CDS formation periods from one month ($J = 1m$) to twelve months ($J = 12m$).[9] CDS formation periods of $J = 3m$ through $J = 6m$ show positive profits of joint momentum strategy at the 1% to 5% statistical significance level. The four-month formation period ($J = 4m$) maximizes the strategy's performance, producing a return of 122 bps per month with a t-statistic of 2.86 and annualized Sharpe ratio of 0.83. The joint winner portfolio generates a return of 165 bps per month (t-statistic of 2.41), while the joint loser portfolio generates a return of 43 bps per month (t-statistic of 0.49).

The last column of Table 2 reports the joint momentum performance in excess of the traditional stock momentum, referred to as the "Advantage." The performance advantage of joint momentum is statistically significant at the 1% to 10% level for almost all CDS formation periods except $J = 1m$ and $J = 2m$. Joint momentum with a formation period of $J = 4m$ shows its maximal advantage over the traditional stock momentum of 122 bps per month (t-statistic of 2.11).

3.1.1 Risk-adjusted Performance

Next we test whether our joint stock/CDS momentum profits can be explained by exposures to commonly used risk factors. We consider market (MKT), Fama and French (1993) *SMB* and *HML*, Carhart (1997) *UMD*, and Novy-Marx (2015) earnings momentum factors (*SUE* and *CAR3*). We construct *Mkt*, *SMB*, *HML*,and *UMD* factors using the daily series on Ken French's website.[10] In addition to *UMD*, we also construct a "localized" stock momentum factor, UMD^S, using our sample of firms and the strategy $J = 12m$ and $K = 1m$, skipping a month between formation and holding periods. *SUE* and *CAR3* are the two earnings momentum factors that are constructed using the standardized unexpected earnings and the three-day cumulative abnormal return around the most recent earnings announcement, respectively. We follow similar construction procedures to Novy-Marx (2015).[11] Using OLS with Newey-West standard errors and a lag length of 12 months, we estimate:

$$r_{Pt} = \alpha_P + \boldsymbol{\beta}'_P \mathbf{F}_t + e_{Pt}, \tag{1}$$

[9] CDS momentum portfolios are constructed without a one-month gap between the formation and holding periods.

[10] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[11] Appendix B provides a more detailed definition of our two earnings-based factors.

where r_{Pt} is the joint-market momentum portfolio returns (JW – JL), α_P is the portfolio's alpha, and $\mathbf{F}_t$ is a vector of common stock market risk factors.

Table 3 presents alpha coefficients from the time-series regressions. The estimated alpha coefficients are economically significant across all five factor models we consider from [M1] through [M5]. The abnormal performance ranges from 107 bps (M[5]) to 163 bps per month (M[1]), all of which are statistically significant at the 1% level. In all five models, our joint-market momentum strategy strongly outperforms the traditional momentum strategy on a risk-adjusted basis.

3.1.2 Joint-market Momentum Signals and Future Firm Fundamentals

In Table 3 for our joint momentum strategy, the most significant factor loadings are on the two fundamental earnings momentum factors (0.854 for β_{SUE} and 1.273 for β_{CAR3}). This is consistent with our *a priori* expectation that past stock and CDS performance signals, if optimally combined, could more sharply identify price under-reactions to firm fundamentals. In this case, the joint signals capture price under-reactions to future earnings surprises. However, our joint-market signals are not limited to capturing only future earnings momentum. The significant joint momentum alpha of 107 bps per month in [M5] of Table 3 suggests that the joint-market signals capture other upcoming corporate events that also materially affect common firm fundamentals through a channel other than earnings surprises. Future credit rating changes are one such potential event (Kisgen, 2006, 2007).

To directly test whether stock/CDS joint-market signals more precisely capture future firm fundamentals in anticipated directions, we examine in Table 4 whether joint-market winners (losers) show faster (slower) earnings growth (%) as well as potential credit rating enhancement (deterioration) over the next 18 months following each portfolio formation date. We further compare the future fundamentals of our joint-market winners/losers to those of traditional stock momentum winners/losers. This comparison identifies the additional marginal value of past CDS signals in correctly predicting future firm fundamentals. To avoid any overlapping observations when we compute the six to 18-month average earnings growth (%) and S&P credit rating sub-notch changes, we compute their monthly average values by equally averaging their one-month stats over relevant time intervals (Jegadeesh and Titman, 1993).[12]

We first find that net earnings growth is much faster in the joint momentum portfolio than the traditional momentum portfolio. For example, after six months following the portfolio formation date, the wedge in net earnings growth between the two momentum strategies is 3.87% (=13.65% - 9.78%) per month. We further find that net credit enhancement in the joint momentum portfolio (-0.067) is also almost twice more likely than the traditional stock momentum portfolio (-0.038).[13] This tendency is observed for the whole 18-month forecasting period. Our results in Table 4 are indicative of a potential information advantage of joint-market momentum signals in predicting future firm prospects.

3.1.3 Robustness to a Finer Sort: Multi-horizon Stock Return Signals

One could argue that past CDS returns have no marginal information over past stock returns, and therefore, our joint stock/CDS momentum strategy is merely a finer sorting strategy using multi-horizon stock return signals.[14] To address these potential concerns, we independently sort our sample stocks using both traditional past 12-month stock returns and various horizon past stock returns. We vary the horizon of the second stock return from one- to nine months.[15]

Table 5 provides our multi-horizon stock return signal results. In Contiguous Formation/Holding Periods columns, we construct the second stock return without skipping the most recent month, which is identical to the way we computed past CDS returns. We find neither significant momentum profits nor any advantage of this multi–horizon stock return momentum strategy over the traditional momentum strategy. In the next two columns of the same table, we further show similar results even if we skip the most recent month in the second stock return signal to avoid any short-run price reversal (Lehmann, 1990; Lo and MacKinlay, 1990). Put together, our results in Table 5 suggest that it is the CDS market

[12]For instance, the six-month period earnings growth (%) per month is computed by equally averaging the one-month earnings growth (%) of six momentum portfolios formed in the current month, one month prior, two months prior, three months prior, four months prior, and five months prior.

[13]S&P credit ratings are converted to numerical scores (1=AAA, 2=AA+, 3=AA, ...).

[14]Novy-Marx (2015) shows that various horizon past stock returns have different signals about continuing price momentum or reversal.

[15]Past 12-month stock signal as a second sorting signal is naturally excluded in this multi-horizon stock return momentum strategy.

information that enhances the performance of the traditional stock momentum strategy, not the finer sort using multiple-horizon stock return signals.

3.1.4 Relative Advantage of CDS Market Information

When is the CDS market information relatively more useful in enhancing traditional stock momentum profits? Credit risk often becomes a greater concern to equity investors in distressed markets, so we address this question by examining the conditional performance of our joint stock/CDS momentum strategy with varying levels of distress risks. We consider both cross-section and time series of our sample by decompose sample firms and time periods into high and low distress risk categories. In this decomposition, we use S&P credit ratings or five-year CDS spread levels as a proxy for corporate credit risk.

Table 6 reports our results. We first divide our sample firms into two equally sized groups according to their S&P credit ratings. For each subgroup, we implement our joint stock/CDS momentum strategy and compare the performance to that of the traditional stock-only signal momentum strategy. In Table 6, we find that joint stock/CDS momentum strategy significantly outperforms the traditional stock momentum strategy for *Risky* entities whose S&P credit ratings fall below the sample median each month. The performance advantage of 1.507% per month is statistically significant at the 5% level.

Next, we split our sample period into *Low Risk* and *High Risk* periods using the value-weighted average five-year CDS daily spread. As shown in Figure 1, the weighted average five-year CDS spread is relatively low prior to the July 2007 – the onset of 2007 financial crisis, and upon the onset of the crisis it spikes up and stays at a relatively higher level thereafter. During the latter time period we term *High Risk*, we find that there is an advantage of our joint momentum strategy over the traditional stock momentum by 1.576% per month. The performance improvement is statistically significant at the 5% level.

Put together, our results in Table 6 show the relative information benefits of the CDS market when the level of distress risk is high. As the region of equity payoffs gets near to the firm's default boundary, any under-reaction signals on future firm fundamentals could be sharpened out by jointly examining the past performance of both equity and CDS contracts.

3.2 The Cross-section of Stock Return Momentum

In this section, we provide evidence that the cross-section of stock momentum consists of two extreme groups whose return behaviors are distinctively different from each other: (1) joint-market winners (JW) and losers (JL) that show continuing price momentum, and (2) "disjoint" entities whose past stock returns strongly disagree with past CDS returns and show subsequent price reversal. We show that a momentum portfolio constructed using the "disjoint" entities, a portfolio that goes long past stock winners but past CDS losers (DW $\equiv \mathrm{W}_S \cap \mathrm{L}_C$) and sells short past stock losers but past CDS winners (DL $\equiv \mathrm{L}_S \cap \mathrm{W}_C$), is closely related to momentum crashes (Daniel and Moskowitz, 2014). Because our joint-market momentum strategy can be viewed as a traditional stock momentum that hedges out "disjoint" entities, the "disjoint" entity momentum crashes could further explain why our joint-market momentum strategy outperforms the traditional stock momentum strategy. In Appendix D we graphically illustrate how we partition the cross-section of stock return momentum.

3.2.1 "Disjoint" Stock/CDS Momentum and Momentum Crashes

We first illustrate the cross-sectional heterogeneity of stock return momentum. In Panel A of Figure 2, one can see that joint-market momentum strategy avoids 2009 momentum crashes, although Panel B clearly depicts that "disjoint" entity momentum significantly contributes to the momentum crashes. Zooming in the 2009 momentum crash period in Panel C, we further find strong outperformance of disjoint stock losers but CDS winners ($\mathrm{L}_S \cap \mathrm{W}_C$) over disjoint stock winners but CDS losers ($\mathrm{W}_S \cap \mathrm{L}_C$), which appears to result in the momentum crashes.

Motivated by this contrasting time series return behavior between "joint" and "disjoint" entity momentum portfolios, we further summarize their distributional characteristics. We specifically compare the return distributions of the following three momentum strategies: (1) traditional stock momentum as a benchmark, (2) joint stock/CDS momentum, and (2) disjoint stock/CDS momentum (disjoint momentum, hereafter).

Figure 3 and Table 7 present the distributional characteristics of the three momentum strategies. In Figure 3, we compare their return distributions either in a violin plot (Panel A) or a histogram (Panel B). One can see that joint momentum portfolio returns are relatively more right-skewed than the traditional momentum strategy with much thinner left tail. In contrast, the disjoint momentum portfolio returns show a much fatter left-tail, where its minimum is overlapped with the worst performance of the traditional stock momentum strategy. In Panel A of Table 7, we re-confirm these distributional properties by reporting the Max, Med, Min, Kurt, and Skew of these three momentum strategies.

From the structural representation of a firm's equity (Merton, 1974), a stock momentum portfolio can be viewed as an option spread that goes long in-the-money call options and sells short at-the-money (or in severe economic downturns, near-out-of-the-money) call options. The net option Gamma of this spread becomes more negative as the economy is in deep recession with high uncertainty, and at that moment, a sudden rebound in market return could cause instantaneously significant losses due to the negative Gamma risk (Daniel and Moskowitz, 2014). In Panel B of Table 7, we compute the ex-ante option Gamma for the three different momentum portfolios using the Merton (1974) framework with each firm's capital structure and daily equity return volatility and compare the risks across the three different momentum strategies.[16] We find that the negative ex-ante Gamma risk is highest (-1.653) for the disjoint momentum portfolio, indicating potentially severe downside losses embedded in this portfolio particularly during highly volatile periods.

3.2.2 Rationales for Momentum Crashes in "Disjoint" Entity Momentum

In this sub-section, we provide two potential rationales for momentum crashes in the disjoint momentum portfolio. One is a risk-based rationale and the other is a rationale based on the relative pricing of credit risk in related securities' markets.

Risk-based Rationale: Time-varying Beta and Option-like Payoff Risk

We test whether the disjoint momentum portfolio shows the most severe option-like payoff risk when a bear market rebounds from its bottom. We use the following test specification in Daniel and Moskowitz (2014):

$$r_{MOMt} = (\alpha_0 + \alpha_{I_B} I_B) + [\beta_{MKT} + I_B(\beta_{MKT\times I_B} + I_U \beta_{MKT\times I_B\times I_U})] r_{MKTt} + e_{MOMt}, \quad (2)$$

[16] We estimate asset value and volatility using three-month rolling daily equity return data through the Bharath and Shumway (2008) approach as we describe in Appendix E.3.

where r_{MOMt} is the momentum portfolio return, I_B is an ex-ante bear market indicator that takes the value of one if two-year lagging market return is negative, I_U is a contemporaneous up-market indicator that takes the value of one if the current month market return is positive, and finally, r_{MKTt} is the market factor. A significantly negative $\beta_{MKT \times I_B \times I_U}$ would confirm the option-like payoff risk that is proposed as a cause of momentum crashes (Daniel and Moskowitz, 2014).

Regression results are reported in Table 8. We find $\beta_{MKT \times I_B \times I_U}$ of -0.985 (column 4) for the traditional momentum portfolio, which is statistically significant at the 1% level. Comparing this result to the two other momentum portfolios — joint and disjoint, we find that only the disjoint momentum portfolio inherits this option-like payoff risk. $\beta_{MKT \times I_B \times I_U}$ is significantly negative (-1.741) for the disjoint momentum portfolio at the 1% level, whereas $\beta_{MKT \times I_B \times I_U}$ is positive (0.161) and statistically indistinguishable from zero for the joint momentum portfolio. This stark difference in time-varying beta exposure between the two extreme momentum strategies – joint and disjoint – explains why the joint momentum strategy avoids the 2009 momentum crashes, whereas the disjoint momentum strategy does not avoid them (Figure 2).

