Related Securities and the Cross-Section of Stock Return Momentum: Evidence from Credit Default Swaps (CDS)*

Jongsub Lee[†], Andy Naranjo[‡], *and* Stace Sirmans[§]

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[†]University of Florida, Assistant Professor, Tel: 352.273.4966, Email: jongsub.lee@warrington.ufl.edu

[‡]University of Florida, Emerson-Merrill Lynch Professor of Finance and Chairman of Finance Department, Tel: 352.392.3781, Email: andy.naranjo@warrington.ufl.edu

[§]University of Arkansas, Assistant Professor, Tel: 850.459.2039, Email: ssirmans@walton.uark.edu

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Abstract

We document that related securities linked through firm fundamentals provide important cross-market return performance information. During 2003-2015, we find significantly stronger stock return momentum for entities whose past stock and CDS returns are in congruence versus entities whose past stock and CDS returns disagree. A dynamic stock trading strategy based on this cross-sectional performance differential earns an annualized alpha of nearly 18% with a Sharpe ratio of 1.37, avoids crash risk, and is robust to out-of-sample tests using international stocks. Relative pricing of credit across related securities explains, in part, the cross-section of stock return momentum. (*JEL* G12, G14)

1 Introduction

Firms often have related securities that trade concurrently in markets, which raises an important question on the extent to which related securities provide cross-market security investment performance information. A long-standing empirical investments literature documents significant return momentum across a range of assets, including assets in both equity and credit markets that are linked through common firm fundamentals.[1] Given these related security fundamental linkages, do firms' past equity and credit return signals agree or disagree, and what do conflicting signals portend for return momentum? In this regard, the literature documents momentum spillover effects from stocks to bonds (Gebhardt, Hvidkjaer, and Swaminathan, 2005) and from CDS to stocks (Lee, Naranjo, and Sirmans, 2014), suggesting that while both the equity and credit exhibit momentum, individual securities may be in different stages of underreaction or overreaction to fundamentals in their momentum cycles (Lee and Swaminathan, 2000). The degree of equity and credit momentum cycle congruence may vary significantly in the cross-section with some high congruence firms exhibiting a similar degree of underreaction or overreaction in the two markets and other low congruence firms in strong discord, experiencing extreme overreaction in one market and severe underreaction in the other market. Importantly, does heterogeneity in momentum cycle congruence across firms impact future returns, trading behavior, and market efficiency?

In this paper, we examine the cross-section of stock return momentum with respect to the performance of a related security, namely, credit default swaps (CDS). Both the stock and CDS represent claims on the same underlying fundamentals of a firm, but their market prices often evolve differentially, providing at times conflicting performance views. We argue that jointly analyzing the performance of related securities provides clarity on the

[1] For details, see Jegadeesh and Titman (1993), Asness, Moskowitz, and Pedersen (2013), and many others for stock return momentum, Jostova, Nikolova, Philipov, and Stahel (2013) for corporate bond return momentum, and Lee, Naranjo, and Sirmans (2014) for CDS return momentum.

stage of each individual security's momentum cycle as well as insights into the strength of the momentum effect. Strong stock performance coupled with weak CDS performance, for example, may indicate that a stock is near the peak of an overreaction stage in its momentum cycle and will soon reverse. If conflicting performance signals are associated with a greater likelihood of reversal, a natural extension is to test whether hedging this disjoint group out of traditional momentum portfolios (Jegadeesh and Titman, 1993) helps avoid stock momentum crashes (Daniel and Moskowitz, 2016). Existing studies on momentum crash risk (Daniel, Jagannathan, and Kim, 2012; Grundy and Martin, 2001; Barroso and Santa-Clara, 2015; Han, Zhou, and Zhu, 2016) have not examined the efficacy of a cross-sectional hedging approach using multi-market momentum signals in lessening momentum tail risk.[2] Hence, our study also provides novel economic insights that underlie well-known risk phenomena in traditional single-signal momentum strategies.

Our arguments on multi-market momentum cycles and the resulting segmentation in the cross-section of stock return momentum are motivated by recent segmentation theory. Goldstein, Li, and Yang (2014) posit that stock markets are segmented by a diverse set of investors with distinct trading opportunities and objectives. Simple investors trade as speculators, participating only in a single stock market, while more sophisticated investors also trade as hedgers, entering offsetting positions in both stock and CDS markets simultaneously. Market prices are therefore influenced not only by speculative trades reacting to new stock market information but also to hedging trades reacting to the relative pricing between the two markets. In practice, while retail and traditional institutional investors primarily participate in stock markets, hedge funds that trade in both stock and CDS mar-

[2] 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, 2016). In comparison to these time series approaches, our cross-sectional hedging approach is consistent with Sagi and Seasholes (2007) who use firm-specific attributes to enhance momentum profits.

kets additionally have the opportunity to implement arbitrage trades when equity and credit valuations become misaligned. Under this setup, at any point in time there is a portion of the stock cross-section with diverging equity and credit prices that is more likely to attract hedgers (i.e., contrarian traders) in proportion to speculators (i.e., momentum traders).

To further illustrate our point, consider two firms A and B in Figure 1 that both fall into the proposed stock momentum winner portfolio at rebalancing date 0. Firm A is also a CDS momentum winner (called a *joint* stock/CDS winner), but firm B is not a CDS momentum winner (called a *disjoint* stock/CDS winner). Firm B's stock price has become overvalued relative to the level implied by its CDS counterpart and will therefore attract cross-market convergence arbitrageurs intending to sell CDS protection while hedging the position by selling stock (Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012). As a result, firm B's stock is more likely to experience a return reversal rather than momentum in comparison to firm A's stock. An interesting question is to what extent do contrarian stock traders whose trades are motivated by cross-market price discrepancies relate to the tendency of some stocks to exhibit reversal while others experience momentum?

To empirically investigate this idea, we decompose the traditional stock momentum strategy (Jegadeesh and Titman (1993)) into two subgroups according to cross-sectional performance ranking agreement between stock and CDS markets. We assign firms in the stock momentum winner and loser portfolios as being either (1) *joint* entities whose past stock and CDS performance signals are in agreement or (2) *disjoint* entities whose past stock returns disagree with past CDS returns. Using a sample of 881 U.S. firms over the period 2003 to 2015, we find significant variation in the cross-section of stock momentum with respect to related security performance. The performance of the joint component of stock momentum exceeds that of the disjoint component by more than 20% per year (1.73% per month). In other words, stocks are much more likely to exhibit a continuation of return momentum when there is past performance agreement across related securities. In contrast, disjoint entities, whose related security price paths are more likely to attract arbitrageurs, create a drag on stock momentum performance and contribute proportionally more to momentum crash risk (Daniel and Moskowitz (2016)). Upon revealing this segmentation structure in the cross-section of stock momentum, we develop a set of novel momentum hedging strategies that take advantage of the wide performance differential between the joint and disjoint subgroups and produce risk-adjusted returns of up to 18% per year (1.47% per month). Put together, our results suggest that related securities at times reduce stock price efficiency and cause excess volatility due to induced market segmentation (Goldstein, Li, and Yang, 2014; Boehmer, Chava, and Tookes, 2016).

We focus on a firm's CDS as a related security to the firm's stock for several reasons. First, there is a clear structural link between stock and CDS prices through the firm's capital structure (Merton, 1974). Second, despite the theoretical link between the two markets, they reveal information non-synchronously with different frequencies, speeds, and content across entities and events (Acharya and Johnson, 2007; Ni and Pan, 2010; Qiu and Yu, 2012; Lee, Naranjo, and Sirmans, 2014).[3] Third, CDS at-market spreads are consistent in their assessment of the underlying credit risk with stock prices without being confounded by other liquidity-related factors (Friewald, Wagner, and Zechner, 2014).[4] In sharp contrast, studies that measure credit risk through corporate bond returns or credit ratings document a "distress risk puzzle" in which expected stock returns are negatively related to credit risk, which is hard to reconcile from a fundamentals perspective (Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008; Avramov, Chordia, Jostova, and Philipov, 2009). Finally, as

[3]Distinct information in the two markets could 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. 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, 2016) in consistent directions.

[4]Han, Subrahmanyam, and Zhou (2016) also find that the term structure of CDS spreads contains useful information on future stock returns.

Yu (2006) notes, instances of mispricing between stock and CDS markets offer attractive opportunities for cross-market arbitraguers, suggesting that past CDS market performance information may be useful in inferring future cross-market trading activity.

Using the Center for Research in Security Prices (CRSP) and Markit data, we identify 881 U.S. firms with actively trading stocks and five-year CDS contracts during 2003-2015. To investigate the cross-section of stock momentum, we independently double-sort stocks into five-by-five portfolios based on (1) the past 12-month stock return, skipping the most recent month, and (2) the past CDS return over various horizons.[5] We subgroup firms in the stock momentum portfolios by labeling them as *joint* entities, entities that are both stock winners (losers) and CDS winners (losers), or *disjoint* entities, entities that are stock winners (losers) but not CDS winners (losers). We then implement the stock momentum strategy for each of these two subgroups, creating joint stock/CDS momentum and disjoint stock/CDS momentum strategies, and compare their performance.

We find that our joint stock/CDS momentum strategy significantly outperforms both its counterpart disjoint stock/CDS momentum and the traditional single-signal stock momentum strategy (Jegadeesh and Titman, 1993) for all formation horizons of past CDS returns, ranging from one to 12 months. The performance of joint stock/CDS momentum peaks at the past four-month CDS performance signal, yielding 1.64% per month (1.45% on a risk-adjusted basis) with an annualized Sharpe ratio of 0.81. The performance differential between joint and disjoint stock/CDS momentum amounts to 1.73% per month with a Sharpe ratio of 1.04. Our results are robust to risk adjustments, including exposure to the market excess return, Fama and French (1993) size and value factors, Carhart (1997) momentum factor, Pastor and Stambaugh (2003) traded liquidity factor, and Novy-Marx

[5]The CDS holding period excess return (net of the risk-free rate) is defined 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.

(2015) earnings momentum factors (*SUE* and *CAR3*).[6] We further show that, relative to traditional stock-only signals, the two markets' joint signals more precisely predict upcoming corporate events in anticipated directions—joint winners (losers) are more likely to exhibit faster (slower) growth in profits and more frequently undergo rating upgrades (downgrades). This relative CDS market information advantage is particularly profound among distressed entities as well as during high credit risk periods.

What explains the lackluster performance of momentum in disjoint entities? We offer a relative pricing framework rationale and show that disjoint winner (loser) stocks substantially underestimate (overestimate) firm credit risks relative to their levels implied by CDS prices. To the extent that stock/CDS cross-market arbitrage is unlimited, any instances of credit risk mispricing will be swiftly corrected by arbitrageurs whose trades cause the equity and credit valuations to converge. This suggests that stocks that misprice the underlying credit risk relative to the CDS may tend to display return *reversal* rather than momentum. Indeed, we find that disjoint entities, during the four months leading up to momentum portfolio formation, experience a nearly 30% widening in the discrepancy between their stock-implied CDS spreads using the CreditGrades model and their observed at-market CDS spreads. Then, post portfolio formation, the two spreads exhibit a tendency to converge. Importantly, we do not find a similar pattern for joint entities. To show the relevance of cross-market arbitrage to the reversing stock price pattern, we implement a capital structure arbitrage trade for the most extreme disjoint entities (Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012) and find significant profits of 1.28% per month.

Given the disparate performance between joint and disjoint stock/CDS momentum, we examine how each contributes to the overall risk-return profile of the traditional stock momentum strategy. It is well-known that stock momentum exhibits an option-like payoff

[6] We also show that combining various horizons of past stock returns (Novy-Marx, 2012) does not yield the same performance enhancement over traditional momentum.

structure with infrequent but severe crashes. In particular, Daniel and Moskowitz (2016) show that its time-varying beta exposure becomes strongly negative at the time a bear market rebounds from its bottom, quickly eroding accumulated profits and leading to large losses. Importantly, we find that only the disjoint momentum portfolio exhibits such behavior in its time-varying beta exposure and sensitivity to bear market rebounds. We further show that the joint-disjoint momentum performance differential is greatest during periods of heightened volatility, precisely when momentum strategies produce less-than-stellar returns (Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015)). These results suggest that related security performance information could be useful in guarding against momentum crash risk in part by providing timely updates on the strategy's systematic market risk exposure.

Building on our cross-section of stock return momentum intuition outlined above as well as prior research on the time-varying risks of stock momentum, we introduce a set of powerful hedging strategies that take advantage of the wide performance differential between the joint and disjoint components of stock momentum. A static hedging strategy that invests 50% in joint momentum and 50% in a disjoint *contrarian* strategy (purchasing disjoint losers and selling short disjoint winners) avoids momentum crashes altogether and generates returns of more than 10% per year (0.86% per month) with a Sharpe ratio of 1.04. Furthermore, a dynamic hedging strategy that invests in joint momentum and hedges with a 50% disjoint contrarian position only during periods of heightened volatility produces more than 19% per year (1.59% per month) with a Sharpe ratio of 1.37. On a risk-adjusted basis, this amounts to nearly 18% per year (1.47% per month). Our findings are complementary to the momentum scaling approaches recently introduced by Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015)—combining our cross-sectional approach with their temporal scaling techniques leads to even higher Sharpe ratios of up to 1.61.

Lastly, we confirm our findings on related security performance and the cross-section of stock momentum using a sample of 1,267 international firms headquartered outside of the U.S. representing 49 countries. We find that our dynamic joint momentum hedging strategy produces nearly 15% per year (1.21% per month) with a Sharpe ratio of 1.05. Importantly, the joint and disjoint momentum segmentation structure is more pronounced among more developed countries that generally face fewer impediments to arbitrage and have investor capital that moves relatively quickly. Developed capital markets are also more likely to exhibit cross-asset arbitrage capital flow, which our U.S. market results arguably indicated as a potential cause of the segmented cross-section of stock return momentum. Our international results are also consistent with the recent findings of Jacobs (2016) that mispricing in stock markets appears to be as least as common in developed markets as it is in developing and emerging markets.

Our contribution to the momentum literature is threefold. First, 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, 2016; Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012). Second, we provide a novel cross-sectional approach to detect a group of stocks that are prone to reversal and are more sensitive to momentum crash risk (Daniel and Moskowitz, 2016; Daniel, Jagannathan, and Kim, 2012; Grundy and Martin, 2001; Barroso and Santa-Clara, 2015; Han, Zhou, and Zhu, 2016). Third, our new and significantly profitable stock trading strategy that cross-sectionally combines momentum and contrarian trades based on multi-market signals provides strong support for 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, 2014; Boehmer, Chava, and Tookes, 2016).[7]

[7] This interactive market (in)efficiency could also have implications for return momentum in other pairs of related securities (e.g., stocks and options, An, Ang, Bali, and Cakici, 2014).

The remainder of this paper is organized as follows: Section 2 summarizes our data and CDS return construction process. Section 3 presents our main results on related security performance and the cross-section of stock return momentum. Section 4 introduces our new momentum hedging strategies. Section 5 provides our international evidence. We conclude in Section 6.

