CDS Momentum: Slow Moving Credit Ratings and Cross-Market Spillovers*

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

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Abstract

Using 5-year credit default swap (CDS) contracts on 1,247 U.S. firms from 2003 - 2011, we show a 3-month formation and 1-month holding period CDS momentum strategy yields 52 bps per month. By incorporating past CDS return signals, we further show traditional stock momentum strategies avoid abrupt losses during the crisis period and improve their performance by net 104 bps per month. Both within CDS market and across CDS-to-stock market momentum profits exist because CDS returns correctly anticipate future credit rating changes. Our results highlight the adverse effects of sluggish rating updates in creating information efficiency distortions and investment anomalies.

JEL Classification: G12, G14
Keywords: Credit default swaps; CDS returns; Credit ratings; Momentum; Spillover; Endogenous liquidity; Credit risk; Information flows

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

[‡]University of Florida, Bank of America Associate Professor and Director of CIBER, Tel: 352.392.3781, Email: andy.naranjo@warrington.ufl.edu

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

1 Introduction

Related markets often reveal information non-synchronously, with different frequencies, speeds, and content. An important question is to what extent does a more informationally efficient market trading alongside a related sluggish, but material, information market generate market anomalies? A case in point is the credit default swap (CDS) market and credit ratings where several recent papers document informational advantages with CDS at-market spreads being more timely and often predicting credit ratings (Hull, Predescu, and White, 2004; Flannery, Houston, and Partnoy, 2010; Chava, Ganduri, and Ornthanalai, 2012; Lee, Naranjo, and Sirmans, 2014). At the same time, credit rating changes have material impacts, including changes in accessibility to capital, investor bases, supply-chain relationships, ability to retain key executives, and/or disclosure requirements (Kliger and Sarig, 2000; Dichev and Piotroski, 2001; Kisgen, 2006, 2007). Figure 1 clearly depicts these patterns; the at-market spreads of 5-year CDS contracts react at least 90 days prior to subsequent S&P credit rating changes, which is followed by a further impact on CDS spreads upon the rating changes.

Researchers generally attribute the CDS market's potential information advantage to its unique structure with trades being brokered by bulge bracket investment banks who are well informed on overall capital markets. Branching into the information content of CDS contracts, others have also recently examined the cross-market informational linkages from CDS to equity markets (Acharya and Johnson, 2007; Ni and Pan, 2010; Han and Zhou, 2011; Qiu and Yu, 2012). These studies generally find significant information flowing from the CDS market to the stock market, particularly for entities with negative news, more informed insiders such as relationship banks, and high CDS contract liquidity.[1] Several studies using CDS market data (Friewald, Wagner, and Zechner, 2012) are also able to reconcile well-known asset pricing puzzles such as a distress puzzle (Campbell, Hilscher, and Szilagyi, 2008) that is documented mostly with traditional default risk measures or corporate bond yields. These documented findings suggest that CDS markets play important information signaling functions and could be helpful in addressing various market inefficiencies.

In this paper, we examine the extent to which a more informationally efficient CDS market trading alongside sluggish, but material, credit ratings generates market anomalies and

[1] An exception to these studies is Hilscher, Pollet, and Wilson (2014) who find that equity returns lead CDS returns using daily and weekly 5-year CDS data from January 2001 to December 2007 for 650 firms.

cross-market spillover effects. We focus our tests on the return momentum anomaly and address two important questions. First, does momentum exist in CDS returns? Second, are there spillover effects between CDS and stock return momentum? Given the sophisticated participants in the CDS market, one might expect that CDS momentum profits would not exist.[2] At the same time, ratings changes, though slow moving, have material impacts (Kisgen, 2006, 2007) and create potential market frictions (Manso, 2013) with a more informationally efficient CDS market.[3] These rating change impacts can affect the information transmission efficiency of both CDS and stock markets, creating significant market efficiency distortions and investment opportunities.

The pervasive finding that return momentum exists across a range of asset classes, markets, and over time is an important phenomenon that has received substantial attention by financial economists (Jegadeesh and Titman, 1993, 2001, 2011). Recent work by Asness, Moskowitz, and Pedersen (2013) further documents strong comovement in return momentum across various asset classes and markets. A puzzling result in the recent return momentum literature is that while stock and bond markets each exhibit return momentum, their contemporaneous comovement is surprisingly low for these related securities (Asness, Moskowitz, and Pedersen, 2013; Jostova, Nikolova, Philipov, and Stahel, 2013). An additional aspect of this puzzle is that momentum returns do not spill over from past bond to stock returns, suggesting that their time series behavior evolves differentially over time (Gebhardt, Hvidkjaer, and Swaminathan, 2005; Jostova, Nikolova, Philipov, and Stahel, 2013).[4]

[2]One could potentially argue that theoretically zero CDS-bond basis should predict the existence of CDS return momentum given the recent findings on the existence of corporate bond return momentum (Jostova, Nikolova, Philipov, and Stahel, 2013). However, lead-lag relations between CDS and cash bond markets are non-trivial (Blanco, Brennan, and Marsh, 2005; Zhu, 2006; Das, Kalimipalli, and Nayak, 2014). Moreover, many recent studies empirically document the evidence of non-zero CDS-bond basis in the post-2001 time period (Kim, Li, and Zhang, 2009; Mitchell and Pulvino, 2012; Bai and Collin-Dufresne, 2013, among others). Nashikkar, Subrahmanyam, and Mahanti (2011) also find that liquidity and several firm- and bond-level variables related to credit risk affect the basis.

[3]It is important to note that the rating agencies' practice of weighing accuracy and stability (rating through the cycle) creates, in part, less informationally efficient and slower ratings adjustments. The ratings agencies argue that an increase in ratings accuracy by increasing their responsiveness to more timely market information has a tradeoff of reducing ratings stability, which they argue is also important to market participants given that rating changes have real consequences (through ratings-based portfolio governance rules and rating triggers) that are costly to reverse (see Moodys, September 2006, "Analyzing the Tradeoff Between Ratings Accuracy and Stability").

[4]Arguably, asset substitutions, conflict of interest between bondholders and shareholders, different market/information structures, among others could potentially be underlying drivers of these perplexing results. Nevertheless, none of these factors have been shown to be the source of the low correlation between stock

In contrast, Gebhardt, Hvidkjaer, and Swaminathan (2005) find that return momentum spills over from past stock to bond returns and provide evidence that such momentum spillovers are closely related to future bond rating changes in "anticipated" directions. High (low) past stock returns predict bond rating upgrades (downgrades) in the future. They argue that both equity and bond returns underreact to common firm fundamentals, but past equity returns—being a better proxy for firm fundamentals than past bond returns—predict future credit rating changes that could further introduce *unforeseen* material impacts on firm fundamentals (Kisgen, 2006, 2007). Similar sluggish corporate rating responses to available market information have also been associated with various equity return anomalies such as return momentum, earnings momentum, and anomalies associated with credit risk, dispersion in analysts' earnings forecasts, idiosyncratic volatility, and capital investments (Avramov, Chordia, Jostova, and Philipov, 2013). Disentangling the sources that lie behind these stylized return momentum findings is a formidable challenge that many empirical and theoretical researchers continue to investigate.

Using 5-year CDS contracts on 1,247 US firms from January 2003 to December 2011, we document the following results. First, we find significant CDS return momentum. A three-month formation and one-month holding period CDS return momentum strategy yields 52 bps per month. The performance is better for entities with lower credit ratings (83 bps per month for junk grade entities) and high CDS depth (80 bps per month for highest depth quintile). As seen in Panel A of Figure 2, a $1,000-investment in this strategy starting in 2003 grows to approximately $1,700 in 2011, with a Sharpe ratio of 0.423. Given Sharpe ratios of 0.29 and 0.33, respectively, for U.S. equity value and momentum strategies in the post-1972 period (see Table 1 of Asness, Moskowitz, and Pedersen, 2013), these CDS momentum profits are substantial even on a simple risk-adjusted basis. The strategy also tends to perform better during the crisis period (97 bps per month for the period of July 2007 to April 2010; see Panel B of Figure 2). We further show that CDS momentum returns are robust to using various formation and holding periods, controlling for fundamental risk factors from both equity and bond markets, and are also profitable on a transaction cost adjusted basis. Finally, we show that CDS momentum profits are generated from incremental information in past CDS returns above and beyond information possessed in past stock returns.

and bond momentum returns.

What are the sources of these CDS momentum profits? We find that the CDS momentum profits are almost entirely due to correct anticipation of future credit rating changes by the CDS market following the formation of the momentum strategy. That is, the winner (loser) portfolio is driven by firms who undergo rating upgrades (downgrades) over a six month horizon. We find a significant cumulative return run-up of 221 bps (run-down of -324 bps) prior to the rating upgrade (downgrade) over the six-month horizon, which is further followed by a return of 44 bps (-133 bps) in the month of the announcement of the rating upgrade (downgrade). This "anticipated" credit rating changes channel works best among the entities with lower credit ratings and high CDS depth, which are arguably most demanded by informed traders in this market. This credit rating changes channel further distinguishes the sources of CDS momentum returns from those of corporate bond momentum returns that are shown to be unrelated to rating changes (Jostova, Nikolova, Philipov, and Stahel, 2013).

Second, we find significant *cross-market* momentum spillovers from CDS markets to stock markets. We show that a CDS-to-stock cross-market momentum strategy yields 52 bps per month and that the same strategy yields greater profits for entities with lower ratings (137 bps per month for junk grade entities) and entities with high CDS depth (81 bps per month). These results suggest that there is greater information flow from the CDS market to the stock market, particularly for entities that attract the highest hedging demand for underlying credit risk and also contracts with greater trade quotes.

Importantly, we show that incremental information in CDS returns significantly improves the performance of traditional stock-to-stock momentum strategies. That is, traditional stock-to-stock momentum strategies improve by net 104 bps per month when we create sharper signals by combining the information in past CDS and stock returns. As seen in Figure 5, this joint-market momentum strategy generates persistent and robust profits even during the crisis period when traditional stock-only signals incur abrupt and very significant losses (Daniel, 2013; Daniel, Jagannathan, and Kim, 2012). Moreover, our joint-market momentum stock trading strategy is also profitable and further minimizes transaction cost adjusted return effects (Frazzini, Israel, and Moskowitz, 2012). We again document a close relation between this enhanced performance of the joint-market momentum strategy and the significant predictability of the marginal information in CDS returns on future credit rating changes in "anticipated" directions. In this joint-market momentum strategy, CDS returns assist stock momentum strategies in more accurately predicting future rating changes and ensuing stock momentum returns.

Overall, our results suggest that greater information signaling in the CDS market, together with sluggish updates on corporate credit ratings assigned by major rating agencies, creates anomalies such as return momentum within the CDS market and across CDS and stock market momentum effects.

We make several important contributions to the literature on return momentum and capital market efficiency, credit risk, and cross-market linkages. In particular, we document profitable CDS return momentum investment strategies, which extends the literature on the existence of return momentum across various asset classes to an economically important and growing market (Okunev and White, 2003; Pirrong, 2005; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012; Asness, Moskowitz, and Pedersen, 2013). Importantly, we show that the underlying mechanisms of CDS and corporate bond return momentum (Jostova, Nikolova, Philipov, and Stahel, 2013) are different and provide evidence of a link between CDS return momentum and the predictability of past CDS returns on future rating changes in "anticipated" directions. In this regard, we contribute to the literature on the informational relation between CDS markets and credit rating agencies, which documents the effectiveness of market CDS rates as a potential alternative credit risk benchmark to credit ratings (Hull, Predescu, and White, 2004; Norden and Weber, 2004; Acharya and Johnson, 2007; Flannery, Houston, and Partnoy, 2010; Chava, Ganduri, and Ornthanalai, 2012; Qiu and Yu, 2012; Lee, Naranjo, and Sirmans, 2014). Relatedly, our CDS return momentum channel highlights how sluggish moves by major ratings agencies in assigning corporate credit ratings influences capital market efficiency, even in a market that is arguably informationally efficient.