In Figure 4, we re-confirm this difference in the time-varying beta dynamics across the three different momentum strategies. Using a three-month rolling window daily times series, we estimate the ex-ante betas of the three momentum strategies. During 2009, one can see that when the market suddenly rebounds, the joint momentum beta becomes quickly positive, minimizing strategy losses, whereas the disjoint momentum beta is severely lagged, not promptly responding to the changing market conditions and consequently incurring large losses. Overall, our results in Table 8 and Figure 4 provide a risk-based rationale for why disjoint momentum is closely related to the momentum crashes.

Relative Pricing-based Rationale: Convergence Arbitrageurs as Hedgers

Based on the notions in Goldstein, Li, and Yang (2013), we provide an additional relative pricing framework rationale for momentum crashes in the disjoint momentum portfolio. Goldstein, Li, and Yang (2013) show that related security market such as CDS market can introduce differential trading motives among stock market investors. In particular, sophisticated arbitrageurs, if they believe stock prices are over-priced (under-priced) relative to CDS prices, would sell (buy) default protections through CDS contracts, while they hedge their CDS trades by selling (buying) stocks. If true, past stock winners but CDS losers (stock losers but CDS winners) are regarded as relatively over-priced (under-priced) stocks, and they consequently attract the cross-market hedgers (Goldstein, Li, and Yang, 2013). This would put significant price convergence pressure on those stocks.

Figure 5 confirms these potential mispriced credit in stock and CDS markets among "disjoint" entities. It shows the average and the median cumulative percentage divergence between implied Merton (1974) CDS spreads and the observed at-market CDS spreads from Markit for various joint and disjoint momentum portfolios. We compute the implied Merton (1974) CDS spreads following Bai and Wu (2010) who extract the constant five-year hazard rate from the risk-neutral default probability of the Merton (1974) model and price the CDS using the ISDA conventional 40% recovery rate assumption.[17] In Figure 5, only disjoint momentum portfolios – past stock winner but past CDS loser ($\mathrm{W}_S \cap \mathrm{L}_C$) and past stock loser but past CDS winner ($\mathrm{L}_S \cap \mathrm{W}_C$) – show a strong divergence over past four months prior to each portfolio formation date. In contrast, we find no such divergence in joint entities (i.e., stock-CDS joint winners ($\mathrm{W}_S \cap \mathrm{W}_C$) and losers ($\mathrm{L}_S \cap \mathrm{L}_C$)). Importantly, Figure 5 further shows quick convergence of the mispriced credit among "disjoint" entities over the subsequent months following the portfolio formation date-0. The divergence and subsequent convergence in mispriced credit suggests that there could be a profitable cross-market convergence trading opportunity for sophisticated cross-market arbitrageurs.

In Table 9, we show that the cross-market convergence trading strategy is indeed profitable. First, in Panel A, we trade only stocks and show that convergence stock trades are profitable due to the diverging and then converging pattern of mispriced credit. Column 1 shows that there is a profitable convergence stock trading (i.e., contrarian strategy) on "disjoint" entities whose past 12-month stock returns strongly disagree with their past four-month CDS returns (148 bps per month with the annualized Sharpe ratio of 0.65). In column 2, we show an equally profitable contrarian trading opportunity based on the past four-month divergence between implied Merton (1974) CDS spreads and the observed at-market CDS spreads (157 bps per month with the annualized Sharpe ratio of 0.89). Lastly,

[17] Implied Merton (1974) CDS (bps)$=-6000 \cdot Ln(N(d))/T$ where d is the distance to default and $T = 5$yrs. For the definition of d see Appendix E.3.

in column 3, we implement column 1's contrarian stock trades conditional on the past four-month implied Merton (1974) CDS returns. Following Novy-Marx (2015), we implement a conditional portfolio sort each month by first creating quintiles of the conditioning variable and then creating quintiles of the variable of interest within the conditioning quintiles. This results in portfolios based on the variable of interest that contain little-to-no variation in the conditioning variable. For instance, the $r_{12}^{S}|r_{4}^{M}$ portfolios vary according to r_{12}^{S} but have no variation in r_{4}^{M}. When this conditional approach is used in column 3, we find a significant reduction in column 1's trading profits, both economically (69 bps =148 - 79 bps) and statistically. These results show the relative importance of r_{4}^{M} signals in generating profitable convergence stock trades in column 1. Put together, the results in Panel A suggest that significant profits of the contrarian stock trades on "disjoint" entities largely come from the expected convergence of their mispriced credit risks.

In Panel B, we show that significant profits are available to sophisticated cross-market arbitrageurs who implement the full capital structure arbitrage on the "disjoint" entities (Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012). We delta–hedge the contrarian stock trades in column 1 of Panel A using CDS contracts where we compute the hedge ratios either statistically (Kapadia and Pu, 2012) or analytically through the Merton (1974) or the CreditGrades models (Yu, 2006; Duarte, Longstaff, and Yu, 2007). We provide the details on how we compute the hedge ratios in Appendix E. In Panel B of Table 9, we find significant capital structure arbitrage profits, with a maximum 158 bps per month and an annualized Sharpe ratio of 0.71 (see column 4 with the CreditGrades hedge ratios). Overall, our results in Table 9 suggest that there is strong price convergence pressure on "disjoint" entities due in part to sophisticated cross-market arbitrageurs. Such trading pressure could help explain why there is price reversal rather momentum in our disjoint momentum portfolio.

3.3 Joint Momentum - Disjoint Contrarian Combination: A Stronger Stock Market Anomaly

This section presents a new and stronger stock market anomaly that is based on our findings and intuition from the cross-section of stock return momentum. We show that a new, joint momentum-disjoint contrarian combination strategy significantly improves the performance of our earlier simple joint stock/CDS momentum strategy. In this new combination strategy, we either weight stocks according to their market capitalizations (Value-Weighted) or equally weight the joint momentum and the disjoint contrarian portfolios (50/50).

Table 10 reports our results. In Table 10, when $J = 4m$ is used as the past CDS return horizon, the momentum-contrarian combination strategy that uses equal capital weights (Combination 50/50) produces an annualized Sharpe ratio of 1.11. This is a net 34% increase in the annual Sharpe ratio of our simple joint momentum strategy (0.83). For the same CDS signal horizon, when we value-weight the stocks, the annual Sharpe ratio of the combination strategy improves even further by a net 42% (=1.18/0.83-1). Such significant Sharpe ratio enhancements are observed for virtually all past CDS return horizons from $J = 1m$ to $J = 9m$, indicating effective risk management in this new momentum-contrarian combination strategy.

Figure 6 graphically summarizes these findings. The stable performance of the combination strategy is evident in Figure 6 where we graphically compare the four different strategy returns: (1) traditional momentum, (2) joint stock/CDS momentum, (3) joint momentum-disjoint contrarian combination (Value-Weighted), and (4) the same combination strategy with equal weights (50/50). The two combination strategies depicted at the top of Figure 6 show strong outperformance over both joint and traditional stock momentum strategies throughout our whole sample period since 2003.

Put together, our results in Table 10 and Figure 6 confirm the recent notion introduced by Goldstein, Li, and Yang (2013) who theoretically demonstrate that stock price informativeness reduces when the market is segmented with different types of traders who might have different trading motives due to related securities' signals. They show that equity markets are more segmented when equity and CDS payoffs are tightly linked through both fundamental and non-fundamental factors, and therefore the two related securities serve as efficient hedging instruments to each other. Boehmer, Chava, and Tookes (2013) provide supporting evidence on this reduced equity market efficiency when related securities such as CDS contracts start trading. We add new empirical evidence to this important discussion by analyzing the cross-section of stock return momentum.

In Table 11, we show that stock-CDS cross-market hedging motives are indeed closely related to our new findings on strong momentum-contrarian combination strategy profits. Che and Kapadia (2012) show that cross-market hedging efficiency improves as equity and CDS payoffs are well-integrated. Using the equity-credit payoff integration measure introduced by Kapadia and Pu (2012), we show that our new momentum-contrarian combination strategy outperforms particularly for the entities whose equity and CDS payoffs are relatively well-integrated.

The equity-credit integration measure, $\kappa_{i,t}^{M}$, is computed as the fraction of days the stock and CDS moved in a congruent direction for firm i during the last M months (i.e., total D business days, for e.g.,D =125 for M =6):

$$\kappa_{i,t}^{M} = \frac{\sum_{t=1}^{D} \mathbb{1}_{[\Delta P_{i,t} \Delta CDS_{i,t} < 0]}}{D}$$

where $\Delta P_{i,t}$ refers to the one-day change in stock price from time $t-1$ to time t, and $\Delta CDS_{i,t}$ refers to the one-day change in CDS spread from time $t-1$ to time t. The integration measure ranges from 0 to 1, with a higher number indicating a greater level of integration between stock and CDS markets. For each formation date of our new combination strategy, we look back M =4, 6, and 12 months.

For the high and low integration entities that are identified by $\kappa_{i,t}^{M}$ on each formation date, we conditionally implement our best-performing momentum-contrarian combination stock trading strategy that is based on 12-month past stock (skipping the most recent month) and four-month CDS returns as sorting signals. In Table 11, we find that our new combination trading strategy yields significant trading profits across all three κ estimation periods (i.e., four-, six-, and 12-months). Importantly, these profits are concentrated in entities whose stock and CDS payoffs are highly integrated, and therefore their stock-CDS cross market hedging is efficient.

4 Conclusion

We introduce a simple, yet powerful, approach to detect relative under- or over-valuation in stock prices to underlying firm fundamentals using related security prices. In particular, we focus on single name CDS contracts as related securities. When pricing signals are extended to include related CDS pricing information, we sharply identify the cross-section of stocks that are under-reacting to firm fundamentals – thereby showing subsequent price momentum. We also show which stocks tend to show price reversal due in part to strong convergence pressure on their share prices that arise from mispriced credit risk in the related security markets.

Using 1,074 U.S. public firms that have actively trading five-year maturity single name CDS contracts during 2003-2014, we document the following important differences in the cross-section of stock return momentum. First, stock/CDS joint-market winners and losers continue to show price momentum and avoid the 2009 momentum crashes. The long/short portfolio return of this joint market momentum strategy outperforms traditional stock momentum strategies (Jegadeesh and Titman, 1993) by 122 bps per month with an annualized Sharpe ratio of 0.83. Second, we further find quick price reversal for "disjoint" entities whose past stock returns strongly disagree with past CDS returns. A momentum strategy that buys (sells short) disjoint stock winners (losers) who are past CDS losers (winners) show strong price reversal and are closely related to momentum crashes. We provide two potential rationales for these strong reversal risks; (1) option-like payoff risks in the disjoint momentum portfolio when a bear market rebounds from its bottom (Daniel and Moskowitz, 2014), and (2) cross-market convergence arbitrageurs who bet on the disjoint stocks that misprice the underlying credit risks relative to their CDS prices. Stock markets are potentially segmented with momentum traders and contrarian hedgers whose trades are motivated by relative pricing in the CDS market. Based on this market segmentation intuition, we show the existence of an even stronger stock market anomaly. Our new stock trading strategy that combines the joint-market momentum trades with contrarian trades on "disjoint" entities yields 135 bps per month with an annualized Sharpe ratio of 1.11. This result is a significant improvement in the Sharpe ratio relative to that of the simple joint stock/CDS momentum strategy (0.83).

Overall, we provide several important contributions to three relevant research streams. First, we provide a novel cross-sectional approach to detect a group of stocks that are more prone to momentum crashes (Daniel and Moskowitz, 2014; Daniel, Jagannathan, and Kim, 2012; Grundy and Martin, 2001; Barroso and Santa-Clara, 2015; Han, Zhou, and Zhu, 2014). Second, we show that related security pricing information is important in identifying individual stock momentum cycles (Lee and Swaminathan, 2000) through a relative pricing framework (Schaefer and Strebulaev, 2008; Friewald, Wagner, and Zechner, 2014; Bai and Wu, 2010; Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012). Third, our results contribute evidence on the recent notion that related securities induce stock market segmentation, which, in turn, can reduce stock price efficiency and cause excess volatility (Goldstein, Li, and Yang, 2013; Boehmer, Chava, and Tookes, 2013).

Our results shed new light on interactive cross-market anomalies rooted in market segmentation structures. We show how a firm's capital structure serves as a bridge for trading activity between stock and CDS markets, providing an explanation for why one might observe segmentation within the U.S. stock market. Given the complexity and increasing connectedness of global capital markets, other cross-asset, cross-market trading networks could further explain market segmentation structures (i.e., the relative volatility pricing between stock options and CDS markets, cross-country equity and credit market integration networks, among others). Identifying such interactive trading networks would further improve our understanding of asset pricing dynamics and capital market efficiency.

References

Acharya, Viral V., and Timothy C. Johnson, 2007, Insider trading in credit derivatives, *Journal of Financial Economics* 84, 110–141.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen, 2013, Value and momentum everywhere, *The Journal of Finance* 68, 929–985.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2009, Credit ratings and the cross-section of stock returns, *Journal of Financial Markets* 12, 469–499.

Bai, Jennie, and Liuren Wu, 2010, Anchoring corporate credit spreads to firm fundamentals, Discussion paper, Working Paper, June.

Barroso, Pedro, and Pedro Santa-Clara, 2015, Momentum has its moments, *Journal of Financial Economics* 116, 111–120.

Batta, George E, Jiaping Qiu, and Fan Yu, 2014, Credit derivatives and earnings announcements, *Claremont McKenna College Robert Day School of Economics and Finance Research Paper*.