2 Data

Our U.S. data set consists of 881 firms from January 2003 to December 2015 for which there is an actively traded stock and an active single-name CDS contract. Later in Section 5, we extend our U.S. data set to an international sample that includes 1,267 firms from 49 countries, and we provide corresponding details on our international sample construction therein. For our U.S. firms, we obtain equity data from CRSP. We require the firm's equity to be ordinary common shares traded on the NYSE, AMEX or Nasdaq. We also require each firm to have a market capitalization of at least $100 million and a price of at least $1 at the time of portfolio formation. 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. We also impose a CDS activity filter at the time of portfolio formation by eliminating contracts with a significant amount of missing and stagnant observations. Specifically, we eliminate contracts that have missing spreads at least 10% of days or stagnant spreads at least 90% of days over the prior six months. 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.[8] As such, our database consists of

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

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 the variables used in this study. The average firm in our sample has an equity market capitalization of $20.47 billion, a BBB S&P credit rating, and a CDS spread of 186 bps. Figure 2 shows the value-weighted average corporate CDS spread over our sample period. 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 6.77.

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 financed at the risk-free 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 in Table 1 show that the mean (median) monthly CDS return of our sample is 0.01% (0.01%) with a standard deviation of 2.57%. The simple correlation between the stock return and CDS return is 0.037.

3 The Cross-Section of Stock Return Momentum

In this section, we uncover significant performance variation in the cross-section of the traditional Jegadeesh and Titman (1993) stock momentum strategy with respect to related security performance. In particular, we show that considering the performance information of both stock and CDS markets *jointly* sharpens signals on future firm fundamentals and can be used to significantly improve the performance of stock momentum trading strategies.

Our primary empirical methodology is to decompose traditional stock momentum into two parts based on firms' cross-sectional performance ranking agreement between stock and CDS markets. To do this, 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. The joint winner portfolio, defined as $\mathrm{JW} \equiv \mathrm{W}_S \cap \mathrm{W}_C$, represents the overlap between the stock momentum winner portfolio W_S and the CDS momentum winner portfolio W_C. Likewise, the joint loser portfolio, defined as $\mathrm{JL} \equiv \mathrm{L}_S \cap \mathrm{L}_C$, represents the overlap between the stock momentum loser portfolio L_S and the CDS momentum loser portfolio L_C. The disjoint winner (disjoint loser) portfolio is the complement to the joint winner (joint loser) portfolio. That is, the disjoint winner portfolio, defined as $\mathrm{DW} \equiv \mathrm{W}_S \setminus \mathrm{W}_C$, includes all firms in the stock winner portfolio that are *not* in the CDS winner portfolio. Similarly, the disjoint loser portfolio, defined as $\mathrm{DL} \equiv \mathrm{L}_S \setminus \mathrm{L}_C$, includes all firms in the stock loser portfolio that are *not* in the CDS loser portfolio.

The joint stock/CDS momentum strategy ("joint momentum," hereafter) purchases stocks in the joint winner portfolio and sells short stocks in the joint loser portfolio. The disjoint stock/CDS momentum strategy ("disjoint momentum," hereafter) purchases stocks in the disjoint winner portfolio and sells short stocks in the disjoint loser portfolio. Positions are held and rebalanced after K months. We focus on the baseline case $K = 1m$ in this paper. Ultimately, our stock momentum decomposition procedure can be summarized as:

$$\text{Stock Momentum} \equiv (W_S - L_S) \begin{cases} \text{Joint Stock/CDS Momentum} & \equiv (W_S \cap W_C) - (L_S \cap L_C) \\ \\ \text{Disjoint Stock/CDS Momentum} & \equiv (W_S \setminus W_C) - (L_S \setminus L_C). \end{cases}$$

Table 2 reports the performance of our joint momentum strategy over the period January 2003 to December 2015 using CDS formation horizons ranging from one month ($J = 1m$) to twelve months ($J = 12m$).[9] We find that CDS formation periods of $J = 3m$ through $J = 5m$ show positive returns for the joint momentum strategy at the 1% to 5% statistical significance level (see column 3). All CDS formation periods from $J = 1m$ to $J = 12m$ produce positive alpha coefficients (see column 4) using a four-factor model that includes the Fama-French market, size, and value factors as well as an in-sample stock momentum factor (denoted as UMD_S hereafter).[10] The four-month formation period ($J = 4m$) maximizes the strategy's performance, producing a return of 1.64% per month (t-statistic of 2.83), an annualized Sharpe ratio of 0.81, and an alpha of 1.45% per month (t-statistic of 4.24).[11] The joint winner portfolio generates a return of 1.49% per month (t-statistic of 2.69), while the joint loser portfolio produces a return of -0.15% per month (t-statistic of -0.16). Figure 3 plots the cumulative profits of our in-sample stock momentum strategy (in black) as well as each of the joint (in blue) and disjoint (in red) components of stock momentum using a CDS

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

[10]The UMD_S factor is constructed in-sample using quintiles of firms' past 12-month stock return ($J = 12m$), skipping the most recent month, and a holding period of one month ($K = 1m$).

[11]Our Internet Appendix shows that average monthly risk-adjusted returns are positive and statistically significant at the 1% level at least up to a six-month holding period ($K = 6m$).

formation horizon of $J = 4m$.

The last three columns of Table 2 report the monthly return differentials between joint momentum, disjoint momentum, and traditional stock momentum. The performance advantage of joint momentum over both traditional stock momentum and disjoint momentum is positive and statistically significant at the 1% to 5% level for all CDS formation periods. The performance advantage of joint momentum is greatest at the four-month CDS return horizon, outpacing traditional stock momentum by 1.34% per month (t-statistic of 4.08 and Sharpe ratio of 1.05) and exceeding disjoint momentum by 1.73% per month (t-statistic of 3.94 and Sharpe ratio of 1.04).

3.1 Risk-adjusted Performance

Next, we test whether our joint stock/CDS momentum profits are explained by exposures to commonly-used asset pricing factors. We consider the market excess return factor (MKT), Fama and French (1993) size and value factors (*SMB* and *HML*, respectively), a "localized" stock momentum factor using firms in our sample (UMD_S), the Pastor and Stambaugh (2003) traded liquidity factor (LIQ), and Novy-Marx (2015) earnings momentum factors (*SUE* and *CAR3*). The factors *MKT*, *SMB*, and *HML* are from Ken French's website.[12] *SUE* and *CAR3* are broad stock market factors constructed using the standardized unexpected earnings and the three-day cumulative abnormal return around the most recent earnings announcement, respectively.[13] Using OLS with Newey-West standard errors and a lag length of 12 months, we estimate:

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

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

[13] We follow similar construction procedures to Novy-Marx (2015). Appendix B provides a more detailed definition of our two earnings-based factors.

where r_{Pt} is the long-short momentum portfolio returns, α_P is the portfolio's alpha, and $\mathbf{F}_t$ is a vector of stock market risk factors.

Table 3 presents alpha coefficients from the time-series regressions. Columns 1 and 2 show that the average risk-adjusted monthly return of our in-sample stock momentum is not statistically different from zero over the period 2003 to 2015. However, segmenting stock momentum into its joint and disjoint components reveals sharp contrasting performance. Columns 3 to 5 show that the alpha coefficients of joint momentum are all positive and statistically significant at the 1% to 5% level across all three models, ranging from 1.21% per month (column 5) to 1.56% per month (column 4). In contrast, all three models explaining disjoint momentum show alpha coefficients that are economically and statistically negative, ranging from -0.45% (column 6) to -0.49% (column 8). These results confirm our segmentation structure of stock return momentum and further reveal that it is not explained by size, value, liquidity, or earnings-based factors.[14]

3.2 Future Firm Fundamentals

Our *a priori* expectation is that past stock and CDS performance signals, if optimally combined, could more sharply identify price underreactions to firm fundamentals.[15] The joint signals could capture price underreactions to earnings announcements, but they are not limited to capturing only earnings-related information. The significant joint momentum alpha of 1.21% per month in column 5 of Table 3 suggests that the joint-market signals capture other upcoming corporate events that also materially affect common firm fundamentals

[14]Our Internet Appendix further shows the robustness of our joint momentum strategy to a larger set of factors, including a Fama-French five-factor model with operating profitability (RMW) and investment (CMA) factors, Novy-Marx (2013) gross profitability factor ($GPROF$), Asness, Frazzini, and Pedersen (2014) quality-minus-junk factor (QMJ), the Stambaugh and Yuan (2016) mispricing factors ($MGMT$ and $PERF$), short-term reversal factor ($STREV$), and long-term reversal factor ($LTREV$).

[15]In Table 3, two of the most significant factor loadings for the joint momentum strategy are on the fundamental earnings momentum factors (1.77 for β_{SUE} and 1.17 for β_{CAR3}).

through a channel other than earnings surprises.[16] An upcoming change in credit rating, for example, is such an event (Kisgen, 2006, 2007).

To directly test whether joint stock/CDS signals more precisely capture future firm fundamentals in correctly anticipated directions, Table 4 presents results on whether joint winners (losers) exhibit faster (slower) growth in gross profits and more frequent credit rating enhancements (deteriorations) in the 18 months following the portfolio formation date. For comparison, we also show these developments for the disjoint winner and loser portfolios and report differences with respect to traditional stock momentum. Our purpose here is to identify the marginal value of past CDS performance signals in more accurately anticipating the state of future firm fundamentals. When generating the cumulative six to 18-month percentage growth in gross profits and S&P rating changes, we avoid an overlapping observations problem by compiling one-month statistics over relevant time intervals (Jegadeesh and Titman, 1993).[17]

Table 4 shows that firm profits grow much faster in the joint momentum portfolio than both the traditional momentum and disjoint momentum portfolios. For example, after six months following the portfolio formation date, the wedge in gross profits growth between the joint winner and joint loser portfolios amounts to 13.64%, which is 4.01% higher than that of traditional stock winner and loser portfolios and 5.72% (= 13.64% − 7.92%) higher than that of disjoint winner and loser portfolios. We further find that net credit enhancement between the joint winner and loser portfolios (-0.52) is more than twice as likely as in traditional stock momentum portfolios and more than three times as likely as in the disjoint momentum portfolios. Our results in Table 4 indicate a potential information advantage for joint momentum signals in predicting future firm prospects.

[16] As evidence of this, Internet Appendix shows that our CDS-based joint momentum strategy explains various SUE-based strategies but not vice-versa.

[17] For instance, the six-month period cumulative gross profits growth (%) is computed by summing the one-month profits 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.

3.3 Marginal Information in the Past CDS Performance over Past Stock Performance

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.[18] To directly address these potential concerns, we perform several exercises to showcase the marginal value of past CDS performance signals for future stock returns.

Panel A of Table 5 presents alpha coefficients of various long-short momentum strategies using a formation period of four months ($J = 4m$). The alpha coefficient is based on a model that includes *MKT*, *SMB*, *HML*, and UMD_S factors. Each strategy purchases stocks in the highest quintile while selling short stocks in the lowest quintile. In the first two columns labeled "Raw Signal," we contrast the value of the past CDS performance signal relative to the past stock performance signal for future stock momentum profits. A long/short momentum strategy that simply purchases (sells short) the stock of firms with good (bad) past four-month CDS performance produces a statistically significant alpha of 0.88% per month (column 2). In fact, this stock momentum strategy using only past CDS performance outperforms a similarly-constructed strategy based on the past four-month stock performance by 0.90% per month [= 0.88% − (−0.02%), see column 1].

Positive correlation in stock and CDS performance implies that past CDS winners tend to have better historical stock performance than past CDS losers. To adjust for this potential bias in our first two column results, we perform a conditional sort similar to that of Novy-Marx (2015) by first creating quintiles of the past four-month stock return and then creating *conditional* quintiles of the four-month CDS return that draws equally from the stock return quintiles. This procedure ensures a minimal past stock performance differential between

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

CDS winners and CDS losers. In columns 3 and 4, labeled "Conditional Signal," we show the results of two conditional sorts, $r_{S,4} \mid r_{C,4}$ and $r_{C,4} \mid r_{S,4}$, respectively. In column 4 we find that even after conditioning on past stock performance, the CDS-based strategy generates a positive alpha of 0.74% that is statistically significant at the 1% level and has a Sharpe ratio of 0.75, providing further evidence that the historical CDS performance signal itself does, in fact, have value for future stock returns. In contrast, conditioning the stock-based strategy on past CDS performance worsens its risk-adjusted performance to a statistically insignificant -0.27% per month. The strategy based on the conditional stock signal underperforms a similar strategy based on the conditional CDS signal strategy by 1.01% per month ($= 0.74\% - -0.27\%$). This sharply identifies the marginal predictive power that the past CDS performance signal has on future stock returns.[19]

3.3.1 Marginal Information in CDS Performance Signals: The Role of CDS Market Depth and Distress Risk

When is the CDS market information most useful in enhancing traditional stock momentum profits? Credit risk often becomes a greater concern to equity investors in distressed markets, so we might expect CDS performance signals to be more relevant among low-grade firms or during periods of high uncertainty and widening credit spreads. Furthermore, more participation in a firm's CDS market may correspond to more informed spreads, particularly if CDS trading is motivated by endogenous credit risk hedging demands as explored by Qiu and Yu (2012). To investigate these possibilities, we consider both cross-sectional and time series effects by decomposing our sample firms and sample period into subgroups based on CDS market depth and levels of distress risk. We use Markit's reported CDS contract depth as a measure of CDS market participation and S&P credit ratings or five-year CDS spread

[19]Our Internet Appendix further confirms the marginal value in the past CDS return using various formation horizons from one to 12 months and also shows that a multi-term stock momentum strategy does not produce statistically significant positive alpha.

levels as a proxy for corporate credit risk.

Panel A of Table 5 shows that higher depth CDS contracts are relatively more informative about future stock returns. The conditional CDS-based strategy in column 4 generates a statistically insignificant alpha of -0.03% per month among low CDS depth firms and a statistically significant 0.94% per month (t-statistic of 3.88) among high depth firms. Next, dividing the sample of firms based on S&P credit rating shows that CDS performance signals are informative for both investment grade and junk grade firms with slightly greater predictability among junk grade firms. The conditional CDS-based strategy generates an alpha of 1.28% per month (t-statistic of 3.61) among junk grade firms and 0.52% (t-statistic of 2.46) among investment grade firms. Similarly, dividing the sample into periods when the value-weighted average corporate CDS spread is above and below its sample period median (0.73%) shows that the CDS signal has important information for future stock returns during both periods, with slightly stronger results during high risk states. The Joint-Disjoint performance differential shows alpha coefficients of 1.60% (t-statistic of 2.80) during the low risk period and 2.59% (t-statistic of 5.39) during the high risk period.

Altogether, our results in Table 5 highlight the increased relative information benefits of the CDS performance signal when the CDS market is active and the level of distress risk is high. As the region of equity payoffs approaches the firm's default boundary, any underreaction signals on future firm fundamentals could be sharpened out by jointly examining the past performance of both equity securities and CDS contracts.