We are also the first to document significant cross-market return momentum spillovers from CDS to stock markets, extending the literature on related asset cross-market interaction effects in momentum returns (Gebhardt, Hvidkjaer, and Swaminathan, 2005). Finally, we highlight the role of CDS depth in explaining significant predictability of CDS returns on future rating changes and also the incremental information content in CDS returns over stock returns. This depth effect is consistent with the recent findings on endogenous liquidity in CDS markets, whereby more information flows from the CDS to stocks when the liquidity of a CDS contract is high (Qiu and Yu, 2012).

The remainder of this paper is organized as follows: Section 2 describes our data and CDS return construction process. We present the results of CDS momentum in Section 3 and the results of both cross- and joint-market momentum spillovers from CDS's to stocks in Section 4. Section 5 concludes.

2 Data and CDS Return Computation

We obtain data from a variety of sources. CDS data are acquired from the Markit Group, a leading financial information services company. The sample covers 1,247 publicly held U.S. companies from January 2003 to December 2011 for which an active single-name CDS contract is traded. There are 667 firms in the sample in 2003, and this number quickly rises to more than 1,000 firms by 2007. All of our selected CDS contracts have five-year maturities since these corporate CDS contracts are the most liquidly traded, and they are denominated in U.S. Dollars. 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.[5] As such, our database consists of MR contracts prior to the "Big Bang" and XR contracts afterward. Markit constructs a composite CDS spread using input from a variety of market makers and ensures each daily observation passes a rigorous cleaning test to ensure accuracy and reliability. Table 1 provides summary statistics and a correlation matrix of variables used in this study. The mean spread of CDS contracts in our sample is approximately 202 basis points. 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 depth of our sample is 6.396.

We gather equity data from the Center for Research in Security Prices (CRSP), and we require the firm's equity to have a share code equal to 10 or 11 and be traded on the NYSE, AMEX or Nasdaq. Monthly equity returns are compounded from daily returns provided by CRSP to match the exact holding period of the CDS contract. Delisting returns from CRSP

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

are used in the event that a stock is delisted. The mean monthly stock return of our sample is 0.396%. Firm size is measured through equity market capitalization and is computed as the number of common shares outstanding multiplied by the price of the firm's stock. Stocks priced at less than $1 at the time of portfolio formation are excluded. The mean market capitalization of our sample is $20.4 billion.

S&P credit ratings are available through Compustat. We convert the rating into a numerical score in which 1 represents "AAA", 2 represents "AA+", ..., and 22 represents "D." The mean S&P rating of our sample is 9.116, which is roughly a "BBB" rating. Our sample represents larger firms in the universe of stocks and is fairly normally distributed across credit ratings. We measure the relative size of our firms by computing decile ranges of equity market capitalization for all stocks in the NYSE/AMEX universe and assigning a corresponding size decile to each firm in our sample (e.g., a size decile value of 10 indicates the firm falls in the highest decile of firms in the NYSE/AMEX universe). Appendix A provides further details on our variable definitions.

Figure 3 portrays the size decile and credit rating distribution of firms in our sample. Panel A is a histogram of the size decile distribution. More than 50% of our firms fall in the highest size decile, and less than 5% are in the smallest five deciles, suggesting that CDS contracts generally trade on large firms and that our results are unlikely to be driven by small firms. The mean size decile is 9.229. Panel B of Figure 3 provides a credit rating histogram and shows that our sample appears to be normally distributed across ratings. A little more than a third of the firms are junk grade (i.e., below BBB-). Furthermore, Panel C of Figure 3 shows that our sample of firms has reasonable representation across industries. A histogram of the CDS depth distribution is also provided in Panel D of the same figure.

2.1 CDS Return Computation

A single-name CDS contract is designed to transfer the credit risk of an underlying entity (often called reference entity) from a protection buyer to a protection seller. The protection buyer pays a periodic coupon to the seller, which is also called the CDS premium, until the maturity of the contract or a credit event (also called a trigger event), whichever comes first.[6] Coupons are usually paid quarterly on the 20$^{\text{th}}$ day of March, June, September, and December, following an Actual/360 day count convention. These quarterly coupon payment dates of a CDS are called the IMM dates inspired by the IMM dates in the interest rate futures markets, though the IMM dates of a CDS are not always the same as the corresponding IMM dates in the interest futures markets—the third Wednesday of the month. If a credit event occurs during the life of a CDS, the protection seller compensates the buyer by making up the difference between the recovery value of the bond and the bond's par value, and therefore the protection seller bears the full loss given default.

To compute the CDS holding period (excess) return, we need to compute the profits/losses (P&L) of a CDS over a given holding interval. 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 a CDS holding period excess return is consistent with Berndt and Obreja (2010). They 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 default-free riskless rate, which serves as the basis for the notion of "excess" return.[7] We interchangeably use the terms—CDS holding period excess return, CDS holding period return, and CDS return—throughout this manuscript.

We illustrate the computation steps of the P&L of a CDS as follows: First, we provide a standard CDS pricing model as in O'Kane (2008).[8] 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.

[6] Credit events include hard events such as bankruptcy, failure to pay, obligation acceleration, obligation default, and also soft events such as restructuring (just in the pre-"Big Bang" period for North American corporate CDS contracts).

[7] This comparison between the par asset swap package and the credit default swap is accurate for a relatively short holding period. For a long holding period, the value of the interest swap component embedded in the asset swap package could diverge from zero, making the comparison inexact.

[8] As explained later, we use a flat hazard rate assumption, which essentially makes O'Kane's (2008) pricing model an ISDA CDS Standard model used by Markit. This model is also called the JP Morgan model by practitioners.

2.1.1 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 5-year CDS. This fresh 5-year contract matures on the first IMM date 5 years after the trade date. For example, a 5-year CDS contract trading on 12/20/2013 matures on 3/20/2018.[9] The premium leg has two components. First, there are 21 scheduled premium payments on a quarterly cycle with the CDS IMM dates—the 20^{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 5-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

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

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

$$S_0 \Delta(t_{n-1}, s) \left(-dQ(t_0, s)\right) Z(t_0, s). \tag{2}$$

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

$$S_0 \sum_{n=1}^{n=21} \int_{t_{n-1}}^{t_n} \Delta(t_{n-1}, s) Z(t_0, s) \left(-dQ(t_0, s)\right). \tag{3}$$

[9] 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. See Section 5.2.1 of O'Kane (2008) for market convention details on determining the maturity date of a standard CDS contract.

By summing up Eq. (1) and (3), the present value of the premium leg becomes

$$\text{Premium Leg PV} = S_0 \cdot RPV01(t_0, t_{21}), \tag{4}$$

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

$$RPV01(t_0, t_{21}) = \sum_{n=1}^{n=21} \Delta(t_{n-1}, t_n) Q(t_0, t_n) Z(t_0, t_n) + \sum_{n=1}^{n=21} \int_{t_{n-1}}^{t_n} \Delta(t_{n-1}, s) Z(t_0, s) \left(-dQ(t_0, s)\right). \tag{5}$$

The integration in the second term in Eq. (5) can be approximated as

$$\int_{t_{n-1}}^{t_n} \Delta(t_{n-1}, s) Z(t_0, s) \left(-dQ(t_0, s)\right) \simeq \frac{1}{2} \Delta(t_{n-1}, t_n) Z(t_0, t_n) \left(Q(t_0, t_{n-1}) - Q(t_0, t_n)\right). \tag{6}$$

Thus, we have

$$\begin{aligned} RPV01(t_0, t_{21}) = & \textstyle\sum_{n=1}^{n=21} \Delta(t_{n-1}, t_n) Z(t_0, t_n) Q(t_0, t_n) \\ & + \textstyle\sum_{n=1}^{n=21} \frac{1}{2} \Delta(t_{n-1}, t_n) Z(t_0, t_n) \left(Q(t_0, t_{n-1}) - Q(t_0, t_n)\right). \end{aligned} \tag{7}$$

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

$$\begin{aligned} \text{Protection Leg PV} & = (1 - R) \textstyle\int_{t_0}^{t_{21}} Z(t_0, s) \left(-dQ(t_0, s)\right) \\ & \simeq (1 - R) \textstyle\sum_{n=1}^{n=21} Z(t_0, t_n) \left(Q(t_0, t_{n-1}) - Q(t_0, t_n)\right). \end{aligned} \tag{8}$$

The second line shows that the integration in the first line is performed by discretizing the 5-year horizon by 21 intervals with each coupon payment date.[10]

Combining the present values of the premium and the protection legs gives the mark-to-market value of a 5-year short protection position of a CDS with a unit \$1-notional as

$$V(t_0) = S_0 \cdot RPV01(t_0, t_{21}) - (1 - R) \sum_{n=1}^{n=21} Z(t_0, t_n) \left(Q(t_0, t_{n-1}) - Q(t_0, t_n)\right), \tag{9}$$

[10]Here we directly use the lower bound of the discretized integration. See Section 6.6 of O'Kane (2008) for more details on this bound discussion.

where $RPV01(t_0, t_{21})$ is as in Eq. (7).[11]

With the quoted spread, S_0, $V(t_0) = 0$ as required.[12] However, soon after the inception of trading, this requirement is no longer true since the market spread of the CDS reference entity moves from the spread that the protection seller/buyer are locked into.

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

$$\text{CDS return}(t_0, t') = -\left(S(t') - S(t_0)\right) \cdot RPV01(t', t_{21}). \tag{10}$$

$S(t_0) \cdot RPV01(t', t_{21})$ in the above Eq. (10) 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. (10) 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.

[11] For a protection buyer, the mark-to-market value would be just the opposite, $-V(t_0)$.

[12] 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.

2.1.2 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 do monthly trading of 5-year contracts. 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 5-year CDS contract.[13] Our monthly trading of a CDS starts at midnight of the 19^{th} of a given month and ends at midnight of the 19^{th} of the next month, and therefore this trading timeline ensures us to trade only 5-year contracts with a fixed maturity date in and out of each trade.[14] With this trading timeline, we do not have to be concerned about the violation of no arbitrage in contract prices across different maturity groups that could exist due in part to our flat hazard rate assumption. We trade only 5-year contracts, and therefore our trading strategy returns are immune from this potential cross-sectional pricing inconsistency in CDS prices. By trading only fresh 5-year contracts, we can further ensure that the liquidity concerns of our trading returns are minimal, which is another potential benefit of our trading timeline. There is no intermediate coupon income for this protection seller during a one-month holding period. All the coupon values are fully embedded in $RPV01(t', t_{21})$.

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 find that 40 firms in our sample experience credit events during our sample 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.[15] In untabulated robustness checks, we further confirm the robustness of our results to these

[13] The flat hazard rate, h, is calibrated such that the clean mark-to-market of the 5-year CDS contract is zero for a given quoted spread, $S(t')$, on a valuation date-t'.