Berndt, Antje, and Iulian Obreja, 2010, Decomposing European CDS returns, *Review of Finance* 14, 189–233.

Bharath, Sreedhar T., and Tyler Shumway, 2008, Forecasting default with the merton distance to default model, *Review of Financial Studies* 21, 1339–1369.

Boehmer, Ekkehart, Sudheer Chava, and Heather Tookes, 2013, Related securities and equity market quality: The case of cds, *Available at SSRN 1658694*.

Campbell, John Y, Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *The Journal of Finance* 63, 2899–2939.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *The Journal of finance* 52, 57–82.

Chava, Sudheer, Rohan Ganduri, and Chayawat Ornthanalai, 2012, Are credit ratings still relevant?, Working Paper, Georgia Institute of Technology and University of Toronto.

Che, Xuan, and Nikunj Kapadia, 2012, Can credit risk be hedged in equity markets?, *University of Massachusetts, working paper.*

Chordia, Tarun, and Lakshmanan Shivakumar, 2002, Momentum, business cycle, and time-varying expected returns, *Journal of Finance* pp. 985–1019.

Conrad, Jennifer, and Gautam Kaul, 1998, An anatomy of trading strategies, *Review of Financial studies* 11, 489–519.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under-and overreactions, *the Journal of Finance* 53, 1839–1885.

Daniel, Kent, Ravi Jagannathan, and Soohun Kim, 2012, Tail risk in momentum strategy returns, Working Paper, Columbia University and Northwestern University.

Daniel, Kent, and Tobias Moskowitz, 2014, Momentum crashes, NBER Working Paper 20439.

Dichev, Ilia D, 1998, Is the risk of bankruptcy a systematic risk?, *The Journal of Finance* 53, 1131–1147.

Duarte, Jefferson, Francis A Longstaff, and Fan Yu, 2007, Risk and return in fixed-income arbitrage: Nickels in front of a steamroller?, *Review of Financial Studies* 20, 769–811.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital, *The Journal of finance* 65, 1237–1267.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of financial economics* 33, 3–56.

Flannery, Mark, Joel Houston, and Frank Partnoy, 2010, Credit default swap spreads as viable substitutes for credit ratings, *University of Pennsylvania Law Review* 158, 10–031.

Friewald, Nils, Christian Wagner, and Josef Zechner, 2014, The cross-section of credit risk premia and equity returns, *The Journal of Finance* 69, 2419–2469.

Goldstein, Itay, Yan Li, and Liyan Yang, 2013, Speculation and hedging in segmented markets, *Review of Financial Studies* p. hht059.

Grundy, Bruce D, and J Spencer Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *The Review of Financial Studies* 14, 29–78.

Han, Bing, and Yi Zhou, 2011, Term structure of credit default swap spreads and cross-section of stock returns, *McCombs Research Paper Series No. FIN-01-11*.

Han, Yufeng, Guofu Zhou, and Yingzi Zhu, 2014, Taming momentum crashes: A simple stop-loss strategy, *Available at SSRN 2407199*.

Hong, Harrison, and Jeremy C Stein, 2003, Differences of opinion, short-sales constraints, and market crashes, *Review of financial studies* 16, 487–525.

Hull, John, Mirela Predescu, and Alan White, 2004, The relationship between credit default swap spreads, bond yields, and credit rating announcements, *Journal of Banking and Finance* 28, 2789–2811.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *The Journal of Finance* 48, 65–91.

Kapadia, Nikunj, and Xiaoling Pu, 2012, Limited arbitrage between equity and credit markets, *Journal of Financial Economics* 105, 542–564.

Kisgen, Darren J., 2006, Credit ratings and capital structure, *The Journal of Finance* 61, 1035–1072.

———, 2007, The influence of credit ratings on corporate capital structure decisions, *Journal of Applied Corporate Finance* 19, 65–73.

Lee, Charles, and Bhaskaran Swaminathan, 2000, Price momentum and trading volume, *The Journal of Finance* 55, 2017–2069.

Lee, Jongsub, Andy Naranjo, and Stace Sirmans, 2014, Cds momentum: Slow moving credit ratings and cross-market spillovers, *Available at SSRN 2423371*.

Lehmann, Bruce N, 1990, Fads, martingales, and market efficiency, *The Quarterly Journal of Economics* 105, 1–28.

Lo, Andrew W, and Archie Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial studies* 3, 175–205.

Merton, Robert C., 1974, On the pricing of corporate debt: The risk structure of interest rates, *The Journal of Finance* 29, 449–470.

Moskowitz, Tobias J, and Mark Grinblatt, 1999, Do industries explain momentum?, *The Journal of Finance* 54, 1249–1290.

Nelson, Charles R., and Andrew F. Siegel, 1987, Parsimonious modeling of yield curves, *Journal of Business* 60, 473–489.

Ni, Sophie, and Jun Pan, 2010, Trading puts and CDS on stocks with short sale ban, Working Paper, Hong Kong University and MIT.

Novy-Marx, Robert, 2012, Is momentum really momentum?, *Journal of Financial Economics* 103, 429–453.

———, 2015, Fundamentally, momentum is fundamental momentum, Working Paper, University of Rochester.

O'Kane, Dominic, 2008, *Modelling Single-name and Multi-name Credit Derivatives* (John Wiley & Sons).

Qiu, Jiaping, and Fan Yu, 2012, Endogenous liquidity in credit derivatives, *Journal of Financial Economics* 103, 611–631.

Schaefer, Stephen M, and Ilya A Strebulaev, 2008, Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds, *Journal of Financial Economics* 90, 1–19.

Svensson, Lars, 1994, Estimating and interpreting forward interest rates: Sweden 1992-1994, Centre for Economic Policy Research, Discussion Paper 1051.

Yu, Fan, 2006, How profitable is capital structure arbitrage?, *Financial Analysts Journal* 62, 47–62.

Appendices

A Variable Definitions

Variable Name	Description	Source
Market Cap	Equity market capitalization, defined as the number of common shares outstanding multiplied by the price of the firm's stock at the time of portfolio formation. (USD, $ Billions)	CRSP
Stock Return (%)	The holding period percentage return of the firm's stock over the course of the month.	CRSP
CDS Spread (bps)	Credit default swap (CDS) spreads (reported in basis points) are based on daily quoted spreads collected from a number of market makers. Each composite spread consists of at least two contributors and has passed a rigorous cleaning test to ensure accuracy and reliability.	Markit Group
CDS Return (%)	The holding period percentage return of the firm's CDS to the protection seller over the course of the month. Computed as the marked-to-market dollar change in value of CDS contract divided by notional value.	Markit Group
CDS Depth	The number of good contributions used to construct the composite spread. Markit requires at least two.	Markit Group
S&P Credit Rating	Standard and Poor's credit rating for the company (provided at the end of each month). It is converted to a numerical score in which 1=AAA, 2=AA+, 3=AA, ...	Standard & Poors: Compustat North America, Monthly Updates

B Factor Definitions

Factor Name	Description	Source
MKT	The value-weighted excess return on all NYSE, AMEX, and Nasdaq stocks.	Ken French's Website
SMB	The value-weighted return on a portfolio of small stocks minus a portfolio of big stocks.	Ken French's Website
HML	The value-weighted return on a portfolio of stocks with high book-to-market equity ratios minus a portfolio of stocks with low book-to-market equity ratios.	Ken French's Website
UMD	The value-weighted return on a portfolio of stocks with relative good performance over the last 12 months minus a portfolio of stocks with relative bad performance over the last 12 months.	Ken French's Website
UMD^S	Traditional stock momentum strategy using firms in our sample. Stocks are sorted based on past 12-month return, skipping the most recent month, and assigned to quintiles. The long/short strategy is formed by purchasing stocks in the highest quintile and selling short stocks in the lowest quintile, and rebalanced monthly. Returns are value-weighted.	CRSP
SUE	Stocks are sorted based on the standardized unexpected earnings (SUE), and assigned to quintiles. SUE is defined as the most recent EPS minus EPS twelve months ago, divided by the standard deviation of quarterly EPS over the last eight quarters. The long/short strategy is formed by purchasing stocks in the highest quintile and selling short stocks in the lowest quintile, rebalanced monthly. Returns are value-weighted.	CRSP, Compustat
$CAR3$	Stocks are sorted based on the cumulative abnormal three-day return (CAR3), and assigned to quintiles. CAR3 is defined as cumulative three-day return around the most recent earnings announcement minus the market return multiplied by beta. The long/short strategy is formed by purchasing stocks in the highest quintile and selling short stocks in the lowest quintile, rebalanced monthly. Returns are value-weighted.	CRSP, Compustat

C CDS Return Computation

First, we provide a standard CDS pricing model as in O'Kane (2008).[18] Then, through this pricing framework, we define the mark-to-market value of a CDS with a unit \$1-notional using at-market spread quotes from Markit. The change of these mark-to-market values over a given holding period determines the CDS holding period return.

C.1 CDS Return: Pricing Framework and Mark-to-market

We split the pricing of a CDS contract with a unit \$1-notional into two legs, the premium leg and protection leg. To simplify our illustration, we assume that we are on the inception date of a five-year CDS. This fresh five-year contract matures on the first IMM date five years after the trade date. Since 2003, at any moment in time, the most liquid $T-$year CDS contract is the one that matures on the first IMM date T years after the trade date. For example, a five-year CDS contract trading on 12/20/2013 matures on 3/20/2018. The premium leg has two components. First, there are 21 scheduled premium payments on a quarterly cycle with the CDS IMM dates – the 20th of March, June, September, and December – until the maturity date as long as the reference entity survives. When there is a credit event, there is a payment of the premium that has accrued since the last quarterly premium payment date. This is the second component of the premium leg.

Let us denote the quarterly premium payment dates over a five-year horizon by t_i, $i = 1, 2, \dots, 21$, and let t_0 denote our valuation date. Given the quoted spread of S_0 at time-t_0, the present value of the first component of the premium leg becomes

$$S_0 \sum_{n=1}^{n=21} \Delta(t_{n-1}, t_n) Q(t_0, t_n) Z(t_0, t_n), \tag{3}$$

where $\Delta(t_{n-1}, t_n)$ denotes the accrual factor for the time period, $[t_{n-1}, t_n]$, and $Q(t_0, t_n)$ and $Z(t_0, t_n)$, respectively, denote the survival probability of the reference entity and default-free discounting factor for the time period, $[t_0, t_n]$.

Now, we consider the premium accrued at default for the n^{th} premium period, $[t_{n-1}, t_n]$.

[18] Under the flat hazard rate assumption, O'Kane's (2008) pricing model becomes an ISDA CDS Standard model used by Markit.

Over an infinitesimal time interval, $[s, s+ds]$ for $s \in [t_{n-1}, t_n]$, the expected present value of the premium accrued upon default is given by

$$S_0 \Delta(t_{n-1}, s) \left(-dQ(t_0, s)\right) Z(t_0, s). \tag{4}$$

Then, the value of the premium accrued upon default for all 21 premium periods is given by

$$S_0 \sum_{n=1}^{n=21} \int_{t_{n-1}}^{t_n} \Delta(t_{n-1}, s) Z(t_0, s) \left(-dQ(t_0, s)\right). \tag{5}$$

By summing up Eq. (3) and (5), the present value of the premium leg becomes

$$\text{Premium Leg PV} = S_0 \cdot RPV01(t_0, t_{21}), \tag{6}$$

where $RPV01(t_0, t_{21})$ is given by

$$RPV01(t_0, t_{21}) = \sum_{n=1}^{n=21} \Delta(t_{n-1}, t_n) Q(t_0, t_n) Z(t_0, t_n) + \sum_{n=1}^{n=21} \int_{t_{n-1}}^{t_n} \Delta(t_{n-1}, s) Z(t_0, s) \left(-dQ(t_0, s)\right). \tag{7}$$

The integration in the second term in Eq. (7) can be approximated as

$$\int_{t_{n-1}}^{t_n} \Delta(t_{n-1}, s) Z(t_0, s) \left(-dQ(t_0, s)\right) \simeq \frac{1}{2} \Delta(t_{n-1}, t_n) Z(t_0, t_n) \left(Q(t_0, t_{n-1}) - Q(t_0, t_n)\right). \tag{8}$$

Thus, we have

$$\begin{aligned} RPV01(t_0, t_{21}) = \;& \textstyle\sum_{n=1}^{n=21} \Delta(t_{n-1}, t_n) Z(t_0, t_n) Q(t_0, t_n) \\ & + \textstyle\sum_{n=1}^{n=21} \frac{1}{2} \Delta(t_{n-1}, t_n) Z(t_0, t_n) \left(Q(t_0, t_{n-1}) - Q(t_0, t_n)\right). \end{aligned} \tag{9}$$

Assuming a constant loss given default, $(1-R)$, together with the standard assumption of independence of interest rate and the default time, we can write the present value of the protection leg as

$$\begin{aligned} \text{Protection Leg PV} \; & = (1-R) \textstyle\int_{t_0}^{t_{21}} Z(t_0, s) \left(-dQ(t_0, s)\right) \\ & \simeq (1-R) \textstyle\sum_{n=1}^{n=21} Z(t_0, t_n) \left(Q(t_0, t_{n-1}) - Q(t_0, t_n)\right). \end{aligned} \tag{10}$$

The second line shows that the integration in the first line is performed by discretizing the five-year horizon by 21 intervals with each coupon payment date. Here we directly use the lower bound of the discretized integration.