3.4 Cross-Market Convergence Trading and the Poor Performance of Disjoint Momentum

In this section, we consider the role of cross-market arbitrageurs in correcting price discrepancies across stock and CDS markets that could contribute to the poor performance of disjoint stock/CDS momentum. Based on the notions in Goldstein, Li, and Yang (2014), we provide a relative pricing framework rationale for the poor performance of stock momentum strategies among disjoint firms. Goldstein, Li, and Yang (2014) show that a related security market, such as the CDS market, can introduce differential trading motives among stock market investors. In particular, when sophisticated arbitrageurs, who actively trade in both markets, believe that a firm's stock is overpriced (underpriced) relative to the CDS, they will sell (buy) default protection through the CDS contract while simultaneously hedging the position by selling (buying) the stock. In the context of the momentum trade, firms that are past stock winners but CDS losers (past stock losers but CDS winners) will be regarded as having become relatively overpriced (underpriced) in their stock and will consequently attract cross-market hedgers (Goldstein, Li, and Yang, 2014). This cross-market hedging activity would put price convergence pressure on these stocks.

Figure 4 confirms the potential mispriced credit risk between stock and CDS markets among disjoint entities. This figure displays the cumulative percentage divergence between implied CreditGrades CDS spreads and the observed at-market CDS spreads from Markit for the winner and loser portfolios of the joint and disjoint momentum strategies.[20] Only the disjoint winner and disjoint loser portfolios show a strong divergence over four months prior to the portfolio formation date. We find no such divergence in the joint winner and joint loser portfolios. Importantly, disjoint entities show a clear trend of convergence in the months following portfolio formation that partially resolves the apparent mispricing. Potential cross-market arbitrage opportunities in mispriced credit, such as those observed among disjoint entities, may be important for explaining the outperformance of joint momentum over disjoint momentum.

[20]Stock-implied CreditGrades CDS spreads are computed following Yu (2006). In generating the CreditGrades model spread, Yu (2006) assumes a standard deviation in global recovery rate of 0.3, a bond-specific recovery rate of 0.5, and a firm-specific global recovery rate that is derived from minimizing the estimated CreditGrades CDS spread to actual observed CDS spreads over the first ten days of each firm's sample period.

To this end, in Table 6 we show that the cross-section of stock return momentum varies widely according to divergence between actual and equity-implied CDS returns. We separate stock momentum winner and loser portfolios into two subgroups based on the expected intensity of reversal pressure from convergence trades enacted by arbitrageurs. Stock winners with high reversal pressure are those with equity-implied CDS spreads that have fallen far below actual CDS spreads and therefore are the stocks that cross-market arbitrageurs are most likely to sell. This selling pressure, which all else equal is more intense the wider is the divergence, contributes to return *reversal* rather than momentum.[21]

Panel A of Table 6 presents the results. For both stock winners and losers, we find that the high reversal pressure group exhibits much weaker momentum than the low reversal pressure group. Specifically, high reversal pressure leads to 1.05% higher future monthly returns among stock losers (see column 1) and 0.63% lower future returns among stock winners (see column 2). In total, column 3 shows that high reversal pressure leads to a statistically significant drop in raw momentum returns of 1.68% per month (t-statistic of 3.59). Furthermore, after accounting for MKT, SMB, HML, and UMD_S factors, the risk-adjusted stock momentum profits among firms with low reversal pressure (shown in column 4) amount to 1.44% per month (t-statistic of 3.96), whereas the high reversal pressure group suffers from losses of -0.43% per month (t-statistic of -2.79).

Next, we examine the sensitivity of our joint momentum strategy to divergence between actual and equity-implied CDS returns. To do this, we augment the original joint-market momentum construction by conditioning both $r_{S,12}$ and $r_{C,4}$ portfolio sorts on the divergence, $r_{C,4} - r_{M,4}$. In the spirit of Novy-Marx (2015), we implement this procedure by first creating quintiles of divergence and then creating *conditional* quintiles of past return, drawing equally from the divergence quintiles to ensure little-to-no variation in divergence between

[21] Our procedure closely follows the joint-market momentum strategy. First, we conduct two independent sorts and create quintiles based on the 12-month stock return, skipping the most recent month, and the divergence defined as actual CDS return minus equity-implied CDS return using the CreditGrades model.

past return winner and loser portfolios. That is, the $r_{S,12} \mid (r_{C,4} - r_{M,4})$ winner and loser portfolios vary according to $r_{S,12}$ but have no variation in $r_{C,4} - r_{M,4}$. Column 1 in Panel B of Table 6 shows that joint momentum profits, net of reversal pressure, generates a statistically insignificant -0.19% per month, providing evidence that convergence pressure from cross-market arbitrageurs plays an important role in explaining the outperformance of the joint stock/CDS momentum strategy.

Lastly, we show that significant profits are available to sophisticated cross-market arbitrageurs who implement the full capital structure arbitrage on the entities with the largest disagreement in cross-sectional ranking of past performance (Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012). Specifically, in this exercise we *sell* (*buy*) stock momentum winners (losers) if they are CDS momentum losers (winners). At the same time, we delta–hedge these contrarian stock trades with CDS contracts using hedge ratios derived from the CreditGrades model (Yu, 2006; Duarte, Longstaff, and Yu, 2007).[22] In column 2 of Panel B in Table 6, we find significant capital structure arbitrage profits of 1.28% per month with an annualized Sharpe ratio of 0.61. Overall, our results in Table 6 suggest that there is strong price convergence pressure on disjoint entities due in part to sophisticated cross-market arbitrageurs, which would explain why we do not observe return momentum in our disjoint momentum portfolio.

4 Addressing Crash Risk of Stock Return Momentum Strategies: A Related Securities Approach

While momentum strategies generate modest positive returns most of the time, they occasionally experience large losses. These extremely negative returns occur almost exclusively in highly volatile environments when the market turns positive after experiencing an extended

[22] Details on CreditGrades hedge ratio calculations are provided in Appendix E.

period of losses.[23] An underlying reason for this is time-varying market beta exposure of the stock momentum strategy, which tends to be positive during bull markets and negative during bear markets. The momentum crashes of 1932 and 2009, for example, are at least partially explained by the strategy's large negative market beta exposure when the market rebounded. However, as shown by Daniel and Moskowitz (2016), hedging attempts by investors using real-time market betas often fail to prevent large losses, in particular because past beta exposure is a poor predictor of future realized beta. That being said, Barroso and Santa-Clara (2015) show that scaling down momentum exposure during times of heightened total volatility of the momentum strategy itself is effective in reducing crash risk mostly because the *strategy-specific* component of momentum risk is highly autocorrelated. Likewise, forecasting momentum returns using their historic relation to market volatility levels is also useful in developing dynamic momentum strategies with smoother performance (Daniel and Moskowitz (2016)). A common theme in the literature is that performance can be significantly improved by scaling back exposure to the momentum strategy when volatility levels become elevated.

Building on our insights from Section 3 as well as prior research on the time-varying risks of stock momentum, we develop a set of implementable momentum hedging strategies that utilize "cross-sectional" related security performance information to enhance the risk-return profile of traditional stock momentum. These novel strategies are rooted in the robust performance differential between the joint and disjoint segments of stock momentum, which we have shown to be statistically positive for all formation horizons of CDS return and unexplained by common risk factors. In this section, we start by showing significant asymmetry in option-like payoff risk between our joint and disjoint momentum strategies when a bear market rebounds from its bottom. We further show that the joint-disjoint performance dif-

[23] Cooper, Gutierrez, and Hameed (2004) were among the first to note that stock momentum performance following up-markets tends to be significantly better than that following down-markets.

ferential is greatest during periods of heightened volatility, precisely when expected stock momentum returns and Sharpe ratios are low, making it a particularly useful risk management tool to improve the risk-return profile of traditional stock momentum strategies. Lastly, we present our momentum hedging strategies that provide superior performance to the traditional stock momentum strategy.

To test whether our joint and disjoint momentum portfolios show severe option-like payoff risk when a bear market rebounds from its bottom, we use the following test specification in Daniel and Moskowitz (2016):

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

where r_{MOMt} is the momentum portfolio return, I_B is an ex ante bear market indicator that takes the value of one if the 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, 2016).

Regression results are reported in Table 7. Comparing $\beta_{MKT\times I_B\times I_U}$ coefficients reveals a sharp contrast in option-like payoff risks between the joint and disjoint momentum strategies. For instance, column 4 shows that $\beta_{MKT\times I_B\times I_U}$ is -0.59 and statistically insignificant for joint momentum while it is -0.92 and statistically significant at the 1% level for disjoint momentum. It is only the disjoint momentum portfolio that exhibits a statistically significant option-like payoff risk, which partially explains why the joint momentum strategy outperforms disjoint momentum during our sample period.

Next, we highlight the contrasting performance of our joint and disjoint momentum strategies during time periods of heightened and lessened volatility. Given the findings of Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015), we consider both volatility levels of the overall stock market (σ_{Mkt}) as well as the joint momentum strategy itself (σ_{Joint}). Because our intention is to provide results based only on the information available to the investor at the time, we construct two high/low volatility indicators, $\mathbb{I}_M$ and $\mathbb{I}_J$, based on whether the two-year *change* in volatility is positive. This eliminates the need to define an absolute value of volatility and avoids the look-ahead bias in using the sample period median volatility.[24]

The performance results during periods of heightened and lessened volatility are presented in Table 8. As anticipated, the performance of both the joint and disjoint momentum strategies are weaker during periods of high volatility. In fact, joint momentum is positive but statistically insignificant when $\mathbb{I}_M = 1$ or when $\mathbb{I}_J = 1$. Importantly, however, the performance differential, measured as joint momentum minus disjoint momentum, is strongest both in terms of magnitude and statistical significance during high volatility environments. During low volatility environments, when the indicator is "volatility by either measure," joint momentum (column 1) generates 2.02% per month with a t-statistic of 5.43 and Sharpe ratio of 1.49 while the joint-disjoint performance differential (column 3) is only 1.07% per month. During high volatility environments, however, the average return on joint momentum is a statistically insignificant 1.27% per month while the joint-disjoint performance differential is 2.33% per month with a t-statistic of 4.77 and Sharpe ratio of 1.26. The results of Table 8 are consistent with our earlier findings that the CDS signal is more valuable during periods of financial distress when credit risk becomes a greater concern to equity investors (shown in Table 5) and that joint momentum is less sensitive to crash risk during bear market up-turns than disjoint momentum (shown in Table 7).

[24]The two-year change in volatility and volatility level itself are naturally highly related—the indicator is triggered as volatility levels begin to elevate. The time-series correlation between the two-year change and the underlying level of volatility is 76% (75%) for market volatility (joint momentum volatility), and the correlation between change in market volatility and change in joint volatility is 81%. We choose two years as the horizon to be consistent with Daniel and Moskowitz (2016).

Next, we take this finding and form a set of implementable stock momentum hedging strategies. The hedging component of these strategies is a *contrarian* position that purchases disjoint losers and sells short disjoint winners in order to guard against any downside risk in joint momentum inherited from traditional stock momentum. Our baseline momentum hedging strategy, called "Hedged Joint Momentum," directly takes advantage of the joint-disjoint cross-sectional momentum performance differential by investing 50% in joint momentum and hedging with 50% in a contrarian strategy on disjoint firms, expressed as

$$\text{Hedged Joint Momentum}_t = 0.5 \times \text{Joint}_t - 0.5 \times \text{Disjoint}_t.$$

We additionally test three strategies that dynamically switch from a pure joint momentum strategy to the hedged strategy during periods of heightened volatility. These dynamic strategies exhibit superior overall performance by capitalizing on the strong outperformance of joint momentum during low volatility environments and the wide joint-disjoint performance differential during high volatility environments.

Table 9 reports our results. Columns 1 and 2 provide raw returns and alpha coefficients, respectively, for the statically hedged joint momentum strategy using CDS formation periods of $J = 1m$ to $J = 12m$. While all months show statistical significance at the 1% to 5% levels, the four month CDS return horizon ($J = 4m$) maximizes the raw return, generating 0.86% per month with an alpha of 0.95% and Sharpe ratio of 1.04. This represents a net 28% increase in Sharpe ratio from our joint momentum strategy alone ($= 1.04/0.81 - 1$) but also a 48% decrease in average monthly return ($= 0.86/1.64 - 1$). To preserve a high expected return while also hedging against downside risk during volatile periods, we consider next a dynamically hedged joint momentum strategy that switches from joint momentum to the hedged strategy during volatile environments.

Columns 3 to 8 of Table 9 report our dynamically hedged joint momentum results. Each dynamic strategy depends on the volatility indicator $\mathbb{I}$ as follows:

$$\text{Dynamically Hedged Joint Momentum} \equiv \begin{cases} \text{Joint Momentum,} & \text{for } \mathbb{I} = 0 \\ \text{Hedged Joint Momentum,} & \text{for } \mathbb{I} = 1. \end{cases}$$

We present results using volatility indicators based on market volatility ($\mathbb{I}_M$, columns 3 and 4), joint momentum volatility ($\mathbb{I}_J$, columns 5 and 6), and either (columns 7 and 8). In all three strategies and across all formation horizons ranging from $J = 1m$ to $J = 12m$, raw returns and alpha coefficients are positive and statistically significant at the 1% level. A CDS return formation horizon of four months ($J = 4m$) maximizes performance with respect to return, alpha, and Sharpe ratio. We find strong results no matter whether the volatility indicator is based on market volatility or joint momentum volatility. In fact, triggering the indicator when *either* market or joint momentum volatility becomes elevated generally provides the highest Sharpe ratios. Column 7 shows a raw return of 1.59% per month with a t-statistic of 6.78 and a Sharpe ratio of 1.37. This amounts to a 69% increase in Sharpe ratio from joint momentum ($= 1.37/0.81 - 1$) with only a 3% reduction in raw return ($= 1.59/1.64 - 1$). The fact that significant Sharpe ratio enhancements are observed across the board serves as evidence that related security performance information can be used for effective risk management of stock momentum strategies.

Figures 5 and 6 graphically summarize our findings. Figure 5 portrays a distributional violin plot for our in-sample traditional stock momentum as well as our statically and dynamically hedged joint momentum strategies. The highly negatively skewed returns of stock momentum, which reaches nearly -40%, are clearly mitigated in our hedged strategies. Similarly, our hedged strategies displayed in Figure 6 show strong and steady outperformance over traditional stock momentum throughout the entire sample period from 2003 to 2015.

Put together, our results in Table 9 and Figures 5 and 6 confirm the recent notion introduced by Goldstein, Li, and Yang (2014) who theoretically demonstrate that stock price informativeness reduces when the market is segmented by trader type with differing motives due to related securities' signals. Boehmer, Chava, and Tookes (2016) 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.