[14] Here is an example of our trading timeline: For the trade ending on 3/19/2013, we sold a 5-year protection at the beginning of 2/20/2013 with the at-market spread on that date and unwound this position by buying a protection at the end of 3/19/2013 with the at-market spread on this unwinding date. Clearly, we are selling and buying a 5-year CDS contract with the same maturity date of 3/20/2018, in and out of this trade. The realized P&L for this holding period is then marked on our trading book at midnight of 3/19/2013.

[15] http://www.creditfixings.com/CreditEventAuctions/AuctionByYear.jsp?year=2013 is the web address of the Creditex Group.

credit event concerns by exclusively focusing on the firms that survive throughout our whole sample period. These results are available on request from the authors.

As explained in the previous Subsection 2.1.1, 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.[16] 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.[17]

Table 1 provides summary statistics on CDS returns for the firms in our sample over the years 2003-2011. The average CDS return over our time period is 0.018% with a standard deviation of 3.947%. Figure 4 displays the equally-weighted average CDS spread (top figure) as well as the time series of equally-weighted CDS and stock returns (bottom figure). The bottom panel shows that CDS returns are highly correlated with stock returns; however, the CDS returns lead the stock returns, particularly during the recent financial crisis period. This pattern suggests a potential information advantage embedded in CDS returns under certain conditions.

[16] For more details on this discussion, see the Section entitled "Trading with a Full Coupon" on page 17 in www.markit.com/cds/announcements/resource/cds_big_bang.pdf.

[17] The annualized 90-day T-Bill rate during our sample period was 1.91% on average.

3 CDS Momentum

Our CDS momentum trading strategy is constructed in the spirit of Jegadeesh and Titman (1993). Firms are sorted at the end of each month into five equally-sized portfolios, P1 to P5, based on their CDS return over the past J months (referred to as the formation period). Formation periods longer than one month are compounded from one-month returns. We write default protection on firms in P5 that have the highest returns (*winners*) and acquire default protection on firms in P1 that have the lowest returns (*losers*). All positions are unwound after K months (referred to as the holding period) and equally-weighted returns are computed for each momentum portfolio. Similar to previous studies ((Jegadeesh and Titman, 1993), among others), returns greater than one month are constructed to avoid overlapping returns.[18]

Table 2 summarizes momentum profits in the CDS market over 2003-2011. In Panel A, we first document the profits of a weekly momentum strategy. Though we primarily trade monthly, in this exercise we separately compute weekly excess returns of trading a 5-year CDS contract. The long/short return using a weekly formation period is 0.193% per week with a t-statistic of 2.99, which implies short-term momentum instead of a reversal. Therefore, unlike Jegadeesh and Titman (1993) who adjust the formation period to avoid short-term reversals in the stock market, our CDS momentum strategy can be implemented without a one-month gap between the formation and holding periods. For these reasons, we use contiguous formation and holding periods for the remaining momentum strategies implemented in this paper.

Panel A of Table 2 also presents CDS momentum returns using various other formation periods J—one month, three months, six months, nine months, and 12 months. The three-month formation period provides the largest momentum profits, producing a one-month return of 52 bps (= 0.520% per month, or 6.42% on an annual basis) with a t-statistic of 3.87 and a Sharpe ratio of 0.423. The loser portfolio P1 produces an equally-weighted monthly return of -0.193%, and the winner portfolio P5 produces a return of 0.327%. While momentum profits are generated from both P1 and P5, the return on P5 (t-statistic of 2.52)

[18] For instance, the three-month holding period return is computed by equally averaging the one-month returns of three strategies using momentum portfolios formed in the current month, one month prior, and two months prior.

is statistically more significant than the return of P1 (t-statistic of -0.86).

CDS momentum profits are also significant for holding periods K longer than one month. For example, the strategy using a three-month formation period ($J = 3m$) generates future three-month ($K = 3m$) and six-month ($K = 6m$) average monthly returns of 0.467% and 0.310%, respectively. However, the magnitude of the average monthly momentum return becomes weaker as the holding period K is extended.

Momentum returns exist for longer formation periods up to nine months. The monthly returns using formation periods of six ($J = 6m$) and nine ($J = 9m$) months are 0.443% and 0.412%, respectively. They are statistically significant at least at the 5% level. When the formation period is extended to 12 months ($J = 12m$), the momentum return becomes relatively weak both economically (0.351% monthly return) and statistically (t-statistic of 1.62).

Also provided in Panel A of Table 2 are the average size decile, rating, and depth characteristics for each portfolio. Recall that the size decile is measured relative to the equity market capitalization of all firms in the NYSE/AMEX universe, the reported S&P rating is a numerical representation of the rating, and CDS depth is a measure of CDS liquidity provided by Markit. The extreme portfolios (P1 and P5) generally contain smaller and less creditworthy firms. Except for the weekly formation portfolio, on average the winner portfolio (P5) contains slightly larger firms than the loser portfolio (P1) and are significantly different at formation periods of six, nine, and 12 months. P5 contains riskier firms than P1, a difference that is statistically significant at all formation periods. Average depth shows that firms in P1 have more liquid CDS contracts than firms in P5. This difference is statistically significant at all formation periods except for the one-month formation period ($J = 1m$). Depending on the formation period (J) length, each momentum portfolio contains between 130 and 180 firms, on average. In Subsection 3.1 later, we show that CDS momentum is robust to these size, rating, and depth characteristics, and we uncover an important credit rating and CDS depth interaction role in generating substantial momentum profits.

In Panel B of Table 2, we present the performance of the three-month momentum strategy ($J = 3m$) during different time periods. The pre-crisis period spans January 2003 to June 2007, the crisis period spans July 2007 to April 2010, and the post-crisis period spans May 2010 to December 2011. One-month holding ($K = 1m$) long/short strategy returns are positive and statistically significant at the 5% level in all three sub-periods. The magnitude is greatest during the crisis period with average returns of 97 bps (= 0.971%) and moderate during the pre-crisis and post-crisis periods with returns of 0.228% and 0.641%, respectively. Although the magnitude varies, the performance in each time period is statistically significant at the 5% level. We find similar CDS momentum return patterns for the other two holding periods $K = 3m, 6m$.

Turning to Panel C of Table 2, we separately compute CDS momentum returns for investment grade (BBB- and above) and junk grade entities (BB+ and below). Consistent with stock momentum evidence (Avramov, Chordia, Jostova, and Philipov, 2007), the CDS momentum long/short strategy is substantially higher for junk grade firms than investment grade firms. Junk grade firms produce a return of 83 bps (= 0.833%) with a t-statistic of 3.81 and Sharpe ratio of 0.320.

Although smaller in magnitude, the investment grade firms still produce a statistically significant momentum return of 27 bps (= 0.268%) with a t-statistic of 2.88 and a Sharpe ratio of 0.310. This result contrasts with earlier research finding that corporate bond momentum does not exist among investment grade entities in the post-1991 time period as documented by Jostova, Nikolova, Philipov, and Stahel (2013). Although the magnitudes of the CDS momentum returns for the two groups are different, their Sharpe ratios are similar—suggesting the return compensation per unit of volatility of each group is almost equivalent.

3.1 Risk Adjustments and Firm Characteristics

In this section, we discuss the robustness of CDS momentum to risk factors and firm characteristics. We show that momentum returns are robust to common stock- and bond-based risk factors as well as characteristic-adjusted returns, though momentum profits are greatest in smaller firms, less creditworthy firms, and firms with higher CDS liquidity measured by contract depth. The momentum strategy analyzed in this subsection uses formation $J = 3m$ and holding $K = 1m$, which was shown to yield the greatest momentum profits as illustrated in Table 2.

We first analyze whether CDS momentum returns are explained by common risk factors. Panel A of Table 3 presents alpha coefficients from regressions on various risk factor models.

Using OLS with Newey-West standard errors and a lag length of 12 months, we estimate:

$$r_{Pt} = \alpha_P + \boldsymbol{\beta}'_P \mathbf{F}_t + e_{Pt}, \tag{11}$$

where r_{Pt} is the CDS return for momentum portfolio P, α_P is the portfolio's abnormal return, and $\mathbf{F}_t$ is a vector of common risk factors from bond and stock markets.

The first bond-based factor, brDEFAULT, captures the difference in returns between BBB-rated and AAA-rated bonds. The second bond-based factor, brTERM, is the difference in returns between long-term and short-term bonds. These two factors are provided as end-of-month series, so there is a slight timing mismatch between these bond factors and our portfolio timing (roughly a week and a half difference, on average). The equity factors—Mkt, SMB, HML, and UMD—are constructed from the daily series on Ken French's website to exactly match the timing of the CDS momentum strategy.[19] In addition, we construct a "localized" stock momentum factor, sMOM, using our sample of firms and the strategy $J = 12m$ and $K = 1m$, skipping a month between formation and holding periods, which is standard in the stock momentum literature (see Asness, Moskowitz, and Pedersen (2013), among others). Appendix B provides further details on our factor definitions.

As reported in Panel A of Table 3, the long/short strategy monthly alphas are between 0.506% and 0.652%, which is similar to the long/short momentum returns (0.520% per month) previously reported in Panel A of Table 2. Across the four different factor models, the alphas are all significant at the 1% level of statistical significance.

We next examine whether the CDS momentum profits are robust to using characteristic-adjusted returns according to firm size, S&P rating, and CDS depth. Motivated by our findings in Panel A of Table 2 that the winner portfolio is comprised of larger and riskier firms with lower contract depth, we examine whether potential risks associated with these characteristics drive the CDS momentum profits. To this end, we compute the characteristic-adjusted momentum returns with firm size, S&P rating, and CDS depth, and we report the results in Panel B of Table 3. The characteristic adjustment is made by removing the mean return at each decile or group from the actual return (see Appendix C). Even after adjusting for these characteristics, the magnitude of CDS momentum remains large and all

[19] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html is the address of Ken French's webpage.

long/short returns are statistically significant at the 1% level. The size-adjusted, rating-adjusted and depth-adjusted returns produce long/short returns of 0.408%, 0.344% and 0.363%, respectively. Adjusting for all three characteristics at the same time still produces a long/short return of 0.314%.

Although we do not find that these firm and contract characteristics are key drivers of momentum profits in CDS returns, their relation to the performance of CDS momentum strategy is still an open and interesting question. An analysis of this relation could provide some insights on pinning down the potential mechanisms that drive CDS momentum profits. In Panel C of Table 3, we present long/short strategy returns within quintiles (Q1 to Q5) of firm size, S&P rating, and CDS depth, respectively. We first create quintiles based on each raw variable. Then, to better isolate each variable's own effect, we orthogonalize it to the other two variables.[20]

We find in Panel C of Table 3 that small firms produce greater momentum returns than large firms. The smallest size quintile produces a long/short return that is 0.682% greater than the largest quintile, a result that is statistically significant at the 5% level. However, this size effect is confounded with the two other characteristics—S&P rating and CDS depth. After orthogonalizing to rating and depth, the size effect is reduced to 0.311% with much weaker statistical significance.[21]

Confirming the result in Table 2 that junk grade firms generate larger momentum returns than investment grade firms, we also find in Panel C that the riskiest rating quintile produces a long/short return that is 103 bps (=1.031%) greater than the safest quintile (see S&P Rating results). This result is statistically significant at the 1% level. Even after orthogonalizing rating to size and depth, the difference is still 69 bps (=0.693%) and is statistically significant at the 1% level (see S&P Rating (Orthogonalized)), indicating a close relation between CDS momentum profits and the reference entities' ratings.