Combining the present values of the premium and the protection legs gives the mark-to-market value of a five-year short protection position of a CDS with a unit \$1-notional as

$$V(t_0) = S_0 \cdot RPV01(t_0, t_{21}) - (1 - R) \sum_{n=1}^{n=21} Z(t_0, t_n) \left(Q(t_0, t_{n-1}) - Q(t_0, t_n)\right), \tag{11}$$

where $RPV01(t_0, t_{21})$ is as in Eq. (9). For a protection buyer, the mark-to-market value would be just the opposite, $-V(t_0)$.

With the quoted spread, S_0, $V(t_0) = 0$ as required.[19] However, soon after the inception of trading, this requirement is no longer true since the market spread of the CDS reference entity moves from the spread that the protection seller/buyer are locked into.

Finally, with this pricing framework, we can easily define the P&L of a CDS with a unit \$1-notional over a holding period, $[t_0, t']$. For simplicity, we assume for a moment that this interval is short enough so that we can ignore any coupon flows and also potential credit event during this holding period. If we entered as a seller of a protection at time-t_0 and unwind the position at time-t' by buying a protection on the same reference entity and the same maturity date, then the CDS holding period excess return is given as

$$\text{CDS return}(t_0, t') = -\left(S(t') - S(t_0)\right) \cdot RPV01(t', t_{21}). \tag{12}$$

$S(t_0) \cdot RPV01(t', t_{21})$ in the above Eq. (12) denotes the time-t' value of the protection we sold at time-t_0, and $-S(t') \cdot RPV01(t', t_{21})$ the time-t' cost to purchase the protection on the same reference entity with the same maturity date. If there is a credit event over our holding period, then the realized return will be equal to $-(1 - \tilde{R})$ where $\tilde{R}$ is a realized recovery rate upon the credit event. Eq. (12) does not take into account coupon flows during our holding period and the accrued premium that should be exchanged at each selling and buying transaction of the default protection. We carefully incorporate these factors when

[19] If our valuation falls between two consecutive coupon payment dates, the quoted spread will make the clean mark-to-market value zero. We need to adjust for accrued premium since the last coupon payment date when we compute the clean mark-to-market.

we implement this CDS return framework using the quoted spreads from Markit. The U.S. $Libor curve retrieved from DataStream is calibrated to fit the Nelson-Siegel-Svensson (NSS) curve (Nelson and Siegel, 1987; Svensson, 1994), and we construct the default-free discounting factors using the fitted values of the NSS curve. After all these considerations, we compute CDS returns based on "clean" P&L's.

C.2 Implementation of the CDS Returns using Markit Data

As illustrated above, we approach CDS returns from the perspective of the protection seller (i.e., a negative return corresponds to an increase in credit risk). We compound monthly trading return of five-year contracts from their daily returns. To compute the CDS return, we need to construct the survival probability curve on a given valuation date-t', $Q(t', t_i)$, for $i = 1, 2, ..., 21$. Instead of bootstrapping this survival probability curve using the quoted spreads of CDS contracts across entire maturity groups, we assume a flat hazard rate, $h(t', t_i) \equiv -\frac{1}{Q(t',t_i)} \frac{\partial Q(t',t_i)}{\partial t_i} = h$ for $\forall i = 1, 2, \ldots, 21$, and calibrate the hazard from the quoted spread of a five-year CDS contract.

It is possible that credit events occur during our monthly holding period. If a credit event occurs, we need to assign the realized loss given default to the CDS return for that holding period. We use the realized recovery rate information that we compiled from the Creditex Group and make appropriate adjustments in our holding period excess returns.

An accrued premium should be adjusted when the CDS trade occurs in between the quarterly coupon payment interval. There are two different ways the accrued premium payment is handled during our sample period. Before the 2009 "Big Bang" protocol, the first premium accrued since the trade date was paid either on the next immediate coupon date (i.e., short-stub) or the following coupon date (i.e., long-stub), depending on the trade date. If the trade date fell within a 30-day window prior to the first upcoming coupon date, it would follow the long-stub rule and the short-stub otherwise. However, post-"Big Bang," these complicated accrued premium payment rules disappeared, and now the single-name CDS contracts trade just like the Markit CDS indices where the new protection seller will receive the full quarterly coupon on each coupon payment date. Any "over"-paid premium to this seller by the protection buyer is rebated upfront. We follow this post-"Big Bang" coupon convention when we adjust the accrued premium to get the clean P&L of our CDS trading.

We compute the P&L's on the running spread basis, instead of using fixed 100 bps/500 bps coupons with upfront adjustments. Since the default-free rate during our sample period is relatively low, the potential errors in our treatment of the stub algorithms should be minimal for CDS returns in the pre-"Big Bang" period.

D Decomposition of the Stock Cross-section and Various Stock/CDS Momentum and Contrarian Trading Strategies: A Graphical Approach

In this appendix, we graphically illustrate how we subgroup stocks based on their past stock and CDS returns. We further show how we implement various stock/CDS momentum strategies as well as the contrarian strategy using these subgroups. Although not shown in the figures, there are intermediate group of stocks that are neither winners nor losers. We omit them in our figures for illustrative purposes.

Figure A1. Decomposition of the Stock Cross-section

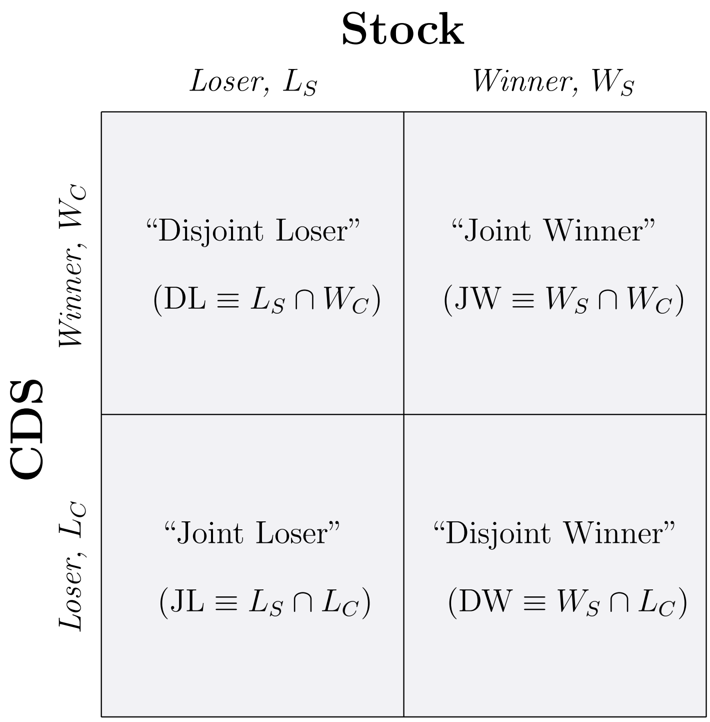


Figure A2. Joint Stock/CDS Momentum Strategy

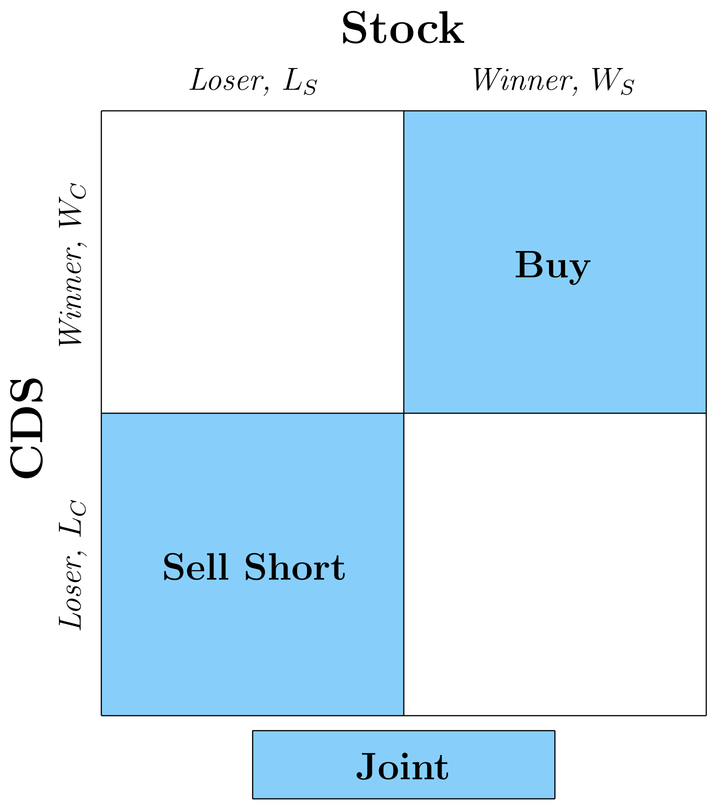


Figure A3. Disjoint Stock/CDS Momentum Strategy

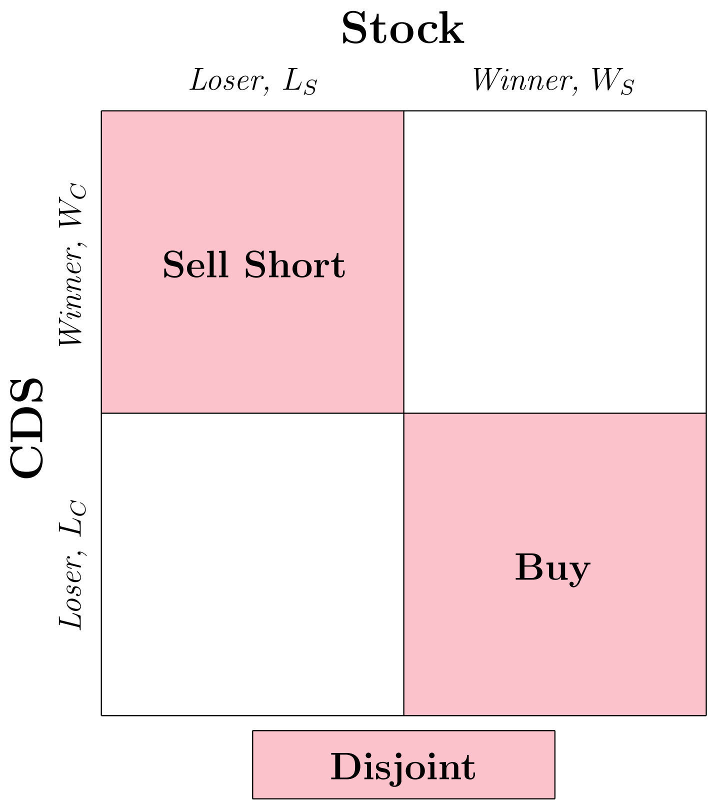
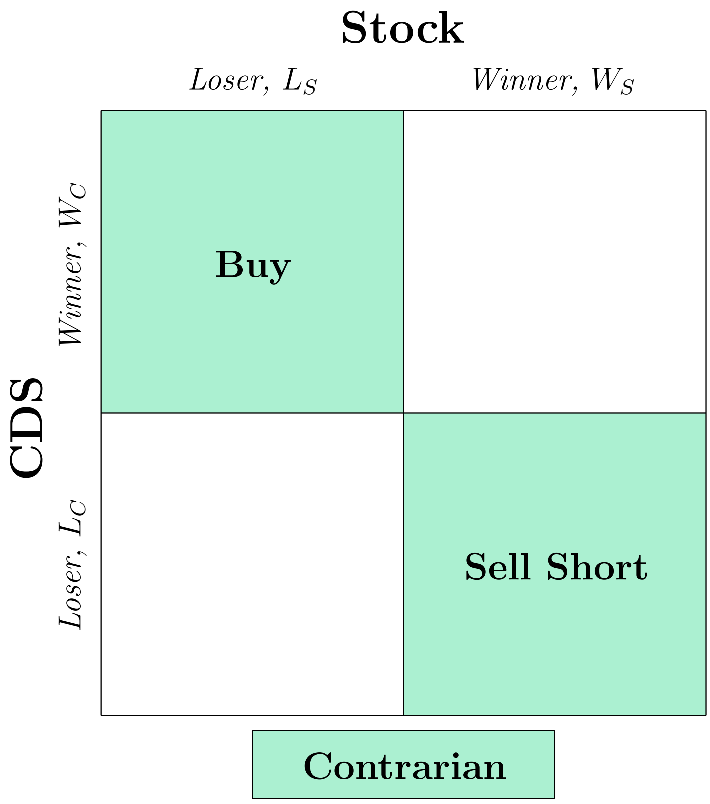


Figure A4. Disjoint Contrarian Strategy (i.e., Reverse Disjoint Momentum)



E Hedge Ratios

We employ four different methods of computing a hedge ratio between equity and CDS. We use these hedge ratios to implement the capital structure arbitrage described in Section 3.2.2 of our main text. The hedge ratio is estimated on each rebalancing date. We scale our CDS position using these hedge ratios during the capital structure arbitrage trade.

E.1 Statistical Hedge Ratio (Portfolio-level)

On each rebalancing date, we assemble a basket of stocks and a basket of CDS contracts corresponding to the disjoint winner/loser momentum portfolio and compute cap-weighted returns. Using daily data over the prior six months, we regress the time series of returns to the basket of stocks on the returns to the basket of CDS contracts in the following manner:

$$r_S = \alpha + \beta_C \times r_C + \epsilon$$

where r_S is the daily return on the basket of stocks and r_C is the return on the basket of CDS contracts. The estimated beta coefficient is assigned as the portfolio-level hedge ratio. One estimation is made for the disjoint momentum winner portfolio and another for the disjoint loser, resulting in two beta coefficients, β_C^W and β_C^L, respectively.