4.1 Temporal and Cross-Sectional Approach Comparison

This section compares our cross-sectional related security approach to addressing crash risk in momentum strategies to the temporal managed-volatility technique of Barroso and Santa-Clara (2015) and the Sharpe-forecasting method of Daniel and Moskowitz (2016). Due to the predictable nature of crash risk in stock momentum, investors can benefit from dynamically scaling their exposure according to observable *ex ante* volatility levels. This is implemented by determining a momentum weight w at time $t-1$ to scale the realized return of the momentum strategy during time t. The investor's return is expressed as:

$$\text{Scaled Momentum}_t = w_{t-1} \times \text{Momentum}_t.$$

For the managed-volatility strategy, we follow Barroso and Santa-Clara (2015) and compute the standard deviation of the long-short strategy's daily returns over the prior six months. Then, using this trailing volatility measure as the volatility estimate for the next period, we scale the momentum exposure to maintain a constant target volatility (i.e., $w_{t-1} = \sigma^*/\sigma_{t-1}$, where σ^* represents a target volatility and σ_{t-1} represents the estimated next period volatility). To implement the Sharpe-ratio-optimizing technique of Daniel and Moskowitz (2016), we first generate expectations for future momentum returns and volatility. To forecast the next period return, we use a rolling time-series regression of the strategy's daily returns on an interaction term between a bear market indicator and stock market variance. Future volatility is approximated using the strategy's standard deviation of daily returns over the past six months. These two estimates are then combined to form an expectation of the next period's Sharpe ratio. The Sharpe-optimized momentum scales the momentum exposure to maximize the expected Sharpe ratio (i.e., $w_{t-1} = (1/2\lambda)(\mu_{t-1}/\sigma^2_{t-1})$, where μ_{t-1} represents the next period return expectation).

While our approach is cross-sectional in nature, it inherently contains elements of these scaling techniques. For instance, we have already shown that the disjoint segment of stock momentum exhibits more extreme option-like behavior and underperforms joint momentum especially during periods of heightened volatility (see Tables 7 and 8, respectively). In this section, we examine whether these temporal scaling techniques explain our cross-sectional-based hedged momentum results and whether our hedging strategy can be further improved by applying these scaling techniques.

Table 10 shows a comparison of various plain and scaled momentum strategies.[25] The table reports both the sample period Sharpe ratio for each strategy and the Treynor and Black (1973) appraisal ratio relative a comparison strategy. The first category, *Traditional Stock Momentum (UMD)*, confirms that the volatility-scaled and Sharpe-forecasted strategies significantly enhance the traditional stock momentum strategy during our sample period from 2003 to 2015. The second category, *Statically Hedged Joint Momentum*, includes scaled variations of our static-hedged joint momentum strategy that is 50% invested in joint momentum and 50% in a disjoint contrarian position. The plain strategy generates a Sharpe ratio of 1.04, which is 27% higher than the best-performing scaled UMD strategy [$= (1.04 - 0.82)/0.82$]. To achieve a similar Sharpe ratio, the Sharpe-forecasted UMD strategy would need to combined with an orthogonal investment exhibiting a Sharpe ratio of 0.64 ($= \sqrt{1.04^2 - 0.82^2}$),

[25]Each scaled strategy targets an annualized volatility of 20%, which mimics that of our plain in-sample stock momentum strategy. Note, however, that while the choice of target volatility can either amplify or dampen the performance of the scaled strategy, it does not affect its Sharpe ratio or appraisal ratio.

which is represented by the appraisal ratio. Furthermore, we find that scaling the hedged strategy significantly improves its performance. For instance, the volatility-scaled hedged joint momentum strategy generates a Sharpe ratio of 1.31 with an appraisal of 0.80 with respect to plain hedged joint momentum.

The last category in Table 10 shows the scaled variations of our *Dynamically Hedged Joint Momentum* strategy that invests in scaled joint momentum but switches to scaled hedged joint momentum only during periods of heightened volatility.[26] We find a large improvement in performance of our dynamically hedged strategy after scaling according to its volatility, producing a Sharpe ratio of 1.61 and an appraisal ratio of 0.85 against the plain strategy. Overall, these results suggest that despite any commonalities between the temporal scaling approaches and our cross-sectional approach, each leads to distinct improvements in the risk-return profile of the stock momentum strategy. Investors can enjoy enhanced risk-managed momentum strategy profits by considering both temporal and cross-sectional hedging approaches.

5 Related Securities and the Cross-Section of Stock Return Momentum: The International Evidence

In this section, we turn to a sample of international firms headquartered outside the U.S. to perform an out-of-sample test on related security performance and the cross-section of stock return momentum and compare the robustness of our momentum segmentation structure across countries with high and low economic development. The international sample consists of 1,267 non-U.S. firms from 49 countries. CDS data are from the Markit Group

[26]For this exercise, the high volatility indicator is triggered when either stock market or joint momentum volatility becomes elevated.

and equity data are from Datastream.[27]

Table 11 presents alpha coefficients on an international four-factor model that includes international (ex-U.S.) MKT, SMB, HML, and UMD_S factors.[28] Using a CDS formation horizon of $J = 4m$, we find positive risk-adjusted returns on the joint stock/CDS momentum strategy and a significant disparity in performance between joint and disjoint momentum. Column 1 shows that joint momentum generates an alpha of 0.83% per month with a t-statistic of 2.69 and Sharpe ratio of 0.55. In column 2 we see that disjoint momentum produces a negative alpha of -0.28% per month (t-statistic of -2.70). An international statically hedged joint momentum portfolio that invests 50% in international joint momentum while hedging with 50% in a disjoint contrarian strategy generates a statistically significant 0.55% per month with a t-statistic of 2.72 and Sharpe ratio of 0.87. The dynamically hedged joint momentum strategy that switches from joint momentum to a hedged strategy during high volatility periods generates 1.21% per month with a t-statistic of 4.03 and Sharpe ratio of 1.05.[29] These international results confirm our earlier findings that CDS performance information is important in explaining the cross-section of stock momentum.

Next, we separate countries by high and low economic development and repeat our analysis. In Section 3.4 we provided a relative pricing framework for our momentum segmentation results and in Table 6 showed that the underperformance of disjoint momentum appears to closely related to arbitrageurs acting on mispricing between stock and CDS markets. Because the stock market segmentation concept of Goldstein, Li, and Yang (2014) is most applicable when there exists a relatively wider variety of trading motives among stock market investors, we hypothesize that the joint-disjoint performance differential is greatest among more de-

[27]Similar to our filters on the U.S. sample, we require firms' equity market capitalization to be greater than \$100 million (USD) at the time of portfolio formation and for the CDS to have no more than 10% missing observations and no more than 90% stagnant observations over the prior six months.

[28]See Ken French's site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) for the international (ex-U.S.) MKT, SMB, and HML.

[29]The high volatility indicator equals one when the two-year change in trailing market volatility is greater than zero.

veloped economies that are populated with a greater number of sophisticated hedgers (i.e., cross-market arbitrageurs) in proportion to speculators (i.e., momentum traders).

The international sample is divided into two roughly equally-sized groups based on GDP-per-capita, assigning 633 firms to the more developed group (high GDP-per-capita) and 634 firms to the less developed group (low GDP-per-capita). International four-factor alpha coefficients for these two groups are presented in Table 11. We find that joint momentum performance (column 1) is much greater in the sample of more developed countries, generating an alpha of 1.15% per month (t-statistic of 3.35 and Sharpe ratio of 0.55), compared to the statistically insignificant 0.38% per month among less developed countries. Similarly, the underperformance of disjoint momentum (column 2) is exacerbated in the sample of more developed countries (-0.40% per month) relative to that of less developed countries (-0.07% per month).

We also find the performance differential between joint and disjoint momentum to be much wider and statistically significant only in the sample of more developed countries. The statically hedged joint momentum strategy (column 3) that maintains a constant 50% in joint momentum and 50% in a disjoint contrarian strategy generates an alpha of 0.78% per month among the more developed countries (t-statistic of 3.11 and Sharpe ratio of 0.83) and only 0.22% per month among the less developed countries (t-statistic of 0.84 and Sharpe ratio of 0.37). The dynamically hedged joint momentum strategy (column 4) proves to be nearly twice as profitable among more developed countries in relation to less developed countries (1.47% per month versus 0.82% per month, respectively) and has greater statistical significance (t-statistic of 3.72 versus 2.38). These findings are closely related to Jacobs (2016) who shows that mispricing-based stock market anomalies appear to be at least as profitable in developed markets as in developing markets.

Figure 7 displays the cumulative profits from an global strategy (50% U.S., 50% Non-U.S.) that uses related security performance information to dynamically hedge risk and improve the performance of traditional stock momentum. The global dynamic hedging strategy exhibits a Sharpe ratio of 1.55, which represents a vast improvement over the 0.13 of the depicted global stock momentum strategy. Put together, our international findings further solidify the robustness of our baseline results and provide further evidence that cross-market arbitrage plays an important role in explaining why related security performance matters in the cross-section of stock momentum.

6 Conclusion

We introduce a simple yet powerful approach to detect relative underreaction and overvaluation 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 underreacting to firm fundamentals – thereby showing subsequent price momentum. Further, we are able to detect which stocks are likely to show price reversal due, in part, to strong convergence pressure on their share prices arising from misaligned equity and credit security prices.

Using 881 U.S. public firms that have actively trading five-year maturity single name CDS contracts during 2003-2015, we document the following important differences in the cross-section of stock return momentum. First, we show that segmenting traditional stock momentum (Jegadeesh and Titman, 1993) based on the degree of cross-sectional past performance ranking agreement between stock and CDS markets reveals a stark contrast in momentum strategy returns. In particular, *joint* entities that have strong agreement in past performance exhibit a much stronger momentum effect than *disjoint* entities with disagreement in past stock and CDS performance. The performance differential between these joint and disjoint components of stock momentum exceeds 20% per year. This finding is consistent with the notion of Goldstein, Li, and Yang (2014) that stock markets may be segmented with momentum traders and contrarian hedgers whose trades are motivated by relative pricing between stock and CDS markets. That is, under a relative pricing framework, the underperformance of disjoint momentum can be explained in part by cross-market arbitrageurs acting on disjoint stocks that misprice underlying credit risks relative to the CDS. We further observe that disjoint momentum is more sensitive to momentum crash risk during bear market rebounds (Daniel and Moskowitz, 2016) and underperforms joint momentum especially during periods of high volatility. Based on these observations, we present various hedging strategies that eliminate crash risk and significantly improve the risk-return profile of the traditional stock momentum strategy, providing an alpha of up to 18% per year and a Sharpe ratio of 1.37. As an additional out-of-sample robustness test, we extend our findings to 1,267 international firms from 49 countries.

Overall, we provide several important contributions to three relevant research streams. First, 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, 2016; Yu, 2006; Duarte, Longstaff, and Yu, 2007; Kapadia and Pu, 2012). Second, we provide a novel cross-sectional approach to detect a group of stocks that are more prone to momentum crashes (Daniel and Moskowitz, 2016; Daniel, Jagannathan, and Kim, 2012; Grundy and Martin, 2001; Barroso and Santa-Clara, 2015; Han, Zhou, and Zhu, 2016). 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, 2014; Boehmer, Chava, and Tookes, 2016).

Our results shed new light on interactive cross-market anomalies rooted in market segmentation. 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 improves our understanding of asset pricing dynamics and market efficiency.

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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 December 2015. 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. Detailed definitions are provided in Appendix A.

Panel A. Summary Statistics

	(1) Mean	(2) St. Dev.	(3) Min	(4) Med	(5) Max	(6) N
Market Cap ($ Billion)	20.47	33.59	0.29	8.91	203.15	71,228
Stock Return (%, monthly)	0.93	10.64	-99.68	1.06	259.66	71,228
CDS Spread (bps)	186.43	354.26	2.67	89.73	9739.77	71,228
CDS Return (%, monthly)	0.01	2.57	-59.12	0.01	110.72	71,228
CDS Depth	6.77	4.47	2.00	6.00	31.00	71,228
S&P Credit Rating (1=AAA, 22=D)	8.92	3.04	1.00	9.00	22.00	70,372

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	-0.188	0.016	1.000			
(4)	CDS Return	0.001	0.037	-0.120	1.000		
(5)	CDS Depth	0.107	-0.016	-0.127	-0.027	1.000	
(6)	S&P Rating	-0.552	0.011	0.508	0.030	-0.172	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, where J ranges from from 1 to 12 months. The holding period is one month ($K = 1$). We segment the traditional stock momentum strategy into two parts based on the overlap between stock and CDS winner and loser portfolios as follows:

$$\text{Stock Momentum} \equiv (W_S - L_S) \begin{cases} \text{Joint Stock/CDS Momentum} \equiv (W_S \cap W_C) - (L_S \cap L_C) \\ \text{Disjoint Stock/CDS Momentum} \equiv (W_S \setminus W_C) - (L_S \setminus L_C). \end{cases}$$

The "4-factor" model includes MKT, SMB, HML, and our in-sample stock momentum factor, UMD_S. The UMD_S factor is constructed in-sample using quintiles of firms' past 12-month stock return ($J = 12m$), skipping the most recent month, and a holding period of one month ($K = 1m$). Percentage returns are monthly and span the time period January 2003 to December 2015. 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-statistic), and annualized *Sharpe ratio*.

	Joint Stock/CDS Momentum				Momentum Segmentation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	JL ≡ $L_S \cap L_C$	JW ≡ $W_S \cap W_C$	Joint ≡ JW-JL	Joint 4-factor α	Joint − (W_S-L_S)	Disjoint − (W_S-L_S)	Joint − Disjoint
$J = 1m$	0.20	1.46***	1.25*	1.00***	0.95***	-0.34***	1.29***
	(0.23)	(2.82)	(1.79)	(2.92)	(2.68)	(-2.77)	(2.98)
	0.08	*0.84*	*0.57*		*0.73*	*-0.91*	*0.84*
$J = 2m$	0.17	1.29**	1.12*	0.86**	0.82**	-0.35***	1.17***
	(0.20)	(2.52)	(1.66)	(2.56)	(2.27)	(-3.52)	(2.73)
	0.07	*0.82*	*0.54*		*0.74*	*-0.98*	*0.85*
$J = 3m$	0.082	1.22**	1.13**	0.85***	0.83***	-0.16	0.98***
	(0.09)	(2.17)	(2.14)	(2.94)	(3.40)	(-1.14)	(2.93)
	0.04	*0.71*	*0.57*		*0.66*	*-0.35*	*0.65*
$J = 4m$	-0.15	1.49***	1.64***	1.45***	1.34***	-0.39***	1.73***
	(-0.16)	(2.69)	(2.83)	(4.24)	(4.08)	(-2.71)	(3.94)
	-0.06	*0.88*	*0.81*		*1.05*	*-0.79*	*1.04*
$J = 5m$	-0.18	1.31**	1.49**	1.25***	1.19***	-0.34***	1.52***
	(-0.21)	(2.33)	(2.56)	(3.83)	(3.61)	(-2.86)	(3.57)
	-0.08	*0.78*	*0.75*		*1.02*	*-0.76*	*1.02*
$J = 6m$	0.11	1.24**	1.14*	0.91**	0.83**	-0.27**	1.10**
	(0.13)	(2.40)	(1.66)	(2.60)	(2.22)	(-2.14)	(2.28)
	0.05	*0.79*	*0.54*		*0.75*	*-0.64*	*0.76*
$J = 9m$	-0.085	1.20***	1.29*	1.04***	0.98***	-0.37*	1.35**
	(-0.09)	(2.66)	(1.82)	(3.26)	(2.72)	(-1.85)	(2.49)
	-0.04	*0.78*	*0.61*		*0.92*	*-0.68*	*0.88*
$J = 12m$	0.062	1.10***	1.04	0.72**	0.74**	-0.34*	1.08**
	(0.07)	(2.61)	(1.54)	(2.40)	(2.32)	(-1.73)	(2.16)
	0.03	*0.71*	*0.51*		*0.78*	*-0.62*	*0.77*

Table 3. Risk-Adjusted Performance

This table presents the results of various spanning tests of traditional stock momentum, joint stock/CDS momentum, and disjoint stock/CDS momentum. MKT, SMB, and HML refer to factors from the Fama-French three-factor model, UMD_S is an in-sample UMD (traditional stock momentum) factor, LIQ is the Paster-Stambaugh traded liquidity 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. 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 stock/CDS momentum strategy trades only the overlapping set of firms in stock and CDS winner and loser portfolios, expressed as Joint $\equiv$ ($W_S \cap W_C$) – ($L_S \cap L_C$). The disjoint stock/CDS momentum strategy trades the complement set to Joint momentum, expressed as Disjoint $\equiv$ ($W_S \setminus W_C$) – ($L_S \setminus L_C$). Percentage returns are monthly and span the time period January 2003 to December 2015. 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.