These CDS momentum results with corporate credit ratings are consistent with Avramov,

[20]To accommodate the nonlinear hump-shaped relationship between rating and depth (Qiu and Yu, 2012), we add a squared rating variable to each depth regression (and vice-versa). For example, orthogonalized depth is computed as the residual from a regression of depth on size, rating, and rating squared (see Appendix A).

[21]Recall that our sample consists of firms that are relatively large. The smallest size quintile still has an average equity market capitalization of $2.5 billion. Therefore, the insignificant size effect is somewhat expected from this sample property.

Chordia, Jostova, and Philipov (2007) who document that stock momentum exists only within firms with poor credit ratings. Related to this point, Avramov, Chordia, Jostova, and Philipov (2013) further show that momentum returns are generated primarily in high credit risk firms that experience continuing financial distress. We find that rating changes, both upgrades and downgrades, are much more frequent in junk grade entities than investment grade entities—there are 10.50% (5.91%) more upgrades (downgrades) among junk grade entities in our sample. In the next Subsection 3.2, we explore the role of ratings upgrades (downgrades) following substantial run-ups (run-downs) in CDS returns in driving CDS momentum profits.

Using our third characteristic, we also analyze the performance of CDS momentum across different contract depths. The relationship between depth and momentum can *a priori* take several forms. If CDS momentum is driven by illiquidity, then we might expect momentum to be concentrated within the least liquid CDS contracts (i.e., lowest CDS depth). Relatedly, if depth is an indicator of the information environment of the firm (similar to analyst coverage), we might expect momentum to be concentrated within opaque firms, particularly if it is driven by slow information diffusion and underreaction (Hong and Stein, 1999; Hong, Lim, and Stein, 2000).

In contrast to these first two hypotheses, we might expect momentum to be greatest among firms with relatively high depth if depth captures a glamour effect. Lee and Swaminathan (2000) find that stock return momentum is more pronounced among high volume stocks, an effect that is primarily driven by a quicker and strong rebound of low volume losers relative to high volume losers. They explain this quicker reversal of the low volume losers through a phenomenon they term as the momentum life cycle (MLC). A fourth hypothesis we consider, which places an emphasis on the endogenous aspect of CDS liquidity (Qiu and Yu, 2012), is that CDS depth is positively correlated with the level of informed trading/quote updating in the CDS market. In this case, the more informed high depth CDS contracts could have richer information on firm default risk, thereby more accurately predicting future credit rating changes. With this endogenous liquidity, more upgrades (downgrades) could exist in the *winner* (*loser*) CDS momentum portfolio. This rating change channel is also documented as a main driver of equity momentum returns (Avramov, Chordia, Jostova, and Philipov, 2013). The third and fourth hypotheses described above predict greater momentum profits in more actively trading entities—i.e., entities with high CDS depth.

In Panel C of Table 3, we find support for the latter two hypotheses that CDS contracts with high depth generate higher momentum returns than those with low depth. The most liquid quintile based on CDS depth produces a long/short return that is 1.092% greater than the least liquid quintile, a result that is statistically significant at the 1% level. The depth effect is strong even after orthogonalization to both size and rating; the difference between Q5 and Q1 remains large at 0.925% and is statistically significant at the 1% level. Moreover, the CDS momentum returns in the highest depth quintile (80 bps=0.798%) are also robust to transaction cost adjustments. Using Datastream, we find that the average bid-ask spread for the entities in the highest depth quintile is 9.5 bps.[22] Even with an extreme 100% turnover assumption, our three-month formation and one-month holding period CDS return momentum strategy yields 42 bps per month, net of transaction costs, for the high depth group.[23]

3.2 Credit Rating Changes

Motivated by our findings on the effects of S&P rating and CDS depth on the profitability of the CDS momentum strategy, this subsection examines whether CDS momentum profits are generated from rating changes in "anticipated directions"—upgrades following run-ups and downgrades following run-downs of cumulative CDS returns. If this is the channel through which CDS momentum profits are generated, it will effectively rule out the MLC hypothesis by Lee and Swaminathan (2000), which also predicts greater momentum profits for high depth CDS contracts.

To analyze the relationship between CDS momentum and credit rating changes, we report separately the returns of firms that experience an upgrade, downgrade, or no rating change within six months after the momentum portfolios are formed. In a similar analysis conducted by Jostova, Nikolova, Philipov, and Stahel (2013), no relation is found between the momentum profits in corporate bond returns and the future rating change channels.

[22]We retrieve the CDS bid-ask spread information from Datastream since Markit does not provide microstructure measures except for CDS contract depth. The CDS bid-ask spread information covers 2005-2010 time period.

[23]Looking more directly into the effect of liquidity on CDS spreads, Tang and Yan (2007) find that the liquidity impact on the CDS spreads is insignificant for high depth contracts.

Contrary to their findings, our results in Table 4 show that CDS momentum and ratings changes are closely related. In Table 4, we focus on the most profitable CDS momentum strategy that uses formation $J = 3m$ and holding $K = 1m$, similar to what we did in the previous Subsection 3.1.

Confirming prior studies on the relationship between CDS and credit ratings, Panel A of Table 4 shows that a firm has positive (negative) CDS returns in the months prior to a rating upgrade (downgrade) and a large positive (negative) return in the month of the announcement. In the month before the new rating announcement, upgraded (downgraded) firms already experience a six-month cumulative CDS return of 221 bps (-324 bps). In the month of the announcement, upgrades (downgrades) further experience a return of 44 bps (-133 bps). To the extent that our momentum portfolios effectively place firms to be upgraded (downgraded) in the winner (loser) portfolio, the long/short return will benefit from the divergence in spread movements between upgrades and downgrades. These rating upgrades (downgrades) following past cumulative CDS return run-up (run-down) are referred to future rating changes in "anticipated directions."

In Panel B of Table 4, we show that CDS momentum profits are generated from these anticipated changes in future credit ratings over the six-month horizon following the formation date of the momentum portfolio. For the firms that never undergo any rating changes over the six-month horizon, we do not find statistically significant returns for the long/short momentum strategy (0.102% monthly return with a t-statistics of 1.04), though only during the post-crisis period does this group generate statistically significant positive long/short returns (= 0.379% with a t-statistics of 2.54).

To provide more direct evidence on our proposed mechanism of momentum profits, we analyze the returns of the firms that experience rating changes in anticipated directions. Looking at the fraction of upgrades and downgrades for the *winner* and *loser* portfolios (labeled n_{up}/N and n_{dn}/N) in Panel B of Table 4, we find that P5 has significantly more upgrades (n_{up}/N of 10.2%) than P1 (n_{up}/N of 5.00%), whereas P1 has significantly more downgrades (n_{dn}/N of 20.6%) than P5 (n_{dn}/N of 11.0%). These wedges between P5 and P1 portfolios are statistically significant at the 1% level for both upgrades and downgrades, and the firms that are upgraded (downgraded) in P5 (P1) in the anticipated directions (i.e., upgraded firms in P5 and downgraded firms in P1) generate statistically significant monthly momentum profits of 2.044% at the 1% level. Strikingly, firms that go through unanticipated rating changes over the same six-month horizon show return reversal (-0.587%) and are statistically significant at the 5% level. From these results, it is clear that when the rating changes occur in the "anticipated" directions, CDS momentum profits are generated.

From the same panel, we find that the difference in the wedges between the fractions of upgraded firms and downgraded firms in the long/short portfolio is at its maximum during the crisis period ($21.00\% = 6.70\% - (-14.3\%)$). These firms in particular generate a statistically significant long/short portfolio monthly return of 3.395% at the 1% level during that time period. Therefore, the future rating change channels we propose appear to consistently explain the greater performance of the CDS momentum strategy we documented earlier for the crisis sub-period.

How are these findings related to the S&P rating and CDS depth characteristics that we found earlier to be positively correlated with the CDS momentum performance? In Panel C of Table 4, we first examine the sensitivity of the relationship between CDS momentum and ratings changes to the rating level. We divide firms into investment grade and junk grade and redo the analysis. Our first observation is that removing firms with credit rating changes eliminates momentum returns in both investment grade and junk grade groups. The long/short strategy produces returns of 0.0784% and 0.148% for investment grade and junk grade firms, respectively, neither of which is statistically significant. Absent firms with future ratings changes, there is no significant difference in momentum returns between investment grade and junk grade firms (0.0696% with a t-statistic of 0.19). The better performance of the momentum strategy among junk grade firms clearly comes from the difference in future rating changes in anticipated directions as documented, with a monthly return difference of 2.607% and a t-statistic of 2.12 at the bottom of Panel C in Table 4.

What is the role of CDS depth in the relationship between CDS momentum and ratings changes? In Panel D of Table 4, we divide firms into high depth and low depth and repeat the previous analysis. It is clear that firms with high CDS depth produce greater CDS momentum profits than those with low CDS depth because the long/short momentum portfolios in the high depth group more effectively predict future ratings changes in the anticipated directions. For example, the excess frequency of upgrades in P5 over P1 in high depth group (0.0494) is greater than that in the low depth group (0.0487), and such a tendency is much stronger in its magnitude for the rating downgrades. The long/short portfolio in the high depth group (-0.120) twice as accurately predicts the credit rating downgrades as the portfolio in low depth group (-0.0640). This superior predictability of high depth CDS returns on future rating changes in the anticipated directions yields a 2.430% monthly long/short portfolio return, whereas the momentum return generated through the same mechanisms in the low depth group (1.084%) is just half of the return. The difference in these returns is substantial at 1.346% (=2.430%-1.084%) and statistically significant at the 5% level.[24]

Our findings regarding these CDS depth effects are consistent with Qiu and Yu (2012) who recently document that CDS depth is a proxy for informed trading in the CDS market. The at-market spreads of CDS contracts with high endogenous liquidity are also shown to reveal information earlier than stock returns, particularly when the credit quality of reference entities deteriorates. The ability of past CDS returns with high depth contracts to predict rating downgrades better than rating upgrades is also in line with their findings.

The analysis in Panel D of Table 4 allows for the possibility that past CDS returns have an informational advantage over stock returns in predicting future ratings changes. If so, it is more likely to be for the entities with lower credit ratings and high contract depth, as suggested in our analysis in Panel C and D of Table 4.

4 CDS Momentum and Stock Returns

In the previous section, we demonstrated a close relation between CDS momentum and the ability of past CDS returns to anticipate future ratings changes. However, it may be that past CDS returns are just noisy signals of past stock returns. In this section, we address this concern and show that there are indeed incremental information benefits in CDS returns above and beyond the information contained in stock returns, and that such informational benefits in the CDS returns generate a momentum spillover from the CDS to the stock market. Gebhardt, Hvidkjaer, and Swaminathan (2005) do not find a momentum spillover from the corporate bond market to the stock market, which suggests important information

[24]However, it should be noted that some momentum profits (0.213% with t-statistics of 2.05) still exist even in the entities with high depth group that never undergo any rating changes over the six-month horizon. The economic magnitude of the profits in these entities, however, is substantially lower than the magnitude of those that undergo future rating changes in anticipated directions.

differences between corporate bond and CDS returns. Lastly, we provide evidence that past CDS returns, when combined with past stock returns, dramatically improve the performance of the traditional stock-to-stock momentum strategy of Jegadeesh and Titman (1993) by sharpening the signals that generate stock momentum profits.

4.1 CDS Momentum and Momentum Elsewhere

In Table 5, we first show that CDS momentum returns are highly correlated with other markets' momentum returns (Panel A). However, we also emphasize that the CDS momentum returns lead those of bond momentum (Panel B), and the CDS returns have incremental information not fully captured by stock returns (Panel C).