E.2 Statistical Hedge Ratio (Firm-level)

On each rebalancing date, we run the following daily time series regression for each firm over a six-month window:

$$r_{i,S} = \alpha_i + \beta_{i,C} \times r_{i,C} + \epsilon_i$$

where $r_{i,S}$ is the firm's daily stock return and $r_{i,C}$ is the firm's daily CDS return. The estimated beta coefficient, $\beta_{i,C}$, is assigned as the firm's hedge ratio. Portfolio-level hedge ratios are computed by cap-weighting all firm-level hedge ratios within the disjoint momentum winner and loser portfolio. This procedure results in two portfolio-level hedge ratios, one for the disjoint winner and another for the loser portfolio.

E.3 Merton (1974) Model Hedge Ratio

Schaefer and Strebulaev (2008) derive the stock to corporate bond elasticity from Merton (1974) model and show that this theoretical hedge ratio successfully explains the relation between stock and bond returns. Given the classic Merton (1974) model assumptions with a diffusion process of a firm value V with volatility σ_V, the face value of the firm's zero-coupon debt D with maturity T, the equity value of the firm denoted by E, and the default-free riskless interest rate of r, the equity to debt price sensitivity is given as

$$\frac{\partial D}{\partial E} = \frac{\partial D/\partial V}{\partial E/\partial V} = \frac{\mathcal{N}(-d-\sigma_V\sqrt{T})}{\mathcal{N}(d+\sigma_V\sqrt{T})} \equiv \frac{1}{\Delta_E} - 1, \tag{13}$$

where $\mathcal{N}(.)$ denotes the cumulative probability density of a standard normal distribution, and d is a distance-to-default:

$$d = \frac{\ln(V/D) + (r - 0.5\sigma_V^2)\cdot T}{\sigma_V\sqrt{T}}. \tag{14}$$

The hedge ratio δ between stock return and bond return is defined as the elasticity between E and D :

$$\delta = \frac{\partial D/D}{\partial E/E} = \left(\frac{1}{\Delta_E} - 1\right)\frac{E}{D}. \tag{15}$$

This hedge ratio could be a good reduced form approximation for our CDS holding period excess return, which is the return (net of default-free riskless rate) of holding a five-year risky-par bond for a given period. In fact, the hedge ratio for our CDS holding period return is approximately the Merton (1974) hedge ratio δ in Equation (15) when the change in Merton (1974) credit spread (∂S_{Merton}) relatively accurately explains the change in at-market CDS spreads (∂S). From Equation (12),

$$\begin{aligned}
\delta^{CDS} &= \tfrac{\partial(\text{CDS return})}{\partial E/E} \\
&= \left(\tfrac{\partial(\text{CDS return})}{\partial S}\right)\cdot\left(\tfrac{\partial S}{\partial S_{Merton}}\right)\cdot\left(\tfrac{\partial S_{Merton}}{\partial E/E}\right) \\
&\approx \underbrace{-(RPV01)}_{\text{ISDA CDS Model Hedge Ratio}} \cdot\left(\tfrac{\partial S}{\partial S_{Merton}}\right)\cdot\left(-\tfrac{1}{T}\cdot\tfrac{\partial D/D}{\partial E/E}\right)
\end{aligned} \tag{16}$$

$RPV01$ is the risky duration of a five-year risky-par bond, which is around $T = 5$ except highly defaultable entities. If $\partial S_{Merton} \approx \partial S$, we have $\delta^{CDS} \approx \frac{\partial D/D}{\partial E/E} = \delta$.

To compute δ, we estimate the total firm value and its volatility based on observed equity value (E) and volatility (σ_E) using the following two equations from Bharath and Shumway (2008):

$$E = V \cdot \mathcal{N}(d + \sigma_V \sqrt{T}) - e^{-rT} \cdot D \cdot \mathcal{N}(d) \tag{17}$$

and

$$\sigma_E = \frac{V}{E} \cdot \mathcal{N}(d + \sigma_V \sqrt{T}) \cdot \sigma_V, \tag{18}$$

The equity value of the firm E is defined as the share price multiplied by the number of shares outstanding, the equity volatility σ_E is approximated using the standard deviation of weekly stock returns over the past year, and the firm's total debt is used for the face value of debt D. We use the one-year Treasury rate as the risk-free rate and fix debt maturity at five years for all firms.

E.4 CreditGrades Model Hedge Ratio

Our Merton (1974) model hedge ratio have several drawbacks besides the approximation issues we addressed in the previous section. One of such drawbacks includes that the Merton (1974) model does not allow any intermediate default before maturity. To overcome this drawback, we use the CreditGrades model which is based on Black and Cox (1976) and Leland (1994). The equity-credit hedge ratios from this CreditGrades model are also known to be commonly used by practitioners in the implementation of capital structure arbitrage.

Similar to Merton (1974), the CreditGrades model assumes that firm value V follows a standard Brown motion (W) with volatility σ_V. The firm's debt-per-share D remains constant, and the recovery rate L follows a lognormal distribution with mean $\bar{L}$. The model allows the potential for default to occur before maturity as firm value falls below a specified threshold (the value of assets that could be recovered in the event of default). The default threshold is represented as

$$LD = \bar{L}De^{\lambda Z - \lambda^2/2}, \tag{19}$$

where λ^2 =Var $\log(L)$ and Z is a standard normal variable. Thus, starting with initial firm value V_0, default does not occur as long as

$$V_0 e^{\sigma_V W_t - \sigma_V^2 t/2} > \bar{L} D e^{\lambda Z - \lambda^2/2}. \tag{20}$$

We derive the T-year CreditGrades-implied CDS spread c using the firm's stock price S, debt-per-share D (total liabilities divided by common shares outstanding), standard deviation of the global recovery rate λ (assumed to be 0.3), bond-specific recovery rate R (assumed to be 0.5), equity volatility σ_S (the annualized standard deviation of weekly returns over the past year), the risk-free rate r (1-year Treasury rate), CDS contract maturity T (set to be 5), and the mean global recovery rate $\bar{L}$. Similar to Yu (2006), we calibrate $\bar{L}$ for each firm by minimizing the sum of squared differences between the CreditGrades model spread and observed Markit spread using the first 10 days of available data. This allows each firm to have a constant $\bar{L}$ that reflects a recovery expectation implied by the data. The implied T-year CDS spread is

$$c_T = r(1-R)\frac{1 - q(0) + H(T)}{q(0) - q(T)e^{-rT} - H(T)}, \tag{21}$$

where survival probability $q(T)$ is expressed as

$$q(T) = \Phi\left[-\frac{\sqrt{\sigma_T^2 T + \lambda^2}}{2} + \frac{\ln d}{\sqrt{\sigma_T^2 T + \lambda^2}}\right] - d\Phi\left[-\frac{\sqrt{\sigma_T^2 T + \lambda^2}}{2} - \frac{\ln d}{\sqrt{\sigma_T^2 T + \lambda^2}}\right], \tag{22}$$

with $\Phi(\cdot)$ being the cumulative normal distribution function, and

$$H(T) = e^{r\xi}\left[G(T+\xi) - G(\xi)\right], \tag{23}$$

$$G(T) = d^{z+0.5}\cdot\Phi\left[-\frac{\ln d}{\sigma_V\sqrt{T}} - z\sigma_V\sqrt{T}\right] + d^{z+0.5}\cdot\Phi\left[-\frac{\ln d}{\sigma_V\sqrt{T}} + z\sigma_V\sqrt{T}\right], \tag{24}$$

$$d = \frac{V_0}{\bar{L}D}e^{\lambda^2}, \tag{25}$$

$$\xi = \frac{\lambda^2}{\sigma_V^2}, \tag{26}$$

and

$$z = \sqrt{\frac{1}{4} + \frac{2r}{\sigma_V^2}}. \tag{27}$$

To relate the asset volatility to equity volatility, CreditGrades uses a simple approximation for the asset value of $V = S + \bar{L}D$, which gives $\sigma_V = \sigma_S S/(S + \bar{L}D)$.

At the time a CDS contract is written, the spread is set such that the credit protection buyer and seller positions are equivalent, resulting in the value of the contract π being zero. The spread will change over time as the equity value changes, and the value of the contract will change proportional to the spread. The hedge ratio δ between the stock S and a T-year CDS contract π_T is expressed as

$$\delta = \frac{\partial \pi_T}{\partial S} = \frac{1}{r}\frac{\partial c_T}{\partial S}\left(q(0) - q(T)e^{-Tr} - e^{r\xi}\left[G(T+\xi) - G(T)\right]\right) \tag{28}$$

where $\frac{\partial c_T}{\partial S}$ is numerically computed.

Table 1. Sample Statistics

This table presents summary statistics in Panel A and a correlation matrix in Panel B of variables used in this study. Data are monthly from January 2003 to April 2014. Equity data are obtained from CRSP, CDS data are provided by Markit, and S&P Ratings are acquired from Compustat. N refers to the number of firm-month observations.

Panel A. Summary Statistics

	Mean	Stdev	Min	Med	Max	N
Market Cap ($ Billion)	18.23	32.19	0.228	8.83	202.14	85,429
Stock Return (%, monthly)	1.01	11.18	-86.87	1.11	259.66	85,429
CDS Spread (bps)	182.76	345.80	2.53	88.25	9739.77	85,429
CDS Return (%, monthly)	0.23	2.17	-93.42	0.51	175.82	85,429
CDS Depth	5.42	3.26	2	5	30	85,429
S&P Rating (1="AAA", 22="D")	9.04	3.16	1	9	22	80,275

Panel B. Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Market Cap	1.000					
(2)	Stock Return	-0.017	1.000				
(3)	CDS Spread	-0.195	0.025	1.000			
(4)	CDS Return	-0.003	0.041	-0.070	1.000		
(5)	CDS Depth	0.095	-0.015	-0.096	-0.028	1.000	
(6)	S&P Rating	-0.539	-0.001	0.511	0.028	-0.080	1.000

Table 2. Joint Stock/CDS Market Momentum

This table presents our joint stock/CDS momentum results. The joint winner and loser portfolios, JW and JL, respectively, are defined as the overlap between stock momentum portfolios and CDS momentum portfolios. We denote stock losers (winners) by L_S (W_S) and CDS losers (winners) by L_C (W_C). Stock momentum portfolios are based on quintiles of the past 12-month stock return, skipping the most recent month. CDS momentum portfolios are based on quintiles of the past J-month CDS return. CDS formation horizons range from $J = 1$ to $J = 12$ months. The holding period of the momentum strategy is one month ($K = 1$). "Advantage" refers to the joint momentum return in excess of traditional stock momentum return using only the past 12-month stock return (skipping the most recent month) as a single sorting signal. The time period spans January 2003 to April 2014. The 12-lag Newey-West t-statistic is provided in parenthesis, and *, **, and *** are indicators of statistical significance at the 10%, 5%, and 1% levels, respectively. Notation for each portfolio return follows the pattern: mean, (t-stat), and annualized *Sharpe* ratio (when reported).

	Joint Loser ($JL \equiv L_S \cap L_C$)	Joint Winner ($JW \equiv W_S \cap W_C$)	Long/Short Return (JW − JL)	Advantage (JW–JL) − (W_S–L_S)
$J = 1m$	0.623%	1.129%	0.506%	0.499%
	(0.71)	(1.58)	(1.16)	(1.11)
			0.36	
$J = 2m$	0.558%	1.251%*	0.693%	0.690%
	(0.60)	(1.81)	(1.59)	(1.49)
			0.47	
$J = 3m$	0.420%	1.355%**	0.934%**	0.931%*
	(0.49)	(2.00)	(2.11)	(1.89)
			0.60	
$J = 4m$	0.427%	1.648%**	1.221%***	1.218%**
	(0.49)	(2.41)	(2.86)	(2.11)
			0.83	
$J = 5m$	0.450%	1.404%**	0.954%**	0.951%*
	(0.50)	(2.11)	(2.26)	(1.94)
			0.63	
$J = 6m$	0.556%	1.500%**	0.944%**	0.941%**
	(0.60)	(2.55)	(2.03)	(2.40)
			0.61	
$J = 9m$	0.572%	1.244%**	0.673%	0.670%**
	(0.62)	(2.18)	(1.32)	(2.08)
			0.45	
$J = 12m$	0.456%	1.205%**	0.749%	0.746%***
	(0.50)	(2.24)	(1.45)	(2.62)
			0.52	

Table 3. Joint Stock/CDS Momentum Risk-adjusted Performance

This table presents the results of various spanning tests of joint stock/CDS momentum. MKT, SMB, and HML refer to factors from the Fama-French three-factor model, UMD denotes a traditional stock momentum factor (obtained from Ken French's website), UMD^S is an in-sample traditional stock momentum factor, SUE is a broad stock market factor based on the standardized unexpected earnings, and $CAR3$ is a broad stock market factor based on the three-day cumulative abnormal return around the most recent earnings announcement. The joint winner and loser portfolios, JW and JL, respectively, are defined as the overlap between stock momentum portfolios and CDS momentum portfolios. Stock momentum portfolios are based on quintiles of the past 12-month stock return, skipping the most recent month. CDS momentum portfolios are based on quintiles of the past four-month CDS return. The joint momentum strategy goes long JW and sells short JL. The time period spans January 2003 to April 2014. The 12-lag Newey-West t-statistic is provided in parenthesis, and *, **, and *** are indicators of statistical significance at the 10%, 5%, and 1% levels, respectively.