	Stock Momentum		Joint Stock/CDS Momentum			Disjoint Stock/CDS Momentum		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	0.51	-0.11	1.45***	1.56***	1.21**	-0.45***	-0.48***	-0.49*
	(1.46)	(-0.45)	(4.24)	(4.92)	(2.54)	(-3.10)	(-3.59)	(-1.92)
β_{MKT}	-0.45**	-0.22*	-0.08	-0.08	-0.26	0.07	0.07	-0.15
	(-2.56)	(-1.68)	(-0.77)	(-0.86)	(-1.34)	(1.20)	(1.28)	(-1.26)
β_{SMB}	0.36	0.30**	-0.20	-0.11	0.10	0.11**	0.09*	0.39***
	(1.59)	(2.01)	(-1.42)	(-0.82)	(0.41)	(2.27)	(1.69)	(2.96)
β_{HML}	-0.51**	0.27	0.17	0.03	0.42	-0.14	-0.10	0.09
	(-2.25)	(1.25)	(0.64)	(0.11)	(1.12)	(-1.07)	(-0.81)	(0.47)
β_{UMD_S}			0.95***	0.96***		0.93***	0.93***	
			(11.50)	(12.40)		(27.70)	(28.92)	
β_{LIQ}	0.09			-0.23**			0.07*	
	(0.79)			(-2.50)			(1.84)	
β_{SUE}		2.05***			1.77***			1.92***
		(11.26)			(5.63)			(10.33)
β_{CAR3}		0.83***			1.17***			0.61***
		(3.80)			(3.21)			(3.17)

Table 4. Future Firm Fundamentals

This table presents the average six to 18-month cumulative growth in profits and change in S&P rating for the joint and disjoint stock/CDS momentum winner and loser portfolios. Multi-month changes in profits and ratings are constructed so as 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. 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 stock/CDS momentum strategy trades only the overlapping set of firms in stock and CDS winner and loser portfolios, expressed as Joint $\equiv$ ($W_S \cap W_C$) – ($L_S \cap L_C$). The disjoint stock/CDS momentum strategy trades the complement set to Joint momentum, expressed as Disjoint $\equiv$ ($W_S \setminus W_C$) – ($L_S \setminus L_C$). The time period spans January 2003 to December 2015. 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 Stock/CDS Momentum				Disjoint Stock/CDS Momentum			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	JL $\equiv$ $L_S \cap L_C$	JW $\equiv$ $W_S \cap W_C$	Joint $\equiv$ JW – JL	Joint – (W_S-L_S)	DL $\equiv$ $L_S \setminus L_C$	DW $\equiv$ $W_S \setminus W_C$	Disjoint $\equiv$ DW – DL	Disjoint – (W_S-L_S)
Gross Profits (% cumulative change)								
6 Months	-8.21***	5.43***	13.64***	4.01*	-4.27**	3.65***	7.92***	-1.71**
	(-3.39)	(3.11)	(4.77)	(1.90)	(-2.25)	(3.44)	(3.88)	(-2.13)
12 Months	-12.32***	6.14**	18.46***	6.01**	-5.45*	4.64**	10.09***	-2.36**
	(-3.19)	(2.14)	(4.69)	(1.99)	(-1.82)	(2.30)	(3.13)	(-2.27)
18 Months	-16.14***	5.62	21.76***	7.59**	-6.74*	4.79	11.54***	-2.63*
	(-3.20)	(1.43)	(4.43)	(2.02)	(-1.71)	(1.62)	(2.80)	(-1.96)
S&P Credit Rating (cumulative change, +1=one sub-notch downgrade)								
6 Months	0.31***	-0.21***	-0.52***	-0.28***	0.11***	-0.05***	-0.15***	0.08***
	(7.16)	(-5.34)	(-8.63)	(-7.23)	(4.02)	(-3.81)	(-5.37)	(6.46)
12 Months	0.51***	-0.36***	-0.87***	-0.47***	0.19***	-0.09***	-0.27***	0.13***
	(7.37)	(-5.16)	(-8.86)	(-7.19)	(4.44)	(-4.36)	(-6.02)	(6.77)
18 Months	0.62***	-0.50***	-1.12***	-0.62***	0.22***	-0.12***	-0.34***	0.16***
	(7.43)	(-5.00)	(-8.78)	(-7.02)	(4.47)	(-4.06)	(-6.25)	(7.18)

Table 5. Marginal Information in past CDS Performance Signals over past Stock Performance Signals: Four-Factor Alpha Coefficients

This table provides evidence on the marginal information in past CDS and stock performance signals to predict future stock returns. Performance numbers are alpha coefficients using a four-factor model that includes MKT, SMB, HML, and UMD_S factors. Columns 1 to 4 present the results of strategies based on raw single-market past performance signals and conditional past performance signals. Column 5 reports joint stock/CDS past performance signals. Results are reported for the entire sample of firms as well as sub-samples based on CDS liquidity (as measured by CDS market depth), firm-level distress (as measured by the S&P rating), and market state (as measured by average corporate CDS spread). 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 stock/CDS momentum strategy trades only the overlapping set of firms in stock and CDS winner and loser portfolios, expressed as Joint $\equiv$ ($W_S \cap W_C$) – ($L_S \cap L_C$). The disjoint stock/CDS momentum strategy trades the complement set to Joint momentum, expressed as Disjoint $\equiv$ ($W_S \setminus W_C$) – ($L_S \setminus L_C$). Performance is monthly and spans the time period January 2003 to December 2015. 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-statistic), and annualized *Sharpe ratio*.

	Raw Signal		Conditional Signal		Joint – Disjoint
	(1)	(2)	(3)	(4)	(5)
	$r_{S,4}$	$r_{C,4}$	$r_{S,4} \mid r_{C,4}$	$r_{C,4} \mid r_{S,4}$	$r_{S,12}$, $r_{C,4}$
All Firms	-0.02	0.88***	-0.27	0.74***	1.90***
	(-0.09)	(3.02)	(-1.15)	(3.02)	(4.15)
	-0.04	*0.71*	*-0.29*	*0.75*	*1.04*
CDS Liquidity (Market Depth)					
Low	-0.73	0.61	-0.63	-0.03	2.41*
	(-1.55)	(1.45)	(-1.23)	(-0.11)	(1.95)
	-0.41	*0.34*	*-0.39*	*0.05*	*0.58*
High	0.09	1.07***	-0.25	0.94***	1.86***
	(0.38)	(3.92)	(-1.03)	(3.88)	(3.65)
	0.02	*0.77*	*-0.25*	*0.87*	*0.85*
Firm-Level Distress (S&P Rating)					
Inv. Grade	-0.11	0.55***	-0.32	0.52**	1.46***
	(-0.49)	(2.99)	(-1.47)	(2.46)	(3.71)
	-0.12	*0.50*	*-0.34*	*0.52*	*0.75*
Junk Grade	-0.02	1.07***	-0.18	1.28***	2.22***
	(-0.05)	(3.51)	(-0.51)	(3.61)	(2.89)
	0.04	*0.70*	*-0.10*	*0.97*	*0.80*
Market State (Average Corporate CDS Spread)					
Lower Risk	-0.02	0.69***	-0.39**	0.68**	1.60***
	(-0.13)	(2.91)	(-2.39)	(2.58)	(2.80)
	0.19	*0.87*	*-0.33*	*0.82*	*1.13*
Higher Risk	0.26	1.28***	0.04	0.80***	2.59***
	(0.61)	(3.32)	(0.09)	(2.76)	(5.39)
	-0.19	*0.62*	*-0.28*	*0.72*	*1.00*

Table 6. Convergence Trades

This table presents results on the relation between convergence strategies and momentum strategies. Panel A decomposes traditional stock momentum into sub-groups based on arbitrage attractiveness, as measured by the divergence in four-month CreditGrades equity-implied and actual CDS returns. A stock momentum winner (loser) is most likely to experience high reversal pressure by arbitrageurs when the stock has become overvalued (undervalued) relative to the CDS. Panel B shows the profitability of joint stock/CDS momentum when past performance signals are conditioned on divergence in four-month equity-implied and actual CDS returns (column 1) and capital structure arbitrage using a four-month horizon (column 2). Percentage returns and alpha coefficients are monthly and span the time period January 2003 to December 2015. Alpha coefficients are based on a 4-factor model that includes MKT, SMB, HML, and UMD_S factors. 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-statistic), and annualized *Sharpe ratio*.

Panel A. Decomposing Stock Momentum Based on Arbitrage Attractiveness

	(1) L_S	(2) W_S	(3) $W_S - L_S$	(4) α
Low Reversal Pressure	-0.20	1.44**	1.64***	1.44***
	(-0.22)	(2.60)	(2.77)	(3.96)
	-0.09	*0.87*	*0.85*	
High Reversal Pressure	0.85	0.81**	-0.03	-0.43***
	(1.65)	(2.00)	(-0.10)	(-2.79)
	0.48	*0.62*	*-0.02*	
Low – High	-1.05**	0.63*	1.68***	1.88***
	(-2.31)	(1.82)	(3.59)	(3.82)
	-0.91	*0.58*	*1.05*	

Panel B. Convergence-Neutral Joint Momentum and Capital Structure Arbitrage

	Joint Momentum, Net of Reversal Pressure	Capital Structure Arbitrage
	(1)	(2)
Signal 1:	$r_{S,12} \mid (r_{C,4} - r_{M,4})$	$r_{M,4}$
Signal 2:	$r_{C,4} \mid (r_{C,4} - r_{M,4})$	$r_{C,4}$
Return	-0.19	1.28***
	(-0.48)	(2.88)
	-0.11	*0.61*
α	-0.29	1.03*
	(-0.71)	(1.90)

Table 7. Time-Varying Beta and Option-Like Payoff Risk of Joint and Disjoint Stock/CDS Momentum Strategies

This table presents results of time-series regressions of joint and disjoint stock/CDS momentum strategy returns. 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 ($MKT \times I_B \times I_U$). 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 stock/CDS momentum strategy trades only the overlapping set of firms in stock and CDS winner and loser portfolios, expressed as Joint $\equiv (W_S \cap W_C) - (L_S \cap L_C)$. The disjoint stock/CDS momentum strategy trades the complement set to Joint momentum, expressed as Disjoint $\equiv (W_S \setminus W_C) - (L_S \setminus L_C)$. Performance is monthly and spans the time period January 2003 to December 2015. 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.

	(1)	(2)	(3)	(4)
Joint Stock/CDS Momentum $\equiv (W_S \cap W_C) - (L_S \cap L_C)$				
α_0	2.03***	2.38***	2.38***	2.28***
	(3.96)	(4.13)	(4.12)	(4.29)
α_{I_B}		-2.07*	-1.42	
		(-1.69)	(-0.72)	
β_{MKT}	-0.53**	-0.40*	-0.40*	-0.39*
	(-2.48)	(-1.88)	(-1.88)	(-1.87)
$\beta_{MKT \times I_B}$		-0.29	-0.19	-0.056
		(-0.80)	(-0.42)	(-0.14)
$\beta_{MKT \times I_B \times I_U}$			-0.24	-0.59
			(-0.30)	(-1.30)
Disjoint Stock/CDS Momentum $\equiv (W_S \setminus W_C) - (L_S \setminus L_C)$				
α_0	0.18	0.41	0.41	0.55
	(0.65)	(1.23)	(1.22)	(1.58)
α_{I_B}		-1.86**	1.93	
		(-2.14)	(1.17)	
β_{MKT}	-0.36	-0.11	-0.11	-0.12
	(-1.59)	(-0.82)	(-0.81)	(-0.90)
$\beta_{MKT \times I_B}$		-0.53	0.049	-0.13
		(-1.54)	(0.20)	(-0.53)
$\beta_{MKT \times I_B \times I_U}$			-1.40**	-0.92***
			(-2.41)	(-2.88)

Table 8. Stock Momentum Segmentation During Periods of Heightened and Lessened Volatility

This table shows raw excess returns of joint and disjoint stock/CDS momentum strategies during periods of heightened and lessened volatility. The real-time high volatility state indicator $\mathbb{I}_M$ ($\mathbb{I}_J$) equals 1 when the two-year *change* in trailing daily volatility of the broad stock market (joint momentum strategy) is positive. The indicator is designed to be implementable and avoids the need to define an absolute volatility level as well as circumvents the look-ahead bias of using a sample median volatility. Percentage returns are monthly and span the time period January 2003 to December 2015. 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-statistic), and annualized *Sharpe ratio*.

	(1) Joint	(2) Disjoint	(3) Joint − Disjoint
Market Volatility			
Low ($\mathbb{I}_M = 0$)	1.85***	0.72**	1.13**
	(4.69)	(2.12)	(2.42)
	1.35	*0.61*	*0.81*
High ($\mathbb{I}_M = 1$)	1.34	-1.17	2.51***
	(1.09)	(-1.40)	(4.70)
	0.50	*-0.57*	*1.28*
Joint Momentum Volatility			
Low ($\mathbb{I}_J = 0$)	1.79***	0.55*	1.24***
	(5.02)	(1.74)	(2.75)
	1.33	*0.45*	*0.90*
High ($\mathbb{I}_J = 1$)	1.42	-0.96	2.38***
	(1.22)	(-1.17)	(4.81)
	0.53	*-0.47*	*1.20*
Volatility by Either Measure			
Low ($\mathbb{I}_M = 0 \cap \mathbb{I}_J = 0$)	2.02***	0.95***	1.07**
	(5.43)	(2.75)	(2.24)
	1.49	*0.78*	*0.75*
High ($\mathbb{I}_M = 1 \cup \mathbb{I}_J = 1$)	1.27	-1.05	2.33***
	(1.18)	(-1.46)	(4.77)
	0.51	*-0.55*	*1.26*

Table 9. Stock Momentum Hedging Strategies using CDS Past Performance Information

This table shows performance results of stock momentum hedging strategies using joint and disjoint stock/CDS momentum portfolios. "Hedged Joint Momentum" is invested 50% in joint momentum and 50% in a disjoint contrarian strategy (i.e., Hedged Joint Momentum$_t$ = 0.5 × Joint$_t$ − 0.5 × Disjoint$_t$). Columns 1 and 2 show the return and alpha coefficients, respectively, for our hedged joint momentum strategy. Alpha coefficients are based on a four-factor model that includes MKT, SMB, HML, and UMD_S factors. Columns 3 to 8 show performance results of dynamic hedging strategies that switch from joint stock/CDS momentum to hedged joint momentum only during risky states as indicated by $\mathbb{I}$, such that

$$\text{Dynamically Hedged Joint Momentum} = \begin{cases} \text{Joint Momentum}, & \text{for } \mathbb{I} = 0 \\ \text{Hedged Joint Momentum}, & \text{for } \mathbb{I} = 1. \end{cases}$$

The risky state variable $\mathbb{I}_M$ ($\mathbb{I}_J$) equals 1 when the two-year *change* in trailing daily volatility of the broad stock market (joint momentum strategy) is positive. This dynamic hedging design avoids having to define an absolute volatility level and circumvents the look-ahead bias of using a sample median volatility. Percentage returns and alpha coefficients are monthly and span the time period January 2003 to December 2015. 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-statistic), and annualized *Sharpe ratio*.