Panel A of Table 5 displays time-series correlation coefficients between CDS momentum and momentum in the stock and bond markets. We use the bond momentum series provided by Jostova, Nikolova, Philipov, and Stahel (2013): all firms, investment grade firms, and junk grade bonds. Over the full sample period, the correlation between CDS momentum and bond momentum is 0.255. Across sample periods, the crisis period shows the highest correlation (0.281). The correlation is much higher for investment grade firms (0.304) than junk grade firms (-0.053). Among investment grade firms, the correlation peaks during the crisis period (0.359).

The stock momentum factor, UMD, exactly matches the rebalancing timing of our CDS momentum. The correlation between CDS momentum and the UMD factor is 0.388, and it peaks during the crisis period (0.560). We construct the other stock momentum return series (All Firms, Investment and Junk Grade, and High and Low Depth) to exactly match both our CDS return rebalancing timing as well as our exact firm sample. Among all firms and over the entire sample period (see All Firms), the correlation between CDS momentum and stock momentum is 0.533. The correlations are low during the pre-crisis period and highest during the crisis and post-crisis periods. Overall, stock and CDS momentum correlation is higher for investment grade firms than junk grade firms (0.443 versus 0.267) and for high depth contracts (0.536 versus 0.407).

Despite these positive correlations between CDS momentum and momentum in the other asset classes, the information content in each market's momentum returns could be different. As reported in Panel B of Table 5, there is no significant lead/lag relation between CDS momentum and stock momentum; however, both lead bond momentum. The results are noteworthy because the contemporaneous bond momentum returns are measured in advance to both the CDS momentum and the stock momentum returns. The bond momentum returns we obtained from Jostova, Nikolova, Philipov, and Stahel (2013) are measured at the end of each month, while the other two momentum returns—CDS and stock—are measured on the 19th of the month. Despite this timing informational advantage that is available in the measured bond momentum returns, both the CDS and stock markets precede the momentum in corporate bond markets — re-ensuring the superior information capacity we expect *a priori* in these two markets over the corporate bond market.

In Panel C of Table 5, we examine whether CDS returns have an incremental information advantage above and beyond that embedded in stock returns. We isolate the CDS return signal from that of the stock market (and vice-versa) by independently sorting the CDS entities by past stock returns (sP1 to sP5) and past CDS returns (P1 to P5). Then, we examine whether past CDS returns generate significant CDS momentum profits, while we control for the signals in the past stock returns (Relative Value of CDS). Similarly, to investigate whether there is valuable incremental information in past stock returns, we form the CDS long/short portfolios based on past stock returns while controlling for past CDS returns (Relative Value of Stock).

Overall, we find that the marginal information in past CDS returns generates significant momentum profits for both entities in sP1 (1.006% monthly return) and sP5 (0.372% monthly return). However, we only find marginal information benefits of past stock returns for the entities in P1, the CDS losers (0.588% monthly). For the entities in P5, the CDS winners, we in fact find return reversal (-0.0462%) based on past stock returns as incremental sorting signals.

These incremental information benefits of CDS returns over stock returns are evident particularly for the entities with lower credit ratings and high CDS depth. The CDS-based long/short return of junk grade firms is 2.707% or 0.570% conditional on the firm falling into sP1 or sP5, respectively, and both are statistically significant. In the opposite case, the relative advantage of the stock signal is positive and statistically significant for P1 ($= 1.347\%$) but negative for P5 ($= -0.790\%$), suggesting that the stock signal actually detracts value in the latter case. We find that greater CDS depth is also associated with a stronger relative advantage of the CDS signal, supporting the argument that high depth CDS contracts contain greater information flow and suggesting potential segmentation in the information content of CDS and stock markets.[25] Conditioning on the firm falling into sP1 (sP5), the CDS-based long/short strategy for high depth firms produces statistically significant returns of 0.325% (0.230%). In contrast, for low depth firms, the CDS signal is weak after considering the stock signal—i.e., the CDS-based long/short returns are insignificant conditioning on falling into one of the extreme stock momentum portfolios.

The findings in Table 5 suggest that the CDS market has incremental information above and beyond the stock market information and that the liquidity of a CDS contract measured by its contract depth is consistent with the notion of the endogenous liquidity in the CDS market (Qiu and Yu, 2012). That is, higher CDS liquidity is associated with greater information flow originating in the CDS market.

4.2 Momentum Spillover from CDS to Stock

An important question that remains is whether or not momentum spills over from the CDS market to the stock market? An affirmative response would reconfirm the incremental informational advantage in using CDS signals to generate *stock* return momentum.

Panel A of Table 6 presents future stock returns of CDS-based momentum portfolios. In this strategy, we sort firms based on past three-month CDS returns and hold the firm's stock for one month (i.e., $J = 3m$, $K = 1m$). We purchase stocks in the CDS-based *winner* portfolio (P5) and sell short stocks in the CDS-based *loser* portfolio (P1). Among all firms in our sample, the long/short strategy generates a return of 0.518%, with a t-statistic of 1.69 and Sharpe ratio of 0.142. Although not statistically significant, the magnitude of the return is largest during the crisis period. In addition, the return is independent of common stock risk factors: Mkt, SMB, HML, and UMD (Car4 Alpha) as well as a "local" stock momentum factor (Loc4 Alpha) constructed using our sample of firms (alpha coefficients of 0.638% and 0.635%, respectively).

To better understand the source of the CDS momentum spillover, we further divide firms by investment grade/junk grade and recompute the cross-market momentum returns. The

[25] Kapadia and Pu (2012) also document information segregation between these two markets.

momentum spillover is concentrated in junk grade firms, producing a long/short return of 1.365%, with a t-statistic of 2.29 and Sharpe ratio of 0.230. The CDS-to-stock cross-market momentum strategy does not produce significant returns among investment grade firms. These results as consistent with the finding in Acharya and Johnson (2007) who document that the CDS market reveals information earlier than the stock market for poorly-rated firms.

The CDS-to-stock cross-market momentum effect is also concentrated in the most liquid CDS contracts. The long/short return is 0.806% for firms with high CDS depth compared to -0.0473% for firms with low depth. It should be noted that the long/short strategy of the high depth group has the largest Sharpe ratio (0.247), which indicates the investment efficiency of this subgroup among all the subgroups we consider in this panel. Again, the returns generated by the high depth firms are not explained by common stock-based risk factors or a stock momentum risk factor constructed for each specific subgroup. The alpha coefficients are 0.954% and 0.956% for the Carhart four-factor model and our localized four-factor model, respectively—with both being significant at the 1% level.

Our results so far suggest that the CDS and stock markets are somewhat informationally segmented and that for groups of firms there is information flow from the CDS market to the stock market. That is, the results in Panel A of Table 6 together with those in Panel C of Table 5 show that potential information flow from the CDS market to the stock market is more likely for firms in financial distress and/or those with high CDS contract depth. In the following analysis, we show how an investor in the stock market could utilize the superior information capacity of the CDS market to enhance his/her stock investment performance.

Panel B of Table 6 presents the stock returns of two momentum strategies: a single-market stock-based strategy and a joint-market strategy that only trades stocks at the intersection of the winner and loser momentum portfolios based on past stock and CDS returns. The joint-market momentum strategy is constructed in two steps. First, stock and CDS momentum portfolios are created independently based on their own market signals. Then, we purchase stocks that fall into both past stock signal winners (sP5) *and* past CDS signal winners (P5) and sell short stocks of those in past stock signal losers (sP1) *and* past CDS signal losers (P1). In this analysis, we take advantage of the positive and negative signals coming from *both* the stock and CDS markets. Given that we trade stocks instead of CDS contracts, transaction cost concerns in this joint-market momentum strategy are also minimal (Frazzini, Israel, and Moskowitz, 2012).[26]

Across all firms, the traditional stock momentum strategy does not produce statistically significant returns during our time period (0.124% with a t-statistics of 0.16). This result not specific to our stock momentum returns. As illustrated in Figure 5, insignificant stock momentum profits are also shown using the Carhart momentum factor, UMD, which is based on a broader cross-section of stocks. Both our stock momentum and UMD returns suffer from abrupt losses during the crisis period (see Figure 5; Daniel (2013); Daniel, Jagannathan, and Kim (2012)).

In contrast, the joint-market strategy produces a large long/short strategy return of 116 bps per month (= 1.160%) that is statistically significant at the 1% level, an improvement of net 104 bps monthly return (= 1.037%). The crisis period appears to be driving the magnitude of the joint-market momentum returns (= 2.647%), which is the period when traditional momentum strategies are well known to break down. Figure 5 shows that strategies incorporating CDS returns as additional sorting signals are able to avoid dramatic losses during the crisis period. Both the cross-market (CDS-to-stock) momentum strategy and the joint-market strategy significantly outperform traditional stock-based strategies during our sample period.

We posit that anticipated future credit rating changes are the mechanism through which CDS momentum spills over to stock momentum in either the pure cross-market momentum or the joint-market momentum strategy. CDS returns assist stock returns in correctly anticipating credit rating changes and then benefit from the realized price divergence between upgraded and downgraded firms. This result can be seen in the relative fraction of upgrades (downgrades) in the *winner* (*loser*) portfolio that we document in Panel B of Table 6. For instance, 32.4% of firms in the joint-market *loser* portfolio (P1, sP1) experience downgrades (n_{dn}/N) as opposed to 18.9% in the single-market stock momentum *loser* portfolio (sP1). Likewise, 18.1% of firms in the joint-market *winner* portfolio (P5, sP5) are upgraded (n_{up}/N), which is much more than the 9.01% in the single market stock momentum *winner* portfolio (sP5). In all subgroups, the joint-market momentum portfolios has the greater fraction of

[26] Frazzini, Israel, and Moskowitz (2012) find that the main return anomalies to standard asset pricing models, such as value and momentum, are robust to transaction costs in stock markets and are therefore implementable and sizeable.

realized anticipated rating changes (n_{ant}/N).

The resulting improvement in performance is evident, particularly for the entities with low credit ratings and/or high CDS depth. When we further compare the return difference between joint- and single-market strategies in the last four columns of Panel B in Table 6, it is evident that high CDS contract depth plays an important information role in explaining CDS information flows to stocks, consistent with endogenous CDS liquidity notions (Qiu and Yu, 2012).

Overall, the results in Table 6 confirm the greater information capacity of the CDS market for certain types of firms and its association with future rating changes in "anticipated" directions as a way for stock investors to improve their momentum investment performance.

5 Conclusion

We examine the extent to which momentum exists in the CDS market and whether it spills over to another closely related asset market that is linked through common firm fundamentals—the stock market. Despite the CDS market's relative information efficiency, we document both economically and statistically significant CDS return momentum profits. We further show that the underlying mechanisms driving CDS return momentum are distinct from those associated with corporate bond return momentum (Jostova, Nikolova, Philipov, and Stahel, 2013) and highlight the role of CDS return information in predicting future credit rating changes in "anticipated" directions—with past CDS winners (losers) undergoing more frequent rating upgrades (downgrades) in subsequent periods. We also document the ability of a future rating change channel in driving the within-CDS market momentum, particularly for firms with poor credit ratings (Acharya and Johnson, 2007) and/or high CDS contract depth (Qiu and Yu, 2012).