	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	β^S_{UMD}	β_{SUE}	β_{CAR3}
[M1]	1.626***	-0.467***	-0.175	-0.103				
	(4.22)	(-3.36)	(-0.23)	(-0.44)				
[M2]	1.476***	-0.278**	-0.113	0.182	0.599***			
	(3.91)	(-2.38)	(-0.63)	(0.87)	(7.17)			
[M3]	1.379***	-0.175*	-0.145	0.104		0.510***		
	(3.79)	(-1.71)	(-0.93)	(0.53)		(9.29)		
[M4]	1.371***	-0.468***	-0.103	0.142			0.854**	
	(3.86)	(-3.38)	(-0.22)	(0.67)			(2.18)	
[M5]	1.070***	-0.358***	-0.067	0.073				1.273***
	(2.86)	(-2.77)	(-0.36)	(0.39)				(3.84)

Table 4. Joint Stock/CDS Momentum and Future Firm Fundamentals

This table presents the average long-term earnings growth and credit rating change within each joint stock/CDS momentum winner and loser portfolio. Multi-month changes in earnings and ratings are constructed to avoid overlapping returns. For example, the six-month change in earnings is computed by equally averaging the one-month percentage change in earnings using momentum portfolios formed in the current month, one month prior, two months prior, three months prior, four months prior, and five months prior. The joint stock/CDS momentum strategy is formed by purchasing (short selling) firms that fall in both the traditional stock winner (loser) *and* the CDS winner (loser) portfolio. JW represents the joint winner portfolio, while JL represents the joint loser portfolio. The traditional stock momentum strategy is formed by buying winners (W_S) and selling losers (L_S) of quintiles based on the past 12-month stock return, skipping the most recent month. The CDS momentum portfolios are quintiles of the past four-month CDS return. The time period spans January 2003 to April 2014. Notation for each statistic below follows the pattern: mean, (t-stat). The symbols *, **, and *** are indicators of statistical significance at the 10%, 5%, and 1% levels, respectively.

	Joint Stock/CDS Momentum			**Traditional Stock Momentum**		
	Loser (JL)	Winner (JW)	Long/Short (JW – JL)	Loser (L_S)	Winner (W_S)	Long/Short (W_S – L_S)
Earnings (% Change)						
6 Months	-8.04%	5.61%	13.65%***	-5.51%	4.27%	9.78%***
			(2.82)			(2.99)
12 Months	-8.23%	4.51%	12.74%***	-6.11%	2.32%	8.44%***
			(2.75)			(2.86)
18 Months	-4.80%	2.71%	7.51%*	-3.55%	1.54%	5.09%*
			(1.87)			(1.94)
S&P Credit Rating (+1.00 = Rating sub-notch downgrade)						
6 Months	0.047	-0.020	-0.067***	0.027	-0.010	-0.038***
			(7.92)			(7.88)
12 Months	0.039	-0.019	-0.058***	0.025	-0.010	-0.035***
			(8.18)			(8.20)
18 Months	0.031	-0.013	-0.044***	0.021	-0.008	-0.029***
			(7.37)			(7.75)

Table 5. Robustness to a Finer Sort: Multi-horizon Stock Return Signals

This table shows results of a strategy that double-sorts on the past 12-month stock return, skipping the most recent month, and a shorter-term J-month stock return. The winner and loser portfolios, W^{MT} and L^{MT}, respectively, are defined as the overlap between independently created quintiles of 12-month stock returns and J-month stock returns, ranging from $J = 1$ to $J = 9$. Results are shown for the contiguous and non-contiguous formation periods of the J-month short-term stock return. The holding period of the momentum strategy is one month ($K = 1$). "Adv" refers to the performance advantage of the double-sorted multi-horizon momentum return over the in-sample 12-month traditional stock momentum return. The time period spans January 2003 to April 2014. The 12-lag Newey-West t-statistic is provided in parenthesis, and *, **, and *** are indicators of statistical significance at the 10%, 5%, and 1% levels, respectively. Notation for each portfolio return follows the pattern: mean, (t-stat), and annualized *Sharpe* ratio (when reported).

	Contiguous Formation/Holding Periods				**Non-Contiguous**	
	L^{MT}	W^{MT}	$W^{MT} - L^{MT}$	Adv	$W^{MT} - L^{MT}$	Adv
$J = 1m$	1.060%	1.286%***	0.226%	0.223%	—	—
	(1.03)	(2.65)	(0.28)	(0.61)		
			0.11			
$J = 2m$	0.820%	1.262%**	0.442%	0.439%	-0.379%	-0.382%
	(0.83)	(2.44)	(0.63)	(1.13)	(-0.61)	(-1.37)
			0.24		*-0.22*	
$J = 3m$	0.751%	1.151%**	0.401%	0.398%	-0.154%	-0.157%
	(0.83)	(2.46)	(0.61)	(1.18)	(-0.25)	(-0.60)
			0.22		*-0.08*	
$J = 4m$	0.988%	1.110%**	0.122%	0.119%	0.0627%	0.0598%
	(1.02)	(2.29)	(0.17)	(0.39)	(0.12)	(0.22)
			0.06		*0.04*	
$J = 5m$	0.857%	1.144%**	0.286%	0.283%	0.263%	0.260%
	(0.94)	(2.33)	(0.43)	(1.00)	(0.50)	(0.94)
			0.15		*0.15*	
$J = 6m$	0.871%	1.071%**	0.200%	0.197%	0.101%	0.098%
	(0.92)	(2.21)	(0.28)	(0.67)	(0.14)	(0.31)
			0.11		*0.05*	
$J = 9m$	0.737%	1.122%**	0.384%	0.381%	0.248%	0.245%
	(0.79)	(2.32)	(0.58)	(1.26)	(0.33)	(0.75)
			0.22		*0.12*	

Table 6. Relative Advantage of CDS Market Information: Distress Levels and Market States

This table reports conditional performance of the joint stock/CDS momentum strategy for groups of firms and time periods of high/low distress risk. We use the S&P credit rating or five-year CDS spread to decompose our sample firms or times series into two groups according to their level of credit risks. Using S&P credit ratings we divided our sample firms into two equally sized groups – Safe and Risky. The low (high) distress market state indicates the months in the pre- (post-) July 2007 time period. The joint winner and loser portfolios, JW and JL, respectively, are defined as the overlap between stock momentum portfolios and CDS momentum portfolios. Stock momentum portfolios are based on quintiles of the past 12-month stock return (skipping the most recent month). CDS momentum portfolios are based on quintiles of the past four-month CDS return. The joint momentum strategy goes long JW and sells short JL. Advantage refers to the performance difference between our joint stock/CDS momentum strategy and the traditional stock momentum strategy. The 12-lag Newey-West t-statistic is provided in parenthesis, and *, **, and *** are indicators of statistical significance at the 10%, 5%, and 1% levels, respectively.

	Joint Loser (JL)	Joint Winner (JW)	Long/Short Return (JW – JL)	Advantage (JW–JL)–(W–L)
S&P Rating				
Safe	1.072*	1.216***	0.145	0.142
	(1.77)	(2.75)	(0.49)	(0.32)
Risky	0.363	1.872**	1.510***	1.507**
	(0.37)	(2.31)	(3.34)	(2.15)
Market State (Corporate CDS Spread Level)				
Low Risk	1.231*	2.010**	0.870**	0.658
	(1.72)	(2.60)	(2.05)	(1.00)
High Risk	-0.00988	1.283	1.445**	1.576**
	(-0.01)	(1.29)	(2.26)	(2.11)

Table 7. Risk Characteristics of Joint versus Disjoint Stock/CDS Momentum Strategy Returns

This table summarizes risk characteristics of the joint and disjoint stock/CDS momentum strategies relative to the traditional stock momentum strategy. The joint momentum strategy is formed by purchasing (short selling) firms that fall in both the traditional stock winner (loser) portfolio *and* the CDS winner (loser) portfolio. The disjoint momentum strategy is formed by purchasing (short selling) firms that fall in the traditional stock winner (loser) *and* the CDS loser (winner) portfolio. The traditional stock momentum strategy is formed by buying winners and selling losers of quintiles based on the past 12-month stock return, skipping the most recent month. The CDS momentum portfolios are quintiles of the past four-month CDS return. The holding period of the momentum strategy is one month ($K = 1$). Panel A shows the distributional summary of the ex-post realized returns of the three distinct momentum strategies. In Panel B, the ex-ante option Gamma is computed at each formation date using daily returns over a rolling three-month period and the firm's capital structure. The Merton (1974) option gamma is computed for each firm and then averaged across firms in each portfolio. The time period spans January 2003 to April 2014. The 12-lag Newey-West t-statistic is provided in parenthesis. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Ex-Post Realized Risk Characteristics (based on full-sample monthly data)

	Mean	Stdev	Max	Med	Min	Kurt	Skew
Traditional Stock Momentum							
($W_S - L_S$)	0.003	6.415	16.58	0.72	-42.56	16.316	-2.315
Joint Stock/CDS Momentum							
($W_S \cap W_C$) − ($L_S \cap L_C$)	1.221	5.068	18.17	1.26	-25.29	8.303	-0.783
Disjoint Stock/CDS Momentum							
($W_S \cap L_C$) − ($L_S \cap W_C$)	-1.478	7.816	26.15	-1.14	-43.99	9.403	-1.213

Panel B. Ex-Ante Call Option Gamma (Merton, 1974; based on three-month rolling daily data)

		Option Gamma
Traditional Stock Momentum	Mean	-0.911
($W_S - L_S$)	Stdev	1.684
Joint Stock/CDS Momentum	Mean	-0.253
($W_S \cap W_C$) − ($L_S \cap L_C$)	Stdev	2.138
Disjoint Stock/CDS Momentum	Mean	-1.653
($W_S \cap L_C$) −($L_S \cap W_C$)	Stdev	2.968
Gamma Difference	Joint Difference	-0.658***
	= (Traditional − Joint)	(-3.87)
	Disjoint Difference	0.742***
	= (Traditional − Disjoint)	(4.34)

Table 8. Time-Varying Beta and Option-Like Payoff Risk of Various Stock/CDS Momentum Strategies

This table presents results of monthly time series regressions of traditional stock momentum and joint and disjoint stock/CDS momentum strategies. The independent variables include a bear market indicator that equals one when the two-year lagging market return is negative (I_B), the market return (MKT), an interaction term between the market return and a bear market indicator ($MKT \times I_B$), and an interaction term between the market return, a bear market indicator, and a contemporaneous up-market indicator that equals one when the current month market return is positive ($MKT \times I_B \times I_U$). The joint momentum strategy is formed by purchasing (short selling) firms that fall in both the traditional stock winner (loser) portfolio *and* the CDS winner (loser) portfolio. The disjoint momentum strategy is formed by purchasing (short selling) firms that fall in the traditional stock winner (loser) *and* the CDS loser (winner) portfolio. The traditional stock momentum strategy is formed by buying winners and selling losers of quintiles based on the past 12-month stock return, skipping the most recent month. The CDS momentum portfolios are quintiles of the past four-month CDS return. The holding period of the momentum strategy is one month ($K = 1$). The time period spans January 2003 to April 2014. The symbols *, **, and *** are indicators of statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	Traditional Stock Momentum (In-Sample) $\equiv \mathrm{W}_S - \mathrm{L}_S$			
α_0	0.479	1.040*	1.040*	1.031*
	(0.93)	(1.81)	(1.82)	(1.90)
α_{I_B}		-2.706**	-0.107	
		(-2.34)	(-0.06)	
β_{MKT}	-0.599***	-0.328*	-0.328*	-0.327*
	(-5.00)	(-1.93)	(-1.94)	(-1.95)
$\beta_{MKT \times I_B}$		-0.490**	-0.0727	-0.0630
		(-2.11)	(-0.21)	(-0.22)
$\beta_{MKT \times I_B \times I_U}$			-0.959*	-0.985***
			(-1.68)	(-2.90)
	Joint Stock/CDS Momentum $\equiv (\mathrm{W}_S \cap \mathrm{W}_C) - (\mathrm{L}_S \cap \mathrm{L}_C)$			
α_0	1.616***	1.556***	1.556***	1.512***
	(4.00)	(3.31)	(3.30)	(3.37)
α_{I_B}		0.259	-0.503	
		(0.27)	(-0.32)	
β_{MKT}	-0.497***	-0.504***	-0.504***	-0.502***
	(-5.29)	(-3.63)	(-3.62)	(-3.62)
$\beta_{MKT \times I_B}$		0.0131	-0.109	-0.0632
		(0.07)	(-0.39)	(-0.27)
$\beta_{MKT \times I_B \times I_U}$			0.281	0.161
			(0.60)	(0.58)
	Disjoint Stock/CDS Momentum $\equiv (\mathrm{W}_S \cap \mathrm{L}_C) - (\mathrm{L}_S \cap \mathrm{W}_C)$			
α_0	-1.533**	-0.942	-0.942	-0.514
	(-2.24)	(-1.23)	(-1.30)	(-0.73)
α_{I_B}		-2.985*	4.882**	
		(-1.93)	(1.99)	
β_{MKT}	0.0691	0.450**	0.450**	0.422*
	(0.43)	(1.98)	(2.09)	(1.95)
$\beta_{MKT \times I_B}$		-0.690**	0.572	0.126
		(-2.23)	(1.33)	(0.34)
$\beta_{MKT \times I_B \times I_U}$			-2.903***	-1.741***
			(-3.99)	(-3.97)

Table 9. Convergence Trades

This table presents the performance of convergence trades on "disjoint" entities based on the expected convergence between stock and CDS prices. Panel A shows the contrarian stock trading strategy (i.e., reverse disjoint momentum strategy) that purchases (short sells) stocks that fall in Signal 1 loser *but* Signal 2 winner (Signal 1 winner *but* Signal 2 loser) portfolio. In that panel, r_{12}^S and r_4^C denote past 12-month stock return (skipping the most recent month) and past four-month CDS returns, respectively. r_4^M denotes past four-month CDS return based on the implied Merton (1974) CDS spreads. The conditional test is done by sorting stocks using r_{12}^S and r_4^C within quintiles of r_4^M. In Panel B, we implement the capital structure arbitrage strategy by purchasing stock and buying CDS protection on firms in the disjoint stock loser/CDS winner portfolio and selling short stock and selling CDS protection on firms in the disjoint stock winner/CDS loser portfolio. Disjoint entities are identified based on r_{12}^S and r_4^C. The strategy equally weights the entities and rebalances them monthly. Four hedge ratios are used to scale the CDS position to match the expected stock return. Two are estimated statistically using stock and CDS returns, and the other two are based on the Merton model (Schaefer and Strebulaev, 2008) and CreditGrades model (Yu, 2006; Duarte, Longstaff, and Yu, 2007). For details, see Appendix E. The time period spans January 2003 to April 2014. Each column reports mean, (t-stat), and annualized *Sharpe* ratio.