	Statically Hedged Joint Momentum		Dynamically Hedged Joint Momentum: *Market Volatility* $\mathbb{I}_M$ ($\Delta\sigma_{Mkt} > 0$)		*Joint Volatility* $\mathbb{I}_J$ ($\Delta\sigma_{Joint} > 0$)		*Either* $\mathbb{I}_M = 1 \cup \mathbb{I}_J = 1$	
	(1) Return	(2) α	(3) Return	(4) α	(5) Return	(6) α	(7) Return	(8) α
$J = 1m$	0.64***	0.70***	1.33***	1.14***	1.52***	1.27***	1.33***	1.15***
	(2.98)	(3.42)	(3.86)	(4.67)	(3.59)	(3.73)	(4.18)	(5.15)
	0.84		*1.08*		*1.14*		*1.14*	
$J = 2m$	0.59***	0.63***	1.28***	1.07***	1.47***	1.19***	1.32***	1.12***
	(2.73)	(3.20)	(3.15)	(3.32)	(3.57)	(3.77)	(3.53)	(3.87)
	0.85		*1.05*		*1.13*		*1.14*	
$J = 3m$	0.49***	0.52***	1.13***	0.92***	1.26***	0.98***	1.14***	0.93***
	(2.93)	(2.64)	(3.97)	(3.30)	(3.77)	(2.94)	(4.37)	(3.67)
	0.65		*0.95*		*0.97*		*1.00*	
$J = 4m$	0.86***	0.95***	1.61***	1.48***	1.72***	1.53***	1.59***	1.47***
	(3.94)	(4.15)	(6.00)	(5.85)	(4.69)	(4.24)	(6.78)	(6.57)
	1.04		*1.32*		*1.33*		*1.37*	
$J = 5m$	0.76***	0.81***	1.46***	1.29***	1.58***	1.35***	1.46***	1.30***
	(3.57)	(3.84)	(5.51)	(5.52)	(4.21)	(3.78)	(5.76)	(5.78)
	1.02		*1.31*		*1.30*		*1.37*	
$J = 6m$	0.55**	0.61***	1.21***	1.06***	1.35***	1.13***	1.18***	1.04***
	(2.28)	(2.75)	(3.70)	(4.09)	(3.06)	(3.04)	(3.82)	(4.29)
	0.76		*1.14*		*1.12*		*1.18*	
$J = 9m$	0.68**	0.74***	1.36***	1.20***	1.42***	1.18***	1.33***	1.18***
	(2.49)	(3.13)	(4.26)	(5.13)	(3.24)	(3.21)	(4.39)	(5.29)
	0.88		*1.21*		*1.09*		*1.23*	
$J = 12m$	0.54**	0.55**	1.15***	0.91***	1.24***	0.92**	1.13***	0.91***
	(2.16)	(2.27)	(3.68)	(3.49)	(3.05)	(2.48)	(3.86)	(3.53)
	0.77		*1.02*		*0.97*		*1.06*	

Table 10. Temporal and Cross-sectional Strategy Comparison

This table presents annualized Sharpe ratios and Treynor and Black (1973) appraisal ratios of scaled exposure results for traditional stock momentum, statically hedged joint momentum, and dynamically hedged momentum over the period January 2003 to December 2015. The momentum exposure weight w is determined at time $t-1$ and impacts the investor's return during time t, such that

$$\text{Scaled Momentum}_t = w_{t-1} \times \text{Momentum}_t.$$

There are two scaling techniques presented: "volatility-scaled" in which the momentum strategy is scaled to maintain a constant volatility (following Barroso and Santa-Clara (2015)) and "Sharpe-forecasted" in which the momentum strategy is scaled to optimize the forecasted Sharpe ratio (following Daniel and Moskowitz (2016)). Volatility is estimated using daily returns over the past 126 trading days. Expected momentum returns used to create the forecasted Sharpe ratio are estimated using an out-of-sample rolling regression of daily momentum returns on an interaction term between a bear market indicator and market variance. The appraisal ratio is measured against a comparison strategy.

	Sharpe Ratio	Appraisal Ratio	
	(1)	(2)	Comparison Strategy
Traditional Stock Momentum (UMD)			
Plain	0.03	–	–
Volatility-scaled	0.52	0.52	UMD, Plain
Sharpe-forecasted	0.82	0.82	UMD, Plain
Statically Hedged Joint Momentum			
Plain	1.04	0.64	UMD, Sharpe-forecasted
Volatility-scaled	1.31	0.80	Statically Hedged Joint, Plain
Sharpe-forecasted	1.26	0.71	Statically Hedged Joint, Plain
Dynamically Hedged Joint Momentum			
Plain	1.37	0.40	Statically Hedged Joint, Vol-scaled
Volatility-scaled	1.61	0.85	Dynamically Hedged Joint, Plain
Sharpe-forecasted	1.42	0.37	Dynamically Hedged Joint, Plain

Table 11. International Joint Stock/CDS Market Momentum: International Four-factor Alpha Coefficients

This table presents international joint stock/CDS momentum results using a sample of 1,267 non-US firms representing 49 countries. Results are generated for all countries as well as more developed and less developed country sub-samples (consisting of 633 firms and 634 firms, respectively). International equity data are from Datastream. 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, where J ranges from from 1 to 12 months. The holding period is one month ($K = 1$). We segment the traditional stock momentum strategy into *joint* and *disjoint* components based on the overlap between stock and CDS winner and loser portfolios as follows:

$$\text{Stock Momentum} \equiv (W_S - L_S) \begin{cases} \text{Joint Stock/CDS Momentum} & \equiv (W_S \cap W_C) - (L_S \cap L_C) \\ \text{Disjoint Stock/CDS Momentum} & \equiv (W_S \setminus W_C) - (L_S \setminus L_C) \end{cases}$$

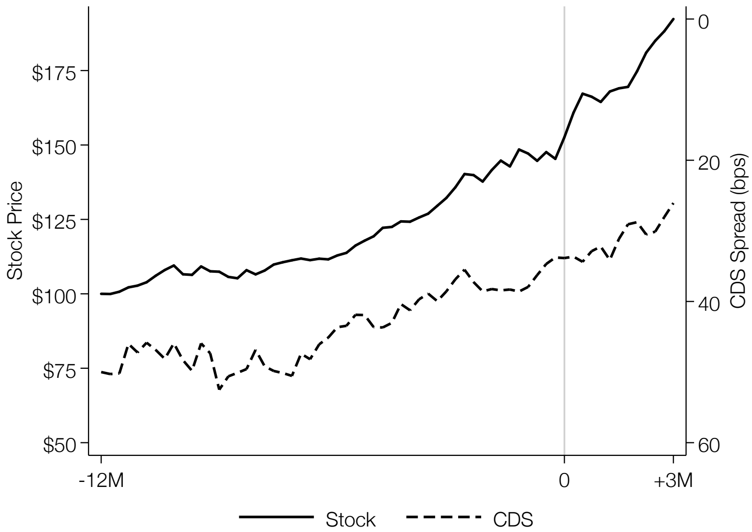
The hedged joint momentum strategy is constructed as a 50-50 combination of a long position in joint momentum and a short position in disjoint momentum (i.e., Hedged Joint Momentum$_t$ = 0.5 × Joint$_t$ − 0.5 × Disjoint$_t$). The "static" strategy maintains a constant position in hedged joint momentum throughout the sample period. The "dynamic" strategy invests in joint momentum and switches to hedged joint momentum only during risky states, where the risky state indicator variable $\mathbb{I}_M$ equals 1 when the two-year *change* in trailing daily volatility of our international (ex-US) stock sample is positive. The international four-factor model consists of Fama-French international (ex-US) three-factor model as well as an international (ex-US) in-sample stock momentum factor. Percentage returns are monthly and span the time period January 2003 to December 2015. 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-statistic), and annualized *Sharpe ratio*.

	Stock Momentum		Hedged Joint Momentum	
	(1)	(2)	(3)	(4)
	Joint	Disjoint	Static	Dynamic
	International Four-Factor α Coefficients			
All Countries (Ex-U.S.)	0.83***	-0.28***	0.55***	1.21***
	(2.69)	(-2.70)	(2.72)	(4.03)
	0.55	*-0.03*	*0.87*	*1.05*
More Developed (Ex-U.S.)	1.15***	-0.40**	0.78***	1.47***
	(3.35)	(-2.41)	(3.11)	(3.72)
	0.55	*-0.14*	*0.83*	*1.04*
Less Developed	0.38	-0.07	0.22	0.82**
	(0.94)	(-0.47)	(0.84)	(2.38)
	0.34	*0.09*	*0.37*	*0.65*

Figure 1. Relative Performance of a Firm's Equity and Credit Securities in the Context of Stock Return Momentum

This figure displays a hypothetical representation of performance behavior between a firm's equity and credit securities in the context of a stock momentum strategy. Panel A (Panel B) represents a "Joint" ("Disjoint") stock winner in which the CDS performance experienced movement in the same (opposite) direction as the stock over the formation period (-12M to date-0). The y-axes show cumulative change in the stock price (left) and CDS spread (right). Initial values are set at \$100 for the stock price and 50 bps for the CDS spread. The x-axis shows months around the rebalancing date-0 where negative values represent past performance (the formation period) and positive values represent future performance (the holding period). I.e., −12M refers to 12 months prior to rebalancing and +3M refers to three months after rebalancing.

Panel A. Joint Stock/CDS Momentum ***Firm A***



Panel B. Disjoint Stock/CDS Momentum ***Firm B***

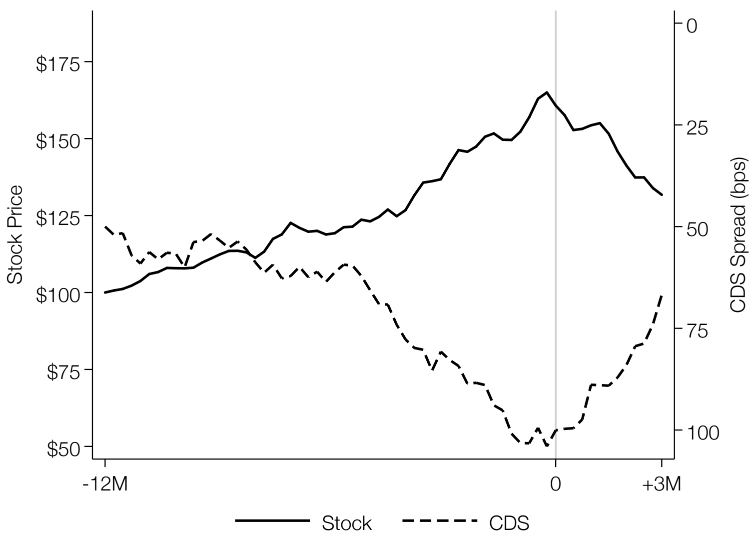


Figure 2. Average Five-Year Corporate CDS Spread over Time

This figure presents the value-weighted average five-year corporate CDS spread of firms in our sample over the period January 2003 to December 2015. CDS data are from Markit.

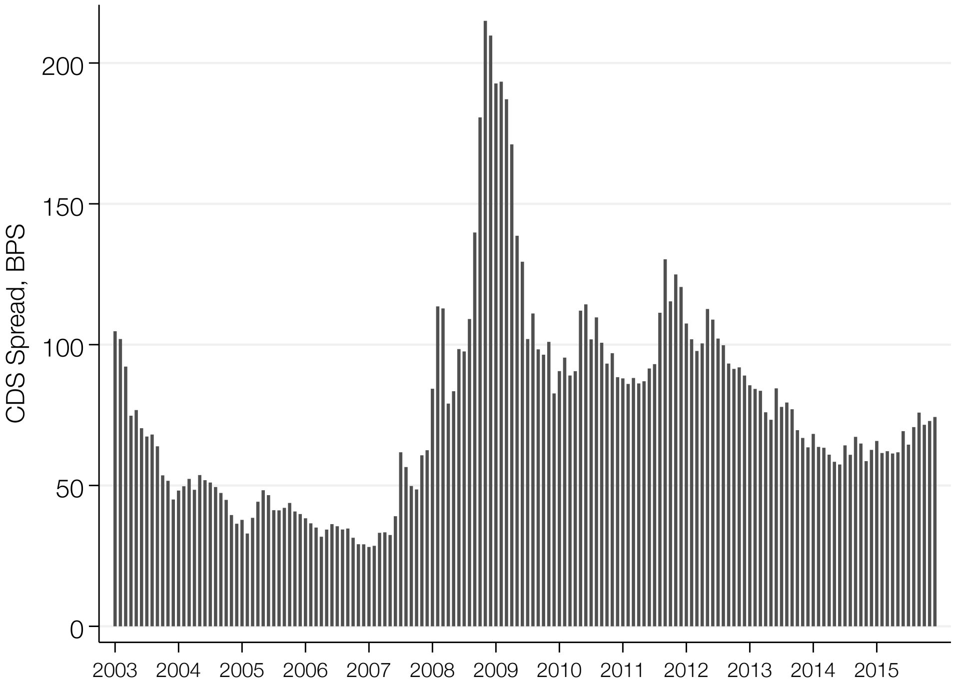


Figure 3. Cumulative Profits of Joint and Disjoint Stock/CDS Momentum Strategies

This figure presents the cumulative profits of a $100 investment in the joint and disjoint stock/CDS momentum strategies in comparison to our in-sample traditional stock momentum (Jegadeesh and Titman (1993)). 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 but not the CDS winner (loser) 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 December 2015.