Importantly, we also document that there is useful incremental information in CDS returns beyond the information in stock returns. We show significant cross-market and joint-market CDS-to-stock momentum returns, both of which are closely related to future rating changes in momentum portfolios that occur in "anticipated" directions. We also find that entities with poor credit ratings and/or greater CDS market liquidity drive these interesting cross-market CDS-to-stock information dynamics. In particular, our novel joint-market momentum strategy that uses both stock and CDS market signals in the portfolio formation process helps traditional stock momentum strategies avoid well-documented break-downs in momentum returns during the recent crisis period (Daniel, 2013; Daniel, Jagannathan, and Kim, 2012). Our new strategy improves monthly momentum returns by net 104 bps during this period.

Overall, our results provide some explanatory evidence regarding a number of important empirical regularities documented in the recent momentum literature: momentum exists across several asset classes and exhibits a strong comovement across these assets and markets (Asness, Moskowitz, and Pedersen, 2013). We uncover some important sources that underlie this cross-market comovement in momentum returns; common corporate credit rating change generates a CDS return momentum anomaly associated with timely CDS credit risk information and sluggish ratings responses. We provide evidence consistent with the existence of such a mechanism by focusing on two closely related asset classes—stocks and CDS—that are linked through underlying firm fundamentals. At the same time, our study also suggests that stock investors can substantially improve their investment returns by paying attention to the incremental information originating in highly liquid CDS contracts. Our results suggest that further investigating the efficacy of CDS market information on investment strategies or in the design of other financial claim contracts could be a useful avenue for future research.

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Appendices

A Variable Definitions

Variable Name	Description	Source
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 Depth	The number of good contributions used to construct the composite spread. Markit requires at least two.	Markit Group
Stock Return (%)	The return of the firm's stock over the course of the monthly CDS holding period.	CRSP
Size	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
S&P Rating	Standard and Poor's credit rating for the company. It is converted to a numerical score in which 1=AAA, 2=AA+, 3=AA, ... , 21=CCC-, 22=D. Ratings are provided on an end-of-month basis.	Standard & Poors: Compustat North America - Monthly Updates, Ratings
NYSE/AMEX Size Decile	Size deciles are computed each month using all US firms with share code 10 or 11 listed on the New York Stock Exchange (NYSE) and AMEX stock exchanges. Firms in our data set are then assigned a decile number from 1 to 10 based on how our firm sizes compare to all firms.	CRSP
Size (orthogonalized)	The residual from a cross-sectional regression of firm size on S&P rating and CDS depth performed each month.	CRSP
S&P Rating (orthogonalized)	The residual from a cross-sectional regression of S&P rating on size, CDS depth and CDS depth squared performed each month.	Standard & Poors
CDS Depth (orthogonalized)	The residual from a cross-sectional regression of CDS depth on size, rating and rating squared performed each month.	Markit Group

B Factor Definitions

Factor Name	Description	Source
brDEFAULT	Bond-based factor computed as the difference in holding period returns of BBB-rated bonds and AAA-rated bonds. The AAA and BBB bond US-only total return series are part of the Citigroup Fixed-Income Index Catalog. Reported at the end of the month.	Citigroup and Calculations
brTERM	Bond-based factor computed as the difference in holding period returns of long-term US government bonds and the three-month T-Bill. The long-term bond index is provided by Ibbotson and the T-Bill series is from CRSP. Reported at the end of the month.	Ibbotson, CRSP, and Calculations
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
sMOM	Traditional monthly stock momentum strategy based on firms in our sample. Stocks are sorted based on past 12-month return (skipping one 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. Returns are value-weighted.	CRSP

C Construction of Characteristic-Adjustment Returns

We construct characteristic-adjusted returns for firm size, CDS depth, and S&P rating in three steps:

1. We define groups for the characteristic. (This includes deciles for firm size, deciles for CDS depth, and the letter of the S&P credit rating.)

2. Equally-weighted average monthly returns are computed within each group.

3. The characteristic-adjusted return is constructed by subtracting the group's average return from the firm's return.

These steps are taken separately for each characteristic. For the combined size, depth and rating adjustment, Step 2 consists of averaging the returns within each cross-section across the groups of all three characteristics.

Table 1. Sample Statistics

This table presents the summary statistics and correlation matrix of variables used in this study. Data are monthly from January 2003 to December 2011. CDS data are provided by Markit, stock returns are from CRSP, and S&P Ratings are acquired from Compustat. Investment grade is defined as "BBB-" rating and better. N refers to the number of firm-month observations. See Appendix A for a detailed description of variable definitions.

Summary Statistics

Variables	**Mean**	**Std. Dev.**	**Min.**	**Median**	**Max.**	N
CDS-based						
CDS Spread (bps)	202.060	400.654	1	85	9714	75522
CDS Return (%)	0.018	3.947	-62.255	0.003	302.635	75522
CDS Depth	6.396	4.764	2	5	33	75322
Stock-based						
Stock Return (%)	0.396	10.743	-89.038	0.563	337.294	75378
Size ($Bil)	20.428	39.993	0.004	7.282	519.894	74922
Credit rating and firm size decile						
S&P Rating (1=AAA, 22=D)	9.116	3.296	1	9	22	71717
Investment Grade Dummy	0.597	0.491	0	0	1	71717
NYSE/Amex Size Decile (1-10)	9.229	1.326	1	10	10	74922

Correlation Matrix

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	CDS Spread (bps)	1.000						
(2)	CDS Return (%)	0.151	1.000					
(3)	CDS Depth	-0.114	-0.016	1.000				
(4)	Stock Return (%)	0.049	0.347	-0.013	1.000			
(5)	Size	-0.158	-0.008	0.107	-0.021	1.000		
(6)	S&P Rating	0.477	0.023	-0.181	0.012	-0.514	1.000	
(7)	Size Decile	-0.386	-0.013	0.226	-0.029	0.275	-0.508	1.000

Table 2. CDS Momentum

This table presents our basic CDS momentum results. Firms are sorted on past CDS return into five equally-sized portfolios in which portfolio 1 (5) is the group with the lowest (highest) past CDS return using a formation period J. The long/short strategy is constructed by purchasing CDS contracts of firms in portfolio 5 (High) and selling CDS contracts in portfolio 1 (Low) and holding for period K. Panel A contains equally-weighted returns (%) of each portfolio as well as the long/short strategy. The Sharpe Ratio is computed as the mean return divided by the standard deviation of returns. "Size Decile" refers to the mean size decile of all NYSE/AMEX listed firms. "S&P Rating" is the numerical score of the firm's credit rating provided by Standard and Poors. "Avg. N" is the mean number of firms in the momentum portfolio (P). The 3-month and 6-month holding periods are reported as monthly returns and are computed so as to avoid overlapping returns. Panel B repeats the analysis after dividing the sample period into the pre-crisis (Jan 2003 - Jun 2007), crisis (Jul 2007 - Apr 2010), and post-crisis periods (May 2010 - Dec 2011). Panel C reports returns of investment grade and junk grade firms. 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. Momentum Returns (Equally-Weighted)

	Momentum Portfolios P					Holding Period K		
	P1	P2	P3	P4	P5	Long/Short Strategy (= P5 − P1)		
						$K = 1w$		
$J = 1w$	-0.0868	-0.0329***	-0.00755	0.0559**	0.106**	0.193***		
	(-1.03)	(-2.92)	(-0.94)	(2.38)	(2.14)	(2.99)		
Sharpe Ratio						0.138		
Size Decile	8.880	9.410	9.390	9.298	8.813	-0.067*		
S&P Rating	9.467	7.713	8.263	9.028	10.67	1.203***		
Depth	5.484	5.040	4.575	4.970	4.922	-0.562***		
Avg. N	183.8	182.9	182.1	182.1	181.9			
						$K = 1m$	$K = 3m$	$K = 6m$
$J = 1m$	-0.0866	-0.0607	-0.0130	0.0164	0.309	0.396***	0.333**	0.238*
	(-0.51)	(-0.90)	(-0.29)	(0.27)	(1.63)	(3.55)	(2.31)	(1.70)
Sharpe Ratio						0.372		
Size Decile	9.004	9.458	9.540	9.426	9.018	0.0136		
S&P Rating	9.891	8.088	7.779	8.421	10.67	0.779***		
Depth	6.376	6.404	6.598	6.615	6.018	-0.358		
Avg. N	148.4	148.6	148.2	148.3	146.2			
						$K = 1m$	$K = 3m$	$K = 6m$
$J = 3m$	-0.193	-0.158*	-0.0332	0.143**	0.327**	0.520***	0.467***	0.310**
	(-0.86)	(-1.79)	(-0.60)	(2.54)	(2.52)	(3.87)	(3.10)	(2.39)
Sharpe Ratio						0.423		
Size Decile	8.923	9.465	9.558	9.450	9.069	0.146		
S&P Rating	10.01	8.071	7.625	8.357	10.77	0.763*		
Depth	6.560	6.420	6.715	6.726	5.943	-0.617*		
Avg. N	146.0	146.2	146.1	146.2	146.2			

Table 2 *(continued)*

Panel A *(continued)*

	Momentum Portfolios P					Holding Period K		
	P1	P2	P3	P4	P5	Long/Short Strategy (= P5 − P1)		
						$K = 1m$	$K = 3m$	$K = 6m$
$J = 6m$	-0.160	-0.0537	-0.00245	0.00317	0.283*	0.443***	0.342**	0.261*
	(-0.73)	(-0.68)	(-0.05)	(0.05)	(1.85)	(3.19)	(2.41)	(1.85)
Sharpe Ratio						0.385		
Size Decile	8.890	9.514	9.574	9.462	9.077	0.187*		
S&P Rating	9.946	7.857	7.610	8.419	10.88	0.934*		
Depth	6.713	6.644	6.925	6.808	5.872	-0.841**		
Avg. N	142.7	142.9	142.9	142.9	143.4			
						$K = 1m$	$K = 3m$	$K = 6m$
$J = 9m$	-0.169	-0.0391	-0.0200	0.0143	0.243*	0.412**	0.292*	0.219
	(-0.67)	(-0.39)	(-0.35)	(0.27)	(1.94)	(2.16)	(1.91)	(1.24)
Sharpe Ratio						0.334		
Size Decile	8.881	9.534	9.577	9.496	9.118	0.237*		
S&P Rating	9.916	7.805	7.515	8.385	10.91	0.994*		
Depth	6.941	6.777	6.970	7.058	5.905	-1.036**		
Avg. N	138.7	138.5	138.6	138.5	138.8			
						$K = 1m$	$K = 3m$	$K = 6m$
$J = 12m$	-0.153	-0.0343	-0.0238	0.00483	0.198*	0.351	0.249	0.182
	(-0.56)	(-0.32)	(-0.46)	(0.10)	(1.91)	(1.62)	(1.32)	(0.94)
Sharpe Ratio						0.297		
Size Decile	8.892	9.541	9.612	9.505	9.142	0.250*		
S&P Rating	9.914	7.740	7.456	8.351	10.88	0.966*		
Depth	7.139	6.893	7.113	7.168	6.034	-1.105**		
Avg. N	132.3	132.4	132.2	132.4	132.5			