Panel A: Contrarian Stock Trades on Disjoint Entities

			Conditional Test
	(1)	(2)	(3)
Sorting Signal 1	r_{12}^S	r_4^M	$r_{12}^S \mid r_4^M$
Sorting Signal 2	r_4^C	r_4^C	r_4^C
	1.478%**	1.572%***	0.791%*
	(2.07)	(2.85)	(1.67)
	0.65	*0.89*	*0.51*

Panel B: Capital Structure Arbitrage

Hedge Ratios Based on	(1) *Statistical (Portfolio-level)*	(2) *Statistical (Firm-level)*	(3) *Merton*	(4) *CreditGrades*
	1.214%**	1.532%*	1.393%**	1.575%**
	(2.03)	(1.87)	(2.05)	(2.21)
	0.65	*0.57*	*0.66*	*0.71*

Table 10. Combinations of Cross-Market Momentum Strategies

This table presents the performance of the joint momentum and disjoint contrarian (i.e., reverse disjoint momentum) strategies as well as combinations of the two. The Combination (VW) strategy combines the joint momentum and contrarian strategies, weighting total long and short positions by the market value of equity. The Combination (50/50) strategy weights the joint momentum and contrarian strategies equally. The joint momentum strategy is formed by purchasing (short selling) firms that fall in both the traditional stock winner (loser) portfolio *and* the CDS winner (loser) portfolio. The contrarian strategy (i.e., reverse disjoint momentum strategy) is formed by purchasing (short selling) firms that fall in the traditional stock loser (winner) *and* the CDS winner (loser) portfolio. The stock momentum portfolios are quintiles of the past 12-month stock return (skipping the most recent month). The CDS momentum portfolios are quintiles of the past J-month CDS return. The holding period of each strategy is one month ($K = 1$). The *Sharpe* ratio is annualized. The time period spans January 2003 to April 2014. The 12-lag Newey-West t-statistic is provided in parenthesis, and *, **, and *** are indicators of statistical significance at the 10%, 5%, and 1% levels, respectively. Notation for each portfolio return follows the pattern: mean, (t-stat), and *Sharpe* ratio.

	Joint Momentum (JW – JL)	Disjoint Contrarian (DL – DW)	Combination (Value-Weighted)	Combination (50/50)
$J = 1m$	0.506%	0.304%	0.429%	0.405%
	(1.16)	(0.45)	(1.17)	(1.45)
	0.36	*0.12*	*0.38*	*0.43*
$J = 2m$	0.693%	0.453%*	0.610%**	0.573%*
	(1.59)	(1.87)	(2.01)	(1.90)
	0.47	*0.51*	*0.59*	*0.61*
$J = 3m$	0.934%**	1.128%*	0.971%**	1.031%**
	(2.11)	(1.84)	(2.24)	(2.35)
	0.60	*0.54*	*0.68*	*0.73*
$J = 4m$	1.221%***	1.478%**	1.307%***	1.349%***
	(2.86)	(2.07)	(4.05)	(3.67)
	0.83	*0.65*	*1.18*	*1.11*
$J = 5m$	0.954%**	1.064%**	0.996%***	1.009%***
	(2.26)	(2.16)	(2.73)	(2.68)
	0.63	*0.57*	*0.79*	*0.78*
$J = 6m$	0.944%**	0.858%*	0.929%**	0.901%**
	(2.03)	(1.83)	(2.35)	(2.24)
	0.61	*0.46*	*0.69*	*0.62*
$J = 9m$	0.673%	0.505%	0.608%	0.589%*
	(1.32)	(1.06)	(1.62)	(1.71)
	0.45	*0.35*	*0.51*	*0.56*
$J = 12m$	0.749%	0.521%	0.686%	0.635%
	(1.45)	(0.97)	(1.26)	(1.14)
	0.52	*0.27*	*0.42*	*0.39*

Table 11. Combination Strategy: Equity-Credit Integration

This table presents the performance of combination strategies for high and low levels of equity-credit integration, where high (low) is defined as greater than (less than) the median value during each time period. The equity-credit integration, $\kappa_{i,t}^{M}$, is computed as the fraction of days the stock and CDS moved in a congruent direction for firm i during the last M months (i.e., total D business days), as follows:

$$\kappa_{i,t}^{M} = \frac{\sum_{t=1}^{D} \mathbb{1}_{[\Delta P_{i,t} \Delta CDS_{i,t} < 0]}}{D}$$

$\Delta P_{i,t}$ refers to the one-day change in stock price from time $t-1$ to time t, and $\Delta CDS_{i,t}$ refers to the one-day change in CDS spread from time $t-1$ to time t. The integration measure ranges from 0 to 1, a higher number indicating a greater level of integration between stock and CDS markets.

The *Combo* (VW) strategy combines the joint momentum and contrarian strategies, weighting all long and short positions by the market value of equity. The *Combo* (50/50) strategy weights the joint momentum and contrarian strategies equally. The joint momentum strategy is formed by purchasing (short selling) firms that fall in both the traditional stock winner (loser) portfolio *and* the CDS winner (loser) portfolio. The contrarian (i.e., reverse disjoint) strategy is formed by purchasing (short selling) firms that fall in the traditional stock loser (winner) *and* the CDS winner (loser) portfolio. The traditional stock momentum strategy is formed by buying winners and selling losers of quintiles based on the past 12-month stock return, skipping the most recent month. The CDS momentum portfolios are quintiles of the past four-month CDS return. The holding period of the momentum strategy is one month ($K = 1$). The Sharpe Ratio is annualized. The time period spans January 2003 to April 2014. The 12-lag Newey-West t-statistic is provided in parenthesis, and *, **, and *** are indicators of statistical significance at the 10%, 5%, and 1% levels, respectively. Notation for each portfolio return follows the pattern: mean, (t-stat), and *Sharpe Ratio*.

	High Integration	**Low Integration**
$M = 4$ months		
Combo (VW)	2.008%***	0.415%
	(3.77)	(1.39)
	1.23	*0.44*
Combo (50/50)	1.998%***	0.441%
	(3.44)	(1.49)
	1.12	*0.47*
$M = 6$ months		
Combo (VW)	1.980%***	0.554%
	(3.84)	(1.45)
	1.30	*0.52*
Combo (50/50)	1.942%***	0.572%
	(3.44)	(1.47)
	1.17	*0.44*
$M = 12$ months		
Combo (VW)	1.866%***	0.340%
	(3.53)	(1.35)
	1.09	*0.39*
Combo (50/50)	1.853%***	0.362%
	(3.41)	(1.44)
	1.07	*0.42*

Figure 1. Average Five-year Corporate CDS Spread Over Time

This figure presents the value-weighted average five-year corporate CDS spread of firms in our sample over the period January 2003 to April 2014. CDS data is from Markit.

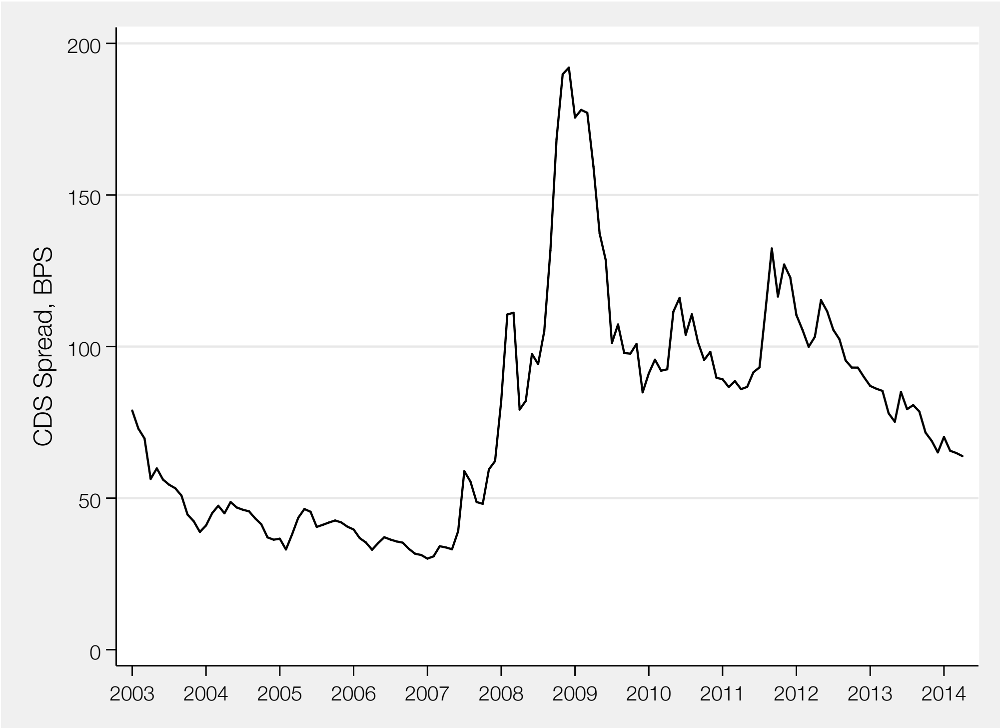
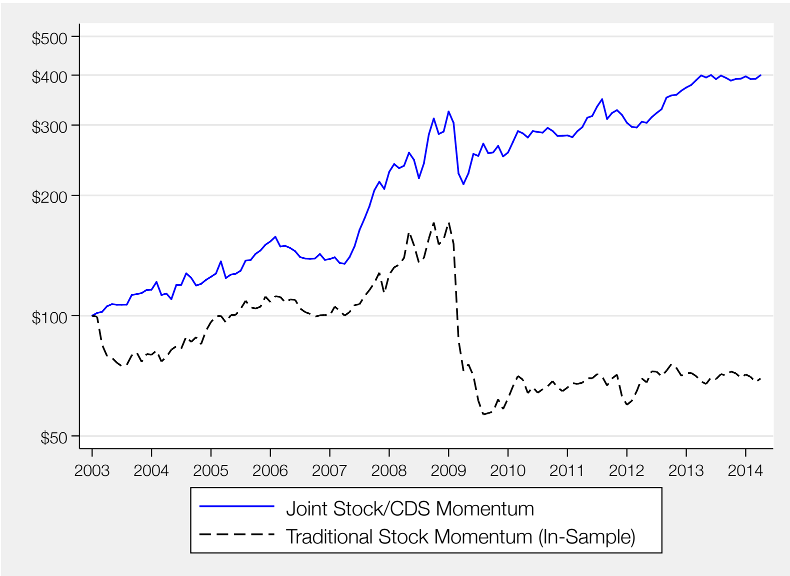


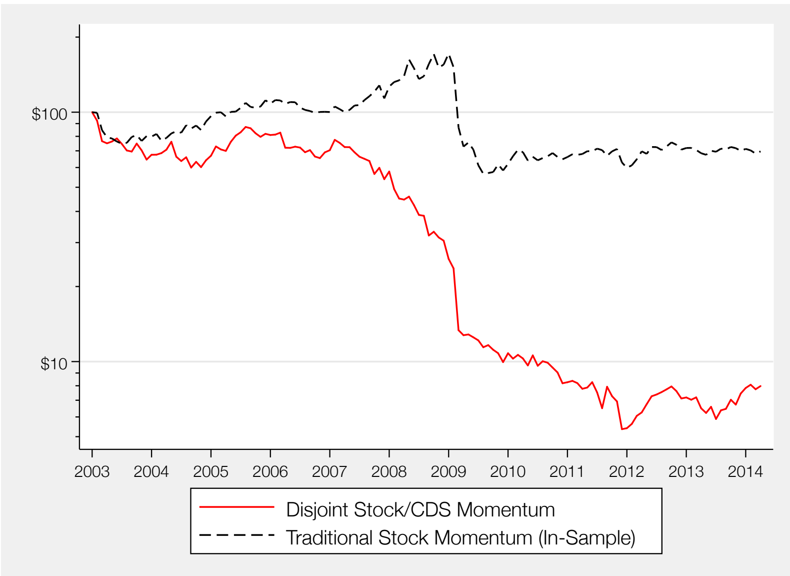
Figure 2. Cumulative Profits of Various Stock/CDS Momentum Strategies

This figure presents the cumulative profits of a $100 investment in the joint and disjoint stock/CDS momentum strategies. Panel A portrays the joint momentum strategy in comparison to traditional stock momentum. Panel B portrays the disjoint momentum strategy in comparison to traditional stock momentum. The joint momentum strategy purchases (short sells) firms that are in both the stock winner (loser) portfolio and the CDS winner (loser) portfolio. The disjoint momentum strategy purchases (short sells) firms that are in the stock winner (loser) portfolio and the CDS loser (winner) portfolio. Stock momentum portfolios are formed from quintiles of the 12-month stock return, skipping the most recent month. CDS momentum portfolios are formed from quintiles of the four-month CDS return. Lastly in Panel C, we show the performance breakdown of disjoint momentum during 2009 momentum crash into two groups, (1) past stock winners/past CDS losers portfolio ($W_S \cap L_C$) and (2) past stock losers/past CDS winners portfolio ($L_S \cap W_C$), respectively. Equity data are from CRSP. CDS data are from Markit. The sample ranges from January 2003 to April 2014.