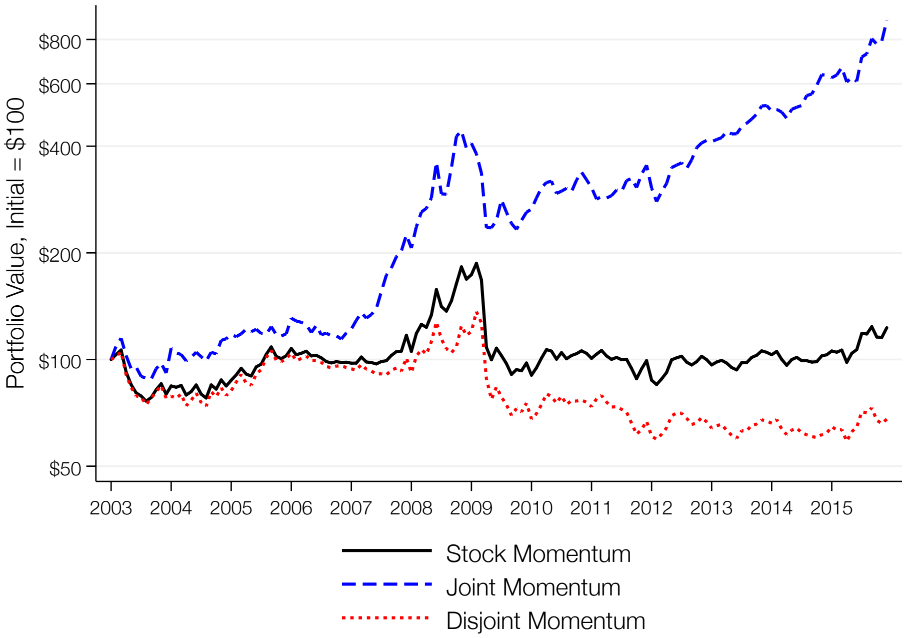


Figure 4. Divergence Between Implied CreditGrades CDS Spread and At-Market CDS Spread from Markit

This figure shows the cumulative percentage divergence between implied CreditGrades 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. ($W_S \setminus W_C$) and ($L_S \setminus L_C$) refer to stock winner but not CDS winner momentum portfolio and stock loser but not CDS loser momentum portfolio, respectively. Cumulative divergence begins at month -4 and is computed for individual firms and aggregated to the portfolio level. Time-0 denotes the formation date of each momentum portfolio. The sample ranges from January 2003 to December 2015.

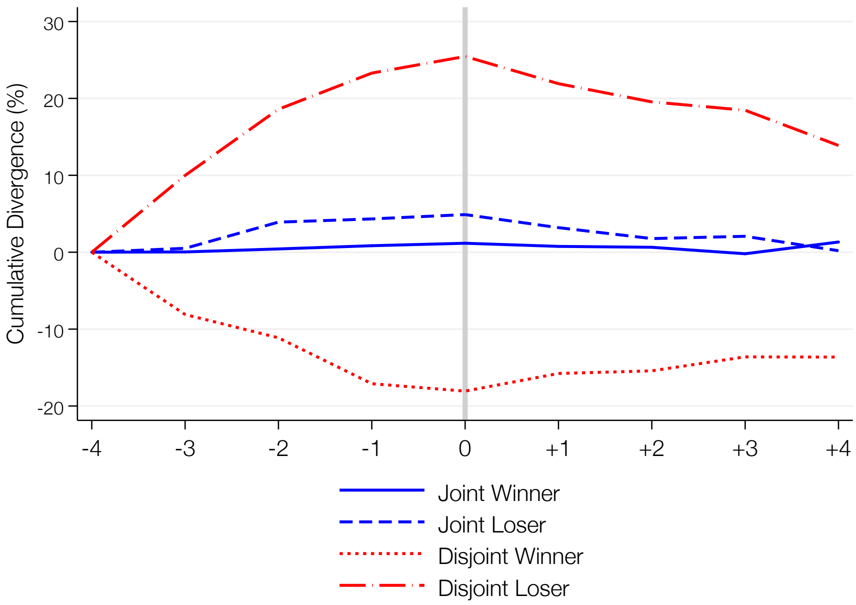


Figure 5. Distribution Plot of Hedged Momentum Strategy Returns

This figure displays a violin plot highlighting the distributional characteristics of the returns of stock momentum to static and dynamic hedged momentum strategies. joint and disjoint stock/CDS momentum strategies. The "Static Hedged" momentum strategy is 50% invested in joint stock/CDS momentum and 50% invested in a disjoint contrarian strategy (that buys disjoint stock losers and sells short disjoint stock winners). The "Dynamic Hedged" momentum strategy invests in joint stock momentum in low volatility periods and 50% hedged momentum in high volatility periods. High (Low) volatility period is defined as when either the two-year change in market volatility or joint momentum volatility is greater than zero (i.e., volatility levels become elevated). 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 contrarian strategy short sells (purchases) firms that are in the stock winner (loser) portfolio but not the CDS winner (loser) 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 December 2015.

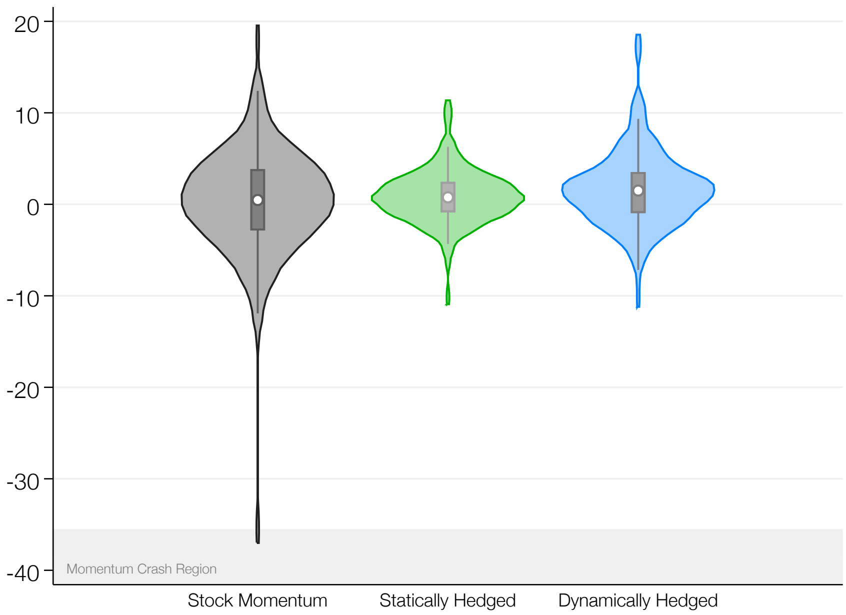


Figure 6. Cumulative Profits of Hedged Momentum Strategies

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) and two hedged momentum trading strategies: static hedged momentum and dynamic hedged momentum. The "Static Hedged" momentum strategy is 50% invested in joint stock/CDS momentum and 50% invested in a disjoint contrarian strategy (that buys disjoint stock losers and sells short disjoint stock winners). The "Dynamic Hedged" momentum strategy invests in joint stock momentum in low volatility periods and 50% hedged momentum in high volatility periods. High (Low) volatility period is defined as when either the two-year change in market volatility or joint momentum volatility is greater than zero (i.e., volatility levels become elevated). 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 contrarian strategy short sells (purchases) firms that are in the stock winner (loser) portfolio but not the CDS winner (loser) 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 December 2015.

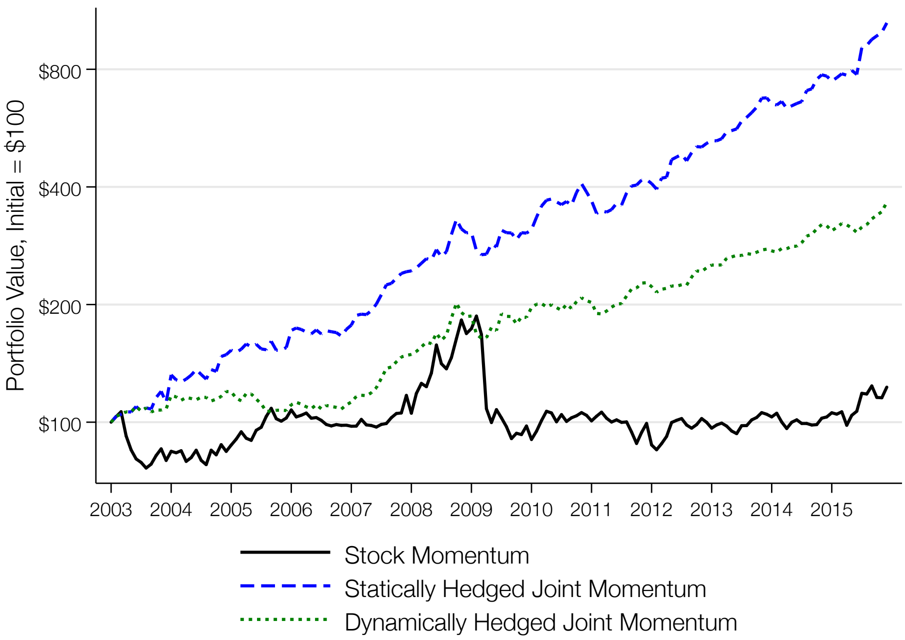
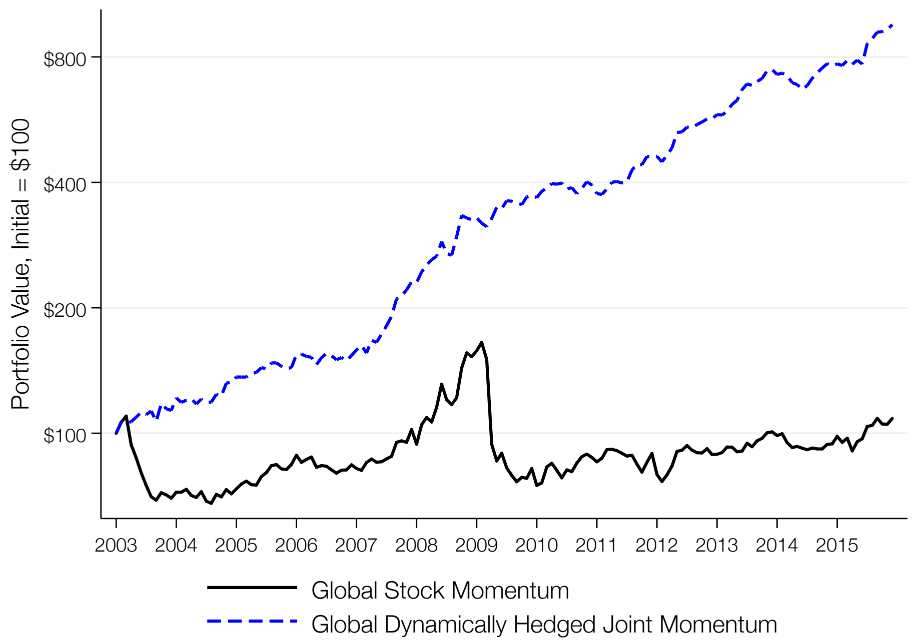


Figure 7. Global Hedged Momentum (50% U.S., 50% Non-U.S.)

This figure presents cumulative profits of a $100 investment in global traditional stock momentum and our dynamic hedge momentum strategies. Each global portfolio maintains 50% in the U.S.-based strategy and 50% in non-U.S.-based strategy. Our "Dynamic Hedged Momentum" strategy invests in joint momentum during low volatility periods and hedged joint momentum (50% in joint momentum and 50% in disjoint contrarian) during high volatility periods. 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 contrarian strategy short sells (purchases) firms that are in the stock winner (loser) portfolio but not the CDS winner (loser) 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. U.S. equity data are from CRSP and international equity data are from Datastream. CDS data are from Markit. The sample ranges from January 2003 to December 2015.



Appendices

A Variable Definitions

Variable Name	Description	Source
Market Capitalization	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
LIQ	The value-weighted return on a portfolio of stocks with high liquidity beta minus a portfolio of stocks with low liquidity beta.	Lubos Pastor's Website
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).[30] 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 20$^{\text{th}}$ 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, $i = 1, 2, \ldots, 21$, 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

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

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

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, $[t_{n-1}, t_n]$. 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

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

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

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

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.[31] 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

[31] 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.

\$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 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 $i =$

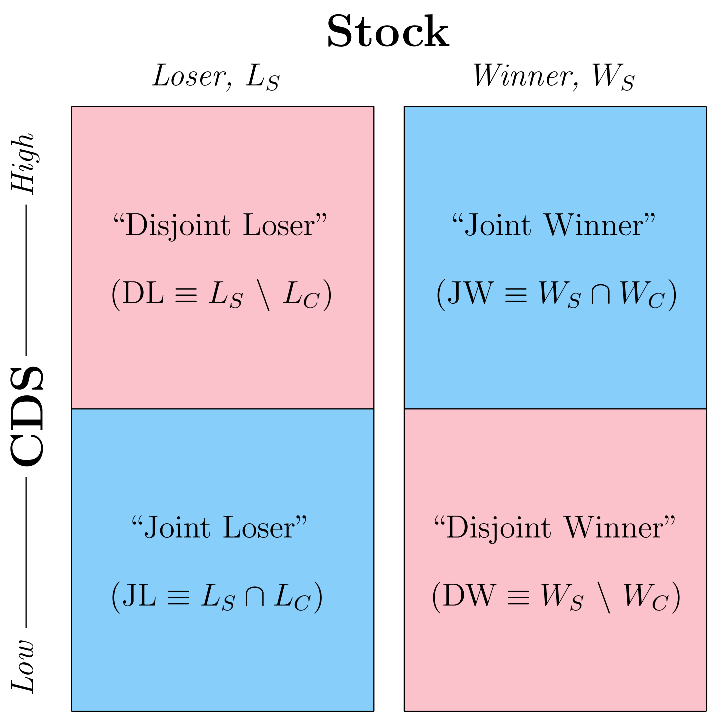
$1, 2, ..., 21$. Instead of bootstrapping this survival probability curve using the quoted spreads of CDS contracts across entire maturity groups, we assume a flat hazard rate, $h(t', t_i) \equiv -\frac{1}{Q(t',t_i)}\frac{\partial Q(t',t_i)}{\partial t_i} = h$ for $\forall i = 1, 2, \ldots, 21$, and 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 Stock Momentum Segmentation by Related Security Performance: A Graphical Representation

In this appendix, we graphically illustrate our process to examine the cross-section of stock return momentum. First, we create quintiles based on the past stock return (traditional stock momentum). Second, we create quintiles based on the past CDS return. The stock winner (loser) portfolio is divided into two parts based on whether the firm is also a CDS winner (loser). The blue (red) boxes represent joint (disjoint) entities.