Table 2 *(continued)*

Panel B. Momentum Returns by Time Period

	Momentum Portfolios P					Holding Period K		
	P1	P2	P3	P4	P5	Long/Short Strategy (= P5 − P1)		
Pre-Crisis Period (January 2003 - June 2007)						$K = 1m$	$K = 3m$	$K = 6m$
$J = 3m$	0.0806	0.0389	0.0322	0.0537	0.309***	0.228**	0.266**	0.240*
	(0.57)	(1.43)	(1.30)	(1.38)	(2.99)	(2.15)	(2.12)	(1.90)
Sharpe Ratio						0.303		
Size Decile	9.159	9.696	9.723	9.584	9.266	0.107		
S&P Rating	9.194	7.006	7.012	8.243	10.95	1.756***		
Depth	8.571	8.131	8.556	8.737	6.959	-1.612**		
Avg. N	140.8	140.0	140.9	140.0	139.7			
Crisis Period (July 2007 - April 2010)								
$J = 3m$	-0.639	-0.356	-0.136	0.150	0.333	0.971**	0.815*	0.484*
	(-0.99)	(-1.44)	(-0.86)	(0.98)	(0.98)	(2.56)	(2.11)	(1.95)
Sharpe Ratio						0.385		
Size Decile	8.737	9.362	9.486	9.369	8.986	0.249		
S&P Rating	10.43	8.652	7.841	8.651	10.75	0.320		
Depth	6.193	6.237	6.353	6.040	5.631	-0.562		
Avg. N	160.7	160.5	160.5	160.5	159.8			
Post-Crisis Period (May 2010 - December 2011)								
$J = 3m$	-0.370	-0.197	-0.0152	0.129*	0.271	0.641**	0.386**	0.186
	(-0.95)	(-1.54)	(-0.24)	(1.65)	(1.19)	(2.85)	(1.96)	(1.54)
Sharpe Ratio						0.560		
Size Decile	8.649	9.316	9.425	9.281	9.011	0.362		
S&P Rating	10.82	8.571	8.127	8.562	10.55	-0.270		
Depth	4.422	3.987	3.956	3.896	4.063	-0.359		
Avg. N	136.1	136.9	136.8	136.9	136.3			

Table 2 *(continued)*

Panel C. Momentum Returns by Investment Grade/Junk Grade

	Momentum Portfolios P					Holding Period K		
	P1	P2	P3	P4	P5	Long/Short Strategy (= P5 − P1)		
Investment Grade (BBB- and above)						$K = 1m$	$K = 3m$	$K = 6m$
$J = 3m$	-0.125	-0.0907	-0.0299	0.0541	0.143**	0.268***	0.271**	0.209*
	(-0.92)	(-1.35)	(-0.67)	(1.26)	(2.04)	(2.88)	(2.19)	(1.78)
Sharpe Ratio						0.310		
Size Decile	9.539	9.680	9.697	9.647	9.574	0.0350		
S&P Rating	7.634	7.067	6.948	7.309	8.149	0.515***		
Depth	7.627	6.621	6.763	6.978	7.187	-0.440		
Avg. N	97.67	97.76	97.64	97.76	98.01			
Junk Grade (BB+ and below)								
$J = 3m$	-0.216	-0.0264	0.133	0.200*	0.617**	0.833***	0.669***	0.443**
	(-0.54)	(-0.15)	(0.76)	(1.70)	(2.36)	(3.81)	(3.05)	(2.19)
Sharpe Ratio						0.320		
Size Decile	7.856	8.473	8.677	8.683	8.343	0.487***		
S&P Rating	13.54	12.88	12.71	12.94	13.76	0.220		
Depth	5.273	4.735	4.981	4.896	4.910	-0.363		
Avg. N	51.85	52.67	52.69	51.67	50.50			

Table 3. CDS Momentum Returns: Size, Rating and Depth

This table shows the robustness of CDS momentum to common risk factors and firm characteristics. Panel A reports the alpha coefficients of four factor model regressions using common stock and bond risk factors. Panel B reports the characteristic-adjusted returns of CDS momentum portfolios and the long/short strategy. Returns are adjusted for size, rating and depth. The size (depth) adjustment is made by subtracting the mean return at each size (depth) decile from the actual return each month. The rating adjustment is made by subtracting the mean return at each rating. Panel C reports momentum profits by quintiles of raw size, rating and depth as well as orthogonalized size, rating and depth. The difference in average returns between Q5 and Q1 is also given and a t-test is given for equivalence to zero. Each CDS momentum strategy utilizes a formation period $J = 3m$ and a holding period $K = 1m$. 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. CDS Momentum Alphas

Model	*Factors*
(1)	brDEFAULT†, brTERM†
(2)	Mkt, SMB, HML, UMD
(3)	brDEFAULT†, brTERM†, Mkt, SMB, HML, UMD
(4)	brDEFAULT†, brTERM†, Mkt, SMB, HML, sMOM

Model	CDS Momentum Portfolio Alphas ($J = 3m$, $K = 1m$)					Long/Short Strategy Alphas (= P5 − P1)			
	P1	P2	P3	P4	P5	**Full Sample**	Pre	Crisis	Post
(1)	-0.298	-0.131	-0.0574	0.0249	0.313***	**0.611*****	0.363***	0.894***	0.648***
	(-1.46)	(-1.62)	(-1.36)	(0.55)	(2.68)	**(4.35)**	(4.54)	(3.25)	(4.07)
(2)	-0.313***	-0.113**	-0.0609*	0.0116	0.270***	**0.583*****	0.416***	0.570***	0.809***
	(-2.75)	(-1.96)	(-1.71)	(0.37)	(3.05)	**(6.04)**	(4.52)	(2.91)	(3.58)
(3)	-0.362***	-0.144**	-0.0637**	0.0170	0.290***	**0.652*****	0.416***	0.718***	0.829***
	(-3.08)	(-2.59)	(-2.20)	(0.54)	(3.19)	**(5.96)**	(4.14)	(3.11)	(3.66)
(4)	-0.173	-0.122	-0.0313	0.101*	0.333**	**0.506*****	0.348***	0.692**	0.604***
	(-0.81)	(-1.52)	(-0.58)	(1.91)	(2.56)	**(4.08)**	(4.56)	(2.07)	(2.91)

†Based on end-of-month data.

Table 3 *(continued)*

Panel B. Robustness of CDS Momentum to Characteristic-Adjusted Returns

	Momentum Portfolios P ($J = 3m$, $K = 1m$)					Long/Short Strategy (= P5 − P1)			
	P1	P2	P3	P4	P5	**Full Sample**	Pre-Crisis	Crisis	Post-Crisis
Size-Adjusted Returns									
	-0.184*	-0.117***	-0.0659**	-0.000376	0.224***	**0.408***	0.286***	0.550*	0.488**
	(-1.64)	(-3.09)	(-2.03)	(-0.01)	(4.22)	**(3.58)**	(4.04)	(1.76)	(2.74)
S&P Rating-Adjusted Returns									
	-0.173*	-0.168**	-0.0309	0.113***	0.171***	**0.344***	0.220***	0.515	0.377**
	(-1.64)	(-2.03)	(-1.25)	(3.12)	(3.82)	**(2.93)**	(2.91)	(1.59)	(2.41)
Depth-Adjusted Returns									
	-0.153	-0.110**	-0.0812	-0.0326	0.210***	**0.363***	0.244***	0.471	0.496**
	(-1.58)	(-2.24)	(-1.29)	(-0.57)	(4.29)	**(3.34)**	(3.46)	(1.61)	(2.60)
Size, Rating and Depth-Adjusted Returns									
	-0.170*	-0.0593**	-0.0309	-0.00169	0.144***	**0.314***	0.234***	0.444**	0.293***
	(-1.74)	(-2.07)	(-1.56)	(-0.07)	(3.64)	**(3.33)**	(2.98)	(1.99)	(3.42)

Table 3 *(continued)*

Panel C. CDS Momentum Returns by Quintiles of Size, Rating and Depth

	Long/Short Momentum Strategy at Quintile Q					Difference Between Quintiles (= Q5 − Q1)			
	Q1	Q2	Q3	Q4	Q5	**Full Sample**	Pre-Crisis	Crisis	Post-Crisis
Size	*Small*				*Large*	*Large − Small*			
	0.811**	0.357**	0.506***	0.435***	0.129	**-0.682****	-0.416	-0.758**	-1.043
	(2.42)	(2.00)	(3.03)	(3.11)	(1.56)	**(-2.07)**	(-1.22)	(-2.33)	(-1.23)
	0.270	0.281	0.382	0.473	0.169				
S&P Rating	*Safe*				*Risky*	*Risky − Safe*			
	0.0822	0.106	0.145*	0.359**	1.113***	**1.031*****	0.767***	1.034***	1.429**
	(0.77)	(0.98)	(1.83)	(2.44)	(4.10)	**(4.56)**	(3.29)	(3.99)	(2.47)
	0.112	0.0980	0.220	0.248	0.488				
CDS Depth	*Low*				*High*	*High − Low*			
	-0.294*	0.326*	0.733***	0.687***	0.798***	**1.092*****	0.416**	1.250***	2.030***
	(-1.78)	(1.76)	(3.20)	(3.64)	(4.56)	**(5.07)**	(2.13)	(3.33)	(3.93)
	-0.207	0.456	0.218	0.306	0.503				
Size (Orthogonalized)	*Small*				*Large*	*Large − Small*			
	0.418**	0.334**	0.242**	0.334**	0.107	**-0.311**	-0.143	0.227	-0.858*
	(2.23)	(2.20)	(2.16)	(2.20)	(0.91)	**(-1.63)**	(-0.71)	(0.97)	(-1.82)
	0.272	0.188	0.210	0.188	0.140				
S&P Rating (Orthogonalized)	*Safe*				*Risky*	*Risky − Safe*			
	0.246	0.309*	0.368***	0.441***	0.939***	**0.693*****	0.408*	0.908**	1.007**
	(1.40)	(1.73)	(3.00)	(3.14)	(3.59)	**(3.20)**	(1.66)	(2.15)	(2.02)
	0.291	0.185	0.341	0.441	0.366				
CDS Depth (Orthogonalized)	*Low*				*High*	*High − Low*			
	-0.220*	-0.125	0.0953	0.653***	0.705***	**0.925*****	0.588***	0.942***	1.427***
	(-1.84)	(-0.96)	(0.48)	(3.27)	(3.96)	**(4.98)**	(3.55)	(3.49)	(2.96)
	-0.229	-0.0477	0.141	0.322	0.436				

Table 4. CDS Momentum and Credit Ratings Changes

This table provides results analyzing the relationship between CDS momentum and future S&P credit rating changes. Panel A presents cumulative CDS returns in % leading up to a credit rating change event in month t. Panel B examines CDS momentum returns and credit rating changes. After forming the momentum portfolios, we track the returns of firms that have a rating change in the next six months and those that do not. Returns are reported separately for firms that have no rating change, firms that are upgraded, firms that are downgraded, and firms that have a rating change in the "anticipated direction," an upgrade for P5 (*winners*) and a downgrade for P1 (*losers*). P5−P1 represents the long/short strategy return within the corresponding group. Also reported are the *fraction* of upgrades and downgrades within P1 and P5, labeled n_{up}/N for upgrades and n_{dn}/N for downgrades, which is computed as the number of firms with the rating change divided by number of firms in the momentum portfolio. Panel C divides firms by investment/junk grade and repeats the analysis. Panel D divides firms by high/low depth and repeats the analysis. 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. Cumulative CDS Returns Prior to Ratings Change Events

	Cumulative CDS Returns (starting at month $t-6$ until $t-1$)						Event Return
	$t-6$	$t-5$	$t-4$	$t-3$	$t-2$	$t-1$	in Month t
Upgrade Event	0.422***	0.691***	0.870***	1.372***	1.633***	2.206***	0.440**
	(3.06)	(3.31)	(3.25)	(3.39)	(3.27)	(4.00)	(1.98)
Downgrade Event	-0.871***	-1.123***	-1.954***	-2.246***	-2.528***	-3.242***	-1.327***
	(-6.68)	(-5.34)	(-7.88)	(-7.57)	(-7.42)	(-7.97)	(-3.89)