Panel A. Joint Stock/CDS Momentum



Panel B. Disjoint Stock/CDS Momentum



Panel C. Disjoint Momentum Breakdown during 2009 Momentum Crash

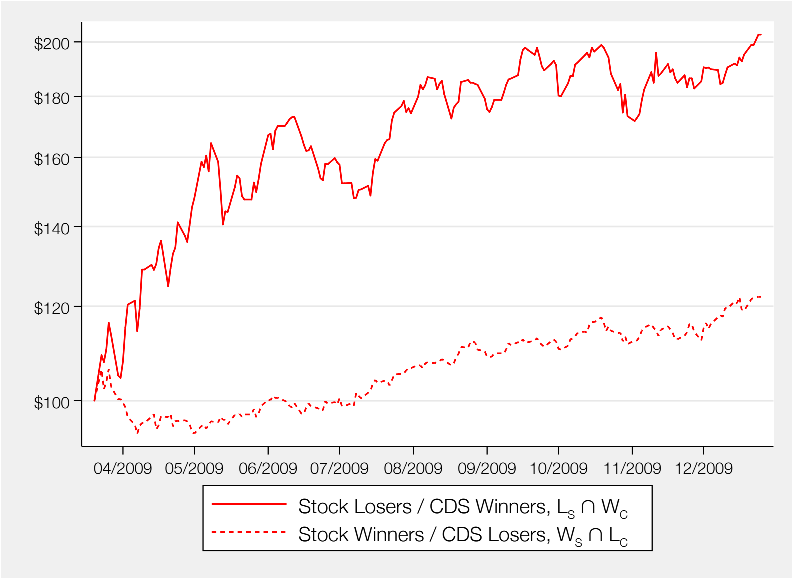
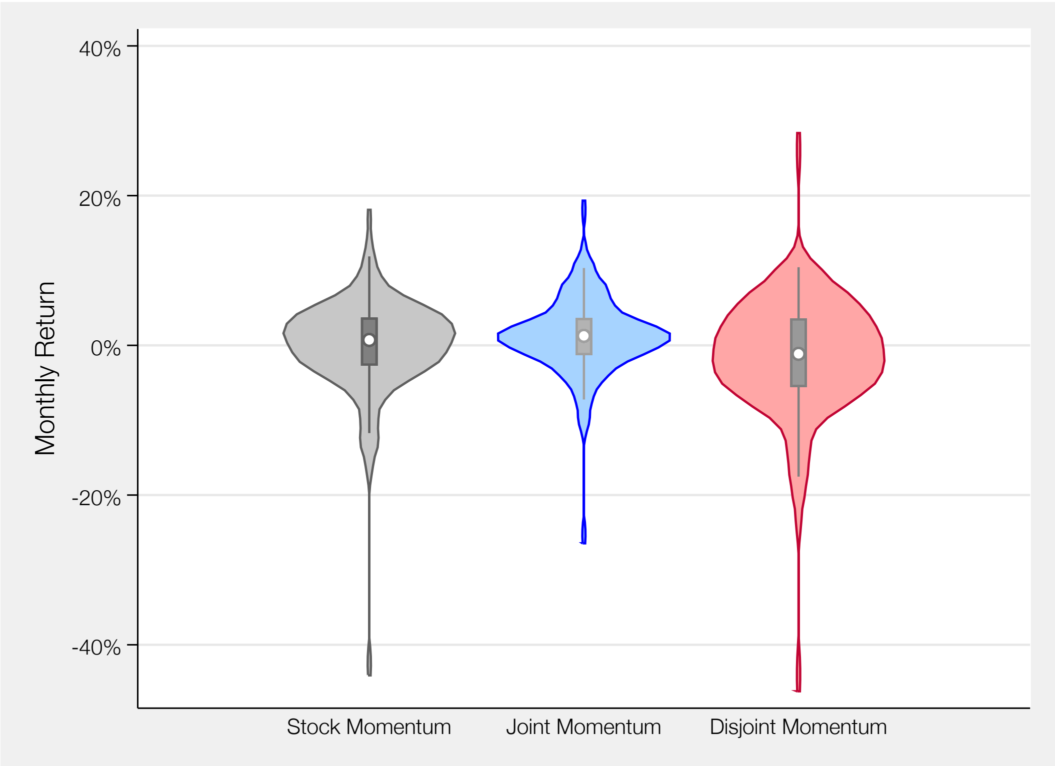


Figure 3. Distributional Characteristics of Joint versus Disjoint Stock/CDS Momentum Strategy Returns

This figure displays distributional characteristics of the returns of joint and disjoint stock/CDS momentum strategies. Panel A presents a violin plot of the monthly returns of each strategy. Panel B presents histograms of joint (left, blue) and disjoint (right, red) momentum strategies. The joint momentum strategy purchases (short sells) firms that are in both the stock winner (loser) portfolio and the CDS winner (loser) portfolio. The disjoint momentum strategy purchases (short sells) firms that are in the stock winner (loser) portfolio and the CDS loser (winner) portfolio. Stock momentum portfolios are formed from quintiles of the 12-month stock return, skipping the most recent month. CDS momentum portfolios are formed from quintiles of the four-month CDS return. Equity data are from CRSP. CDS data are from Markit. The sample ranges from January 2003 to April 2014.

Panel A. Violin Plot



Panel B. Histogram

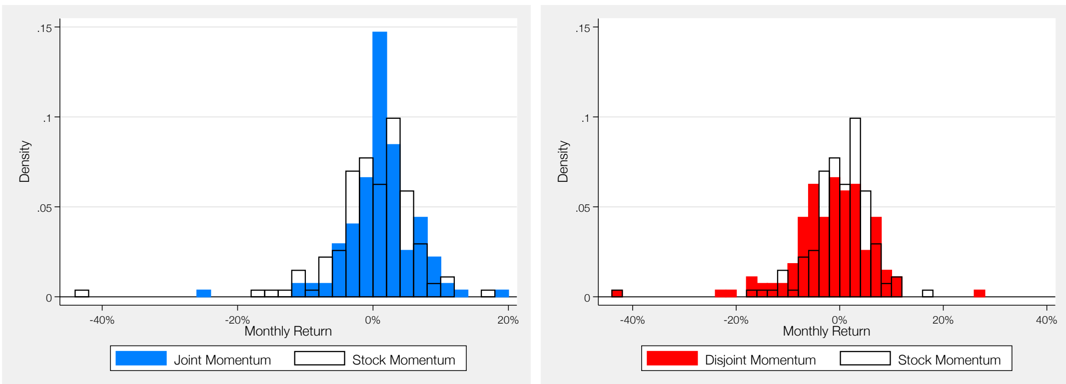


Figure 4. Ex-ante Beta Exposures of Joint versus Disjoint Stock/CDS Momentum Strategies

This figure presents ex-ante beta exposures of joint and disjoint stock/CDS momentum strategies. The stock market beta is computed for individual winner and loser portfolios at each formation date using a regression of daily returns over the prior three months. The joint momentum strategy purchases (short sells) firms that are in both the stock winner (loser) portfolio and the CDS winner (loser) portfolio. The disjoint momentum strategy purchases (short sells) firms that are in the stock winner (loser) portfolio and the CDS loser (winner) portfolio. Stock momentum portfolios are formed from quintiles of the 12-month stock return, skipping the most recent month. CDS momentum portfolios are formed from quintiles of the four-month CDS return. Equity data are from CRSP. CDS data are from Markit. The sample ranges from January 2003 to April 2014.

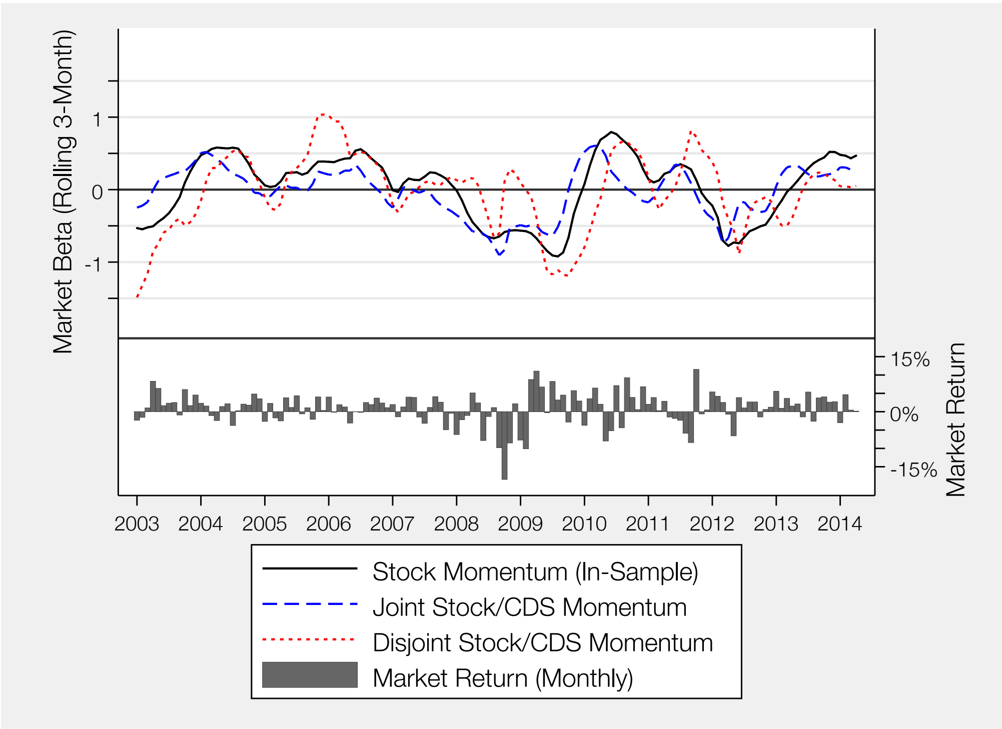
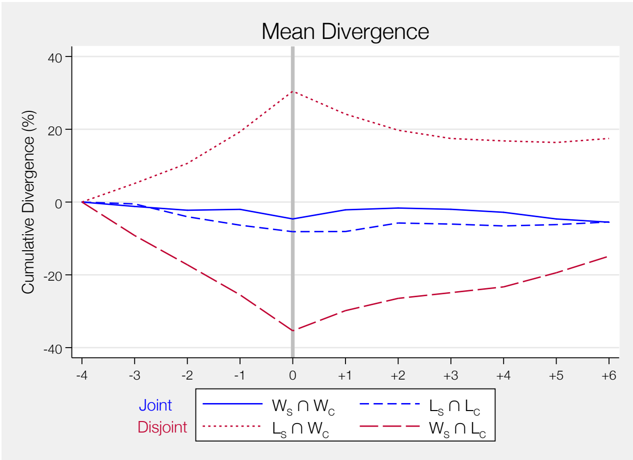


Figure 5. Divergence between Implied Merton (1974) CDS Spread and At-market CDS Spread from Markit

This figure shows the cumulative percentage divergence between implied Merton (1974) CDS spreads and the observed Markit CDS spreads for various joint and disjoint momentum portfolios. The following pairs ($W_S \cap W_C$) and ($L_S \cap L_C$) denote joint market winner and loser momentum portfolios, respectively. ($W_S \cap L_C$) and ($L_S \cap W_C$) refer to stock winner but CDS loser momentum portfolio and stock loser but CDS winner momentum portfolio, respectively. Divergence is computed for individual firms and aggregated to the portfolio level using the mean (top) and median value (bottom). Time-0 denotes the formation date of each momentum portfolio. The sample ranges from January 2003 to April 2014.



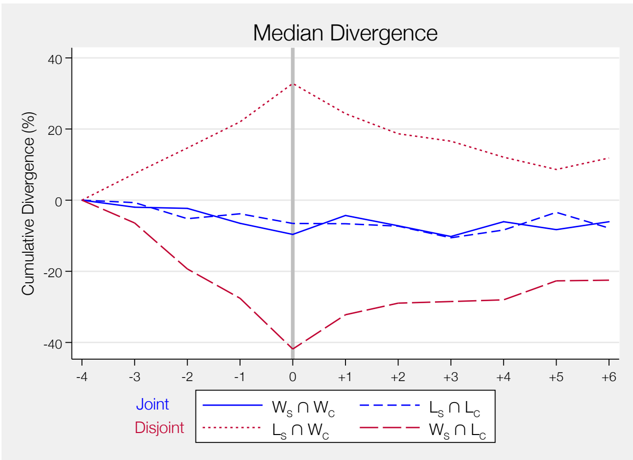


Figure 6. Cumulative Profits of Cross-Market Momentum Strategies

This figure presents cumulative profits of a $100 investment in various momentum strategies. It shows cumulative profits for the traditional stock momentum strategy (Jegadeesh and Titman, 1993), joint stock/CDS momentum strategy, and two momentum-contrarian mixed trading strategies — Combo (VW) and Combo (50/50). Stock momentum portfolios are formed from quintiles of the 12-month stock return, skipping the most recent month. CDS momentum portfolios are formed from quintiles of the four-month CDS return. Equity data are from CRSP. CDS data are from Markit. The sample ranges from January 2003 to April 2014.