E CreditGrades Hedge Ratio

We use the CreditGrades hedge ratio to implement the capital structure arbitrage described in Section 3.4 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. The CreditGrades model, which is based on Black and Cox (1976) and Leland (1994), is 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

$$LD = \bar{L}De^{\lambda Z - \lambda^2/2}, \tag{13}$$

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

$$V_0 e^{\sigma_V W_t - \sigma_V^2 t/2} > \bar{L}De^{\lambda Z - \lambda^2/2}. \tag{14}$$

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

$$c_T = r(1-R)\frac{1-q(0)+H(T)}{q(0)-q(T)e^{-rT}-H(T)}, \tag{15}$$

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

$$q(T) = \Phi\left[-\frac{\sqrt{\sigma_T^2 T+\lambda^2}}{2}+\frac{\ln d}{\sqrt{\sigma_T^2 T+\lambda^2}}\right] - d\Phi\left[-\frac{\sqrt{\sigma_T^2 T+\lambda^2}}{2}-\frac{\ln d}{\sqrt{\sigma_T^2 T+\lambda^2}}\right], \tag{16}$$

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

$$H(T) = e^{r\xi}\left[G(T+\xi)-G(\xi)\right], \tag{17}$$

$$G(T) = d^{z+0.5}\cdot\Phi\left[-\frac{\ln d}{\sigma_V\sqrt{T}}-z\sigma_V\sqrt{T}\right]+d^{z+0.5}\cdot\Phi\left[-\frac{\ln d}{\sigma_V\sqrt{T}}+z\sigma_V\sqrt{T}\right], \tag{18}$$

$$d = \frac{V_0}{\bar{L}D}e^{\lambda^2}, \tag{19}$$

$$\xi = \frac{\lambda^2}{\sigma_V^2}, \tag{20}$$

and

$$z = \sqrt{\frac{1}{4}+\frac{2r}{\sigma_V^2}}. \tag{21}$$

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

$$\delta = \frac{\partial \pi_T}{\partial S} = \frac{1}{r}\frac{\partial c_T}{\partial S}\left(q(0) - q(T)e^{-Tr} - e^{r\xi}\left[G(T+\xi) - G(T)\right]\right) \tag{22}$$

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

Internet Appendix:

Related Securities and the Cross-Section of Stock Return Momentum

Jongsub Lee[*], Andy Naranjo[†], *and* Stace Sirmans[‡]

[*]University of Florida, Assistant Professor, Tel: 352.273.4966, Email: jongsub.lee@warrington.ufl.edu

[†]University of Florida, Emerson-Merrill Lynch Professor of Finance and Chairman of Finance Department, Tel: 352.392.3781, Email: andy.naranjo@warrington.ufl.edu

[‡]University of Arkansas, Assistant Professor, Tel: 850.459.2039, Email: ssirmans@walton.uark.edu

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A Stock/CDS Momentum Portfolio Statistics

This appendix table provides various statistics of the joint and disjoint stock/CDS momentum portfolios. Number of Unique Entities refers to the total number of unique entities that appear in the portfolio during the course of the sample period. Each additional statistic is averaged across all entities in the portfolio during the month and then averaged over all months in the entire sample period. Size refers to average equity market capitalization defined as end-of-month price multiplied by shares outstanding. S&P Rating is the average S&P credit rating. Portfolio Turnover measures the average monthly trading activity during end-of-month rebalancing. 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 sample period spans January 2003 to December 2015.

	Stock Winner (W)	Stock Loser (L)	Joint Winner (JW)	Joint Loser (JL)	Disjoint Winner (DW)	Disjoint Loser (DL)
No. of Unique Entities	735	695	563	588	713	679
Size ($, billions)	$19.1	$15.4	$11.9	$9.7	$22.0	$18.6
S&P Rating	BBB-	BBB-	BB+	BB+	BBB	BBB-
Portfolio Turnover	31%	33%	56%	55%	39%	45%

B Joint and Disjoint Momentum Profitability at Longer Holding Periods: Four-Factor Alpha Coefficients

This table shows the monthly alpha coefficients of joint and disjoint stock/CDS momentum at longer holding periods. The four-factor model includes the MKT, SMB, HML, and UMD_S factors. Returns longer than one month are constructed so as to avoid an overlapping returns problem. For example, to calculate the three-month holding period return, we take the average of the one-month returns of strategies based on the current quintiles, the one-month lagged quintiles, and the two-month lagged quintiles. Joint stock/CDS momentum purchases (sells short) stocks in both the top (bottom) past 12-month stock return quintile and the top (bottom) past four-month CDS return quintile. Disjoint stock/CDS momentum purchases (sells short) stocks in the top (bottom) past 12-month stock return quintile but not in the top (bottom) past four-month CDS return quintile. The time period spans January 2003 to December 2015. 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*.

	Holding Period (K)					
	(1)	(2)	(3)	(4)	(5)	(6)
	$1m$	$2m$	$3m$	$4m$	$5m$	$6m$
	Monthly Four-Factor α Coefficients					
Joint Stock/CDS Momentum	1.45***	1.34***	0.95***	0.75***	0.57***	0.56***
	(4.24)	(4.36)	(3.41)	(3.19)	(2.64)	(2.70)
	0.81	*0.77*	*0.62*	*0.58*	*0.51*	*0.52*
Disoint Stock/CDS Momentum	-0.45***	-0.45***	-0.38**	-0.26*	-0.17	-0.15
	(-3.10)	(-3.54)	(-2.60)	(-1.75)	(-1.07)	(-0.89)
	-0.05	*-0.05*	*-0.02*	*0.05*	*0.10*	*0.10*
Joint – Disjoint	1.90***	1.79***	1.33***	1.02***	0.74**	0.71**
	(4.15)	(4.45)	(3.69)	(3.32)	(2.55)	(2.46)
	1.04	*1.05*	*0.86*	*0.77*	*0.64*	*0.67*

C Comparison of Strategies Based on Earnings Momentum (SUE), past CDS Performance, and past Stock Performance

This table shows the results of spanning tests examining various SUE-based strategies as well as joint stock/CDS momentum. There are three SUE-based strategies in the table. "SUE" refers to a strategy that purchases (sells short) stocks in the top (bottom) SUE quintile. "SUE | $r_{2,12}$" refers to a strategy that purchases (sells short) stocks in the top (bottom) SUE quintile that is conditioned on the past 12-month stock return. "$r_{S,12} \cap$ SUE" refers to a strategy that purchases (sells short) stocks in both the top (bottom) SUE quintile and the top (bottom) past 12-month stock return quintile. The firm-level standardized unexpected earnings (SUE) is computed as the one-year change in quarterly reported earnings divided by the standard deviation of quarterly earnings changes over the past eight quarters. The time period spans January 2003 to December 2015. 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.

	SUE-based Strategies						Joint Stock/CDS Momentum		
	SUE		SUE | $r_{2,12}$		$r_{S,12} \cap$ SUE		$r_{S,12} \cap r_{C,4}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
α	0.052	-0.062	0.086	0.052	0.45*	-0.28	1.64***	1.83***	1.46***
	(0.75)	(-0.55)	(1.44)	(0.70)	(1.95)	(-0.85)	(3.69)	(3.66)	(4.35)
β_{MKT}	0.017	-0.013	0.027	0.020	-0.019	-0.15	-0.36*	-0.51**	0.059
	(0.49)	(-0.30)	(0.84)	(0.65)	(-0.16)	(-1.16)	(-1.78)	(-2.30)	(0.56)
β_{SMB}	-0.025	0.032	0.010	0.025	-0.32**	-0.027	0.067	0.13	-0.074
	(-0.76)	(0.80)	(0.28)	(0.67)	(-2.64)	(-0.19)	(0.28)	(0.46)	(-0.36)
β_{HML}	-0.24***	-0.31***	-0.19**	-0.21**	-0.43**	-0.92***	0.36	-0.083	0.44***
	(-2.66)	(-2.62)	(-2.02)	(-2.07)	(-2.47)	(-7.73)	(0.81)	(-0.23)	(4.21)
β_{UMD_S}	0.19***		0.052***		1.04***				
	(6.40)		(2.95)		(12.15)				
β_{Joint}		0.11***		0.032**		0.67***			
		(5.29)		(2.46)		(8.29)			
β_{SUE}							2.11***		
							(6.36)		
$\beta_{SUE\|UMD}$								1.32**	
								(2.23)	
$\beta_{Joint_{SUE}}$									0.86***
									(10.93)

D Marginal Information in past CDS Returns using Various Formation Horizons: Four-Factor Alpha Coefficients

This table presents evidence on the marginal information of past CDS returns over multiple time horizons from one to twelve months. Columns 1 and 2 are strategies based on unconditional single-market signals. Columns 3 and 4 are strategies based on signals that are conditioned on the other market's signal. The conditional strategy is constructed by creating quintiles of the signal of interest *within* quintiles of the conditioning signal so that the top and bottom quintiles are roughly equal with respect to the average value of the conditioning signal. Each long-short strategy purchases stocks in the top quintile (winners) and sells short stocks in the bottom quintile (losers). The time period spans January 2003 to December 2015. 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*.

	Raw Signal		Conditional Signal	
	(1)	(2)	(3)	(4)
	$r_{S,J}$	$r_{C,J}$	$r_{S,J} \mid r_{C,J}$	$r_{C,J} \mid r_{S,J}$
$J = 1m$	0.21	0.66***	-0.21	0.46*
	(0.68)	(2.81)	(-0.74)	(1.78)
	-0.03	*0.55*	*-0.37*	*0.53*
$J = 2m$	-0.09	0.39	-0.20	0.53***
	(-0.29)	(1.38)	(-0.83)	(2.85)
	-0.13	*0.31*	*-0.27*	*0.50*
$J = 3m$	-0.14	0.48**	-0.20	0.54**
	(-0.44)	(2.05)	(-0.81)	(2.59)
	-0.13	*0.44*	*-0.25*	*0.66*
$J = 4m$	-0.02	0.88***	-0.25	0.74***
	(-0.07)	(3.03)	(-1.02)	(3.02)
	-0.04	*0.71*	*-0.27*	*0.76*
$J = 5m$	0.07	0.72***	-0.35	0.69***
	(0.28)	(3.00)	(-1.38)	(3.42)
	0.06	*0.61*	*-0.26*	*0.83*
$J = 6m$	-0.13	0.52**	-0.32	0.79***
	(-0.49)	(1.99)	(-1.33)	(3.28)
	0.00	*0.44*	*-0.14*	*0.91*
$J = 9m$	-0.06	0.81**	-0.44*	0.76***
	(-0.29)	(2.53)	(-1.95)	(2.88)
	0.10	*0.70*	*-0.17*	*0.91*
$J = 12m$	-0.04	0.51**	-0.51**	0.60**
	(-1.49)	(2.02)	(-2.29)	(2.51)
	0.16	*0.47*	*-0.15*	*0.77*

E Multi-Term Stock Momentum Strategies: Four-Factor Alpha Coefficients

This table reports alpha coefficients of multi-term stock momentum strategies. The four-factor model includes the MKT, SMB, HML, and UMD_S factors. The multi-term stock momentum strategy is constructed by double-sorting on the past 12-month stock return and the past J-month stock return, where J ranges from one to nine months. These strategies purchase (sell short) stocks that fall in both the 12-month stock winner (loser) portfolio and the J-month stock winner (loser) portfolio. The time period spans January 2003 to December 2015. 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*.

	Multi-Term Stock Momentum $r_{S,J} \cap r_{S,12}$
$J = 1m$	0.05
	(0.08)
	0.15
$J = 2m$	0.01
	(0.03)
	0.16
$J = 3m$	0.21
	(0.89)
	0.26
$J = 4m$	0.07
	(0.33)
	0.20
$J = 5m$	0.17
	(0.82)
	0.25
$J = 6m$	-0.03
	(-0.21)
	0.16
$J = 9m$	-0.21*
	(-1.73)
	0.06

F Factor Exposures of Joint Momentum and Statically Hedged Joint Momentum

This table shows a more comprehensive list of factor exposures of joint momentum and statically hedged joint momentum. The joint momentum strategy purchases (sells short) stocks that are both stock winners (losers) and CDS winners (losers). The statically hedged joint momentum strategy is 50% invested in joint momentum and 50% invested in a disjoint contrarian strategy that purchases (sells short) stock losers (winners) that are not CDS losers (winners). Factors included in the table are the Fama-French three factors (MKT, SMB, HML) as well as a broad stock market UMD factor and our in-sample UMD_S factor. Other factors include Fama-French five-factor model operating profitability (RMW) and investment (CMA) factors, Novy-Marx (2013) gross profitability factor ($GPROF$), Asness, Frazzini, and Pedersen (2014) quality-minus-junk factor (QMJ), the Stambaugh and Yuan (2016) mispricing factors ($MGMT$ and $PERF$), short-term reversal factor ($STREV$), and long-term reversal factor ($LTREV$). The time period spans January 2003 to December 2015. 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.

Panel A. Joint Stock/CDS Momentum

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	1.67***	1.64***	1.35***	1.51***	1.42***	1.09***	1.45***	1.47***
	(4.08)	(2.68)	(3.53)	(4.31)	(3.80)	(2.66)	(4.15)	(4.27)
β_{MKT}	-0.15	-0.35**	-0.07	-0.08	-0.06	0.00	-0.08	-0.08
	(-1.01)	(-2.06)	(-0.59)	(-0.82)	(-0.45)	(0.02)	(-0.74)	(-0.70)
β_{SMB}	-0.02	0.27	-0.17	-0.18	-0.18	0.26	-0.22	-0.20
	(-0.12)	(0.84)	(-1.14)	(-1.23)	(-1.15)	(1.26)	(-1.53)	(-1.48)
β_{HML}	0.25	-0.61**	0.11	0.10	0.19		0.16	0.13
	(1.15)	(-2.37)	(0.39)	(0.46)	(0.78)		(0.60)	(0.53)
β_{UMD_S}			0.93***	0.95***	0.94***		0.94***	0.95***
			(10.11)	(11.43)	(10.44)		(11.69)	(11.58)
β_{UMD}	1.07***							
	(8.46)							
β_{RMW}		0.64	0.07					
		(1.46)	(0.28)					
β_{CMA}		1.02*	0.27					
		(1.88)	(0.94)					
β_{GPROF}				-0.14				
				(-0.55)				
β_{QMJ}					0.07			
					(0.26)			
β_{MGMT}						0.39		
						(1.33)		
β_{PERF}						0.99***		
						(7.89)		
β_{STREV}							0.12	
							(1.04)	
β_{LTREV}								0.16
								(0.94)

Panel B. Statically Hedged Joint Stock/CDS Momentum

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	0.93***	0.88***	0.88***	1.00***	0.92***	0.95***	0.95***	0.96***
	(4.03)	(3.42)	(3.55)	(4.30)	(3.73)	(4.16)	(4.04)	(4.17)
β_{MKT}	-0.07	-0.07	-0.07	-0.08	-0.06	-0.06	-0.08	-0.07
	(-0.91)	(-0.84)	(-0.94)	(-1.09)	(-0.64)	(-0.89)	(-0.99)	(-0.98)
β_{SMB}	-0.15*	-0.15	-0.15	-0.14	-0.14	-0.14	-0.17*	-0.16*
	(-1.89)	(-1.54)	(-1.48)	(-1.62)	(-1.40)	(-1.65)	(-1.97)	(-1.92)
β_{HML}	0.15	0.12	0.11	0.08	0.17		0.15	0.13
	(0.78)	(0.61)	(0.53)	(0.56)	(1.00)		(0.77)	(0.71)
β_{UMD_S}			-0.00	0.01	0.00		0.00	0.01
			(-0.06)	(0.17)	(0.04)		(0.07)	(0.14)
β_{UMD}	0.01							
	(0.15)							
β_{RMW}		0.03	0.03					
		(0.19)	(0.19)					
β_{CMA}		0.20	0.20					
		(1.17)	(1.06)					
β_{GPROF}				-0.14				
				(-0.72)				
β_{QMJ}					0.06			
					(0.34)			
β_{MGMT}						0.09		
						(0.75)		
β_{PERF}						-0.03		
						(-0.27)		
β_{STREV}							0.08	
							(1.21)	
β_{LTREV}								0.12
								(1.05)

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