Panel B. CDS Momentum Returns and Credit Rating Changes

	Momentum Portfolios P		Long/Short Strategy (= P5 − P1)			
	P1	P5	Entire Sample	Pre-Crisis	Crisis	Post-Crisis
No Rating Change	0.0188	0.121	0.102	0.0272	0.0647	0.379**
	(0.12)	(1.04)	(1.04)	(0.31)	(0.26)	(2.54)
Upgrade	0.282	0.840**	0.558**	0.317	0.925	0.551
	(1.59)	(2.52)	(2.16)	(1.52)	(1.40)	(1.38)
Downgrade	-1.204**	-0.305*	0.899**	0.424	1.217	1.638
	(-2.13)	(-1.84)	(2.01)	(1.36)	(1.21)	(1.15)
n_{up}/N (fraction)	0.0500	0.102	0.052***	0.0326***	0.0670***	0.0858***
n_{dn}/N (fraction)	0.206	0.110	-0.096***	-0.0844***	-0.143***	-0.0379*
	Downgrade	*Upgrade*				
Anticipated Direction	-1.204**	0.840**	2.044***	0.904***	3.395***	2.734*
	(-2.13)	(2.52)	(4.70)	(3.57)	(4.57)	(1.84)
	Upgrade	*Downgrade*				
Unanticipated Direction	0.282	-0.305*	-0.587**	-0.128	-1.282***	-0.441
	(1.59)	(-1.84)	(2.14)	(-0.70)	(-3.30)	(-1.08)

Table 4 *(continued)*

Panel C. CDS Momentum and Credit Rating Changes: Investment/Junk Grade

	Momentum Portfolios P		Long/Short Strategy (= P5 − P1)			
	P1	P5	Entire Sample	Pre-Crisis	Crisis	Post-Crisis
by CREDIT RATING						
Investment Grade						
No Rating Change	0.0195	0.0979	0.0784	0.0356	0.124	0.112
	(0.18)	(1.30)	(1.13)	(0.70)	(0.65)	(1.23)
n_{up}/N (fraction)	0.0376	0.0595	0.0219***	0.0132**	0.0198**	0.0531***
n_{dn}/N (fraction)	0.184	0.0938	-0.0908***	-0.0810***	-0.127***	-0.0418*
	Downgrade	*Upgrade*				
Anticipated Direction	-0.521	0.232*	0.753**	0.535*	1.038	0.838*
	(-1.46)	(1.89)	(2.55)	(1.86)	(1.39)	(1.76)
Junk Grade						
No Rating Change	0.0903	0.238	0.148	0.0293	-0.00935	0.760***
	(0.35)	(0.98)	(0.89)	(0.14)	(-0.03)	(3.81)
n_{up}/N (fraction)	0.0920	0.167	0.0750***	0.0293*	0.126***	0.157***
n_{dn}/N (fraction)	0.273	0.122	-0.151***	-0.147***	-0.205***	-0.0597*
	Downgrade	*Upgrade*				
Anticipated Direction	-2.289***	1.071**	3.360***	2.091***	4.972***	3.930*
	(-2.99)	(1.96)	(5.79)	(3.53)	(6.12)	(1.95)
Return Difference (Junk − Investment): No Rating Change			**0.0696**			
			(0.19)			
Return Difference (Junk − Investment): Anticipated Direction			**2.607****			
			(2.12)			

Table 4 *(continued)*

Panel D. CDS Momentum and Credit Rating Changes: CDS Depth

	Momentum Portfolios P		Long/Short Strategy (= P5 − P1)			
	P1	P5	Entire Sample	Pre-Crisis	Crisis	Post-Crisis
by CDS DEPTH						
High Depth						
No Rating Change	0.0112	0.224*	0.213**	0.105	0.248	0.445**
	(0.06)	(1.69)	(2.05)	(1.25)	(0.94)	(2.62)
n_{up}/N (fraction)	0.0479	0.0973	0.0494***	0.0274***	0.0733***	0.107***
n_{dn}/N (fraction)	0.235	0.115	-0.120***	-0.102***	-0.186***	-0.0659**
	Downgrade	*Upgrade*				
Anticipated	-1.393**	1.037**	2.430***	0.994***	4.154***	3.260**
Direction	(-2.14)	(2.27)	(4.45)	(2.95)	(4.08)	(1.98)
Low Depth						
No Rating Change	0.0258	0.0178	-0.0080	-0.0552	-0.109	0.307**
	(0.19)	(0.16)	(-0.08)	(-0.54)	(-0.49)	(2.45)
n_{up}/N (fraction)	0.0593	0.108	0.0487***	0.0333***	0.0554***	0.0855***
n_{dn}/N (fraction)	0.175	0.111	-0.0640***	-0.0565***	-0.0940***	-0.0107
	Downgrade	*Upgrade*				
Anticipated	-0.642	0.442*	1.084***	0.780**	1.958**	0.322
Direction	(-1.48)	(1.80)	(3.15)	(2.12)	(2.45)	(0.70)
Return Difference (High Depth − Low Depth): No Rating Change			**0.221***			
			(1.72)			
Return Difference (High Depth − Low Depth): Anticipated Direction			**1.346****			
			(1.99)			

Table 5. CDS Momentum and Momentum Elsewhere

This table explores the relation between CDS momentum and return momentum in other markets. Panel A shows the time-series correlation between CDS momentum and stock as well as bond momentum over various time horizons and across multiple subgroups based on S&P rating and CDS depth. Panel B reports lead/lag effects in the momentum time-series of CDS, bonds, and stock. Panel C presents joint-market momentum results. Reported are CDS returns at intersections of CDS momentum portfolios P and stock momentum portfolios sP. For example, the combination (P1, sP1) includes firms that fall into P1 *and* sP1 (i.e., the CDS and stock signals point in the same direction). The relative value of the CDS (stock) is defined as the CDS-based (stock-based) long/short return conditional on the firm falling into a winner or loser stock (CDS) momentum portfolio. For example, P5−P1 in sP1 measures the marginal ability of the CDS signal (past CDS return) to predict future CDS returns conditional on the negative stock signal. 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. Time-Series Correlation between CDS Momentum and Momentum Elsewhere

	Full Sample	Pre-Crisis	Crisis	Post-Crisis
BOND MOMENTUM				
All Firms†	**0.255**	0.103	0.281	0.043
Investment Grade†	**0.304**	0.163	**0.359**	0.261
Junk Grade†	-0.053	-0.071	-0.082	0.102
STOCK MOMENTUM				
UMD Factor	**0.388**	-0.024	**0.560**	**-0.599**
All Firms (in sample)	**0.533**	0.258	**0.574**	**0.657**
Investment Grade	**0.443**	0.077	**0.484**	**0.599**
Junk Grade	**0.267**	0.015	**0.440**	0.271
High Depth	**0.536**	0.196	**0.598**	**0.585**
Low Depth	**0.407**	0.275	**0.432**	0.483

Bold font indicates statistical significance at the 1% level.
†Based on end-of-month series & ends June 2011

Panel B. Lead/Lag Effects in Time-Series of CDS, Bond and Stock Momentum Returns

	Dependent Variable					
	CDS MOM	CDS MOM	Bond MOM	Bond MOM	Bond MOM	Stock MOM
CDS MOM			0.432***		0.475***	2.472***
			(3.26)		(3.10)	(6.54)
L.CDS MOM	-0.104	0.0167	0.629***		0.367**	-0.122
	(-0.95)	(0.17)	(4.58)		(2.30)	(-0.27)
Bond MOM	0.228***					
	(3.26)					
L.Bond MOM	-0.104		0.380***	0.492***	0.411***	
	(-1.64)		(4.77)	(6.11)	(5.15)	
Stock MOM		0.120***		0.0437	-0.0161	
		(6.54)		(1.47)	(-0.48)	
L.Stock MOM		0.0100		0.145***	0.0956***	-0.0809
		(0.46)		(4.98)	(2.90)	(-0.82)
Observations	101	106	101	101	101	106
R^2	0.101	0.296	0.419	0.385	0.470	0.302

Table 5 *(continued)*

Panel C. CDS Returns of Joint-market Momentum Strategies

	Intersection of CDS and Stock Momentum				Relative Value of CDS		Relative Value of Stock	
	P1, sP1	P1, sP5	P5, sP1	P5, sP5	P5-P1 in sP1	P5-P1 in sP5	sP5-sP1 in P1	sP5-sP1 in P5
ALL FIRMS								
	-0.631**	-0.0430	0.375**	0.329***	1.006***	0.372***	0.588**	-0.0462
	(-2.55)	(-0.27)	(2.17)	(3.25)	(6.23)	(2.72)	(2.05)	(-0.37)
by CREDIT RATING								
Investment Grade	-0.218	0.0470	0.0313	0.117*	0.249*	0.0702	0.265	0.0857
	(-1.28)	(0.40)	(0.30)	(1.82)	(1.79)	(0.61)	(1.64)	(0.97)
Junk Grade	-1.387***	-0.0404	1.320***	0.530***	2.707***	0.570**	1.347***	-0.790*
	(-3.60)	(-0.18)	(2.79)	(2.99)	(6.12)	(2.53)	(3.86)	(-1.83)
by CDS DEPTH								
High Depth	-0.243	0.0135	0.0822	0.243**	0.325*	0.230*	0.257	0.161
	(-0.99)	(0.09)	(0.40)	(2.24)	(1.88)	(1.80)	(1.57)	(1.00)
Low Depth	0.200	0.963***	0.181	0.423*	-0.0190	-0.540	0.763*	0.242
	(0.75)	(2.65)	(1.10)	(1.95)	(-0.03)	(-1.40)	(1.83)	(0.93)

Table 6. Momentum Spillover from CDS to Stocks

This table presents evidence of momentum spillover from the CDS market to the stock market. Panel A presents cross-market momentum results. Reported are stock returns in % and Sharpe ratios of momentum portfolios based on the past 3-month CDS return. Also reported are the alpha coefficients of a Carhart four-factor model (Car4) that includes the factors Mkt, SMB, HML, and UMD and a localized four-factor model (Loc4) that includes Mkt, SMB, HML, and sMOM. Panel B presents joint-market momentum results. Reported are the stock returns in % of stock-based momentum portfolios and the intersection of CDS and stock portfolios. For example, (P1, sP1) includes firms that fall into both the CDS-based momentum portfolio P1 and the stock-based momentum portfolio sP1. The *fraction* of firms that have a rating change is also reported (e.g., The label n_{dn}/N (n_{up}/N) [n_{ant}/N] refers to the fraction of firms in the portfolio that have a downgrade (upgrade) [anticipated change] relative to the total number of firms in the portfolio). 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. Cross-market Momentum Returns: CDS to Stocks

	CDS-based Momentum Portfolios (P)					Long/Short Strategy (= P5 − P1)				Risk-Adjusted Returns	
	P1	P2	P3	P4	P5	**Full Sample**	Pre-Crisis	Crisis	Post-Crisis	Car4 Alpha	Loc4 Alpha
ALL FIRMS											
	0.0574	0.392	0.530	0.401	0.575	**0.518****	0.128	1.263	0.230	0.638*	0.635*
	(0.07)	(0.65)	(0.99)	(0.73)	(0.81)	**(1.69)**	(0.58)	(1.58)	(0.47)	(1.91)	(1.82)
						0.142	0.0748	0.246	0.108		
by CREDIT RATING											
Investment Grade	0.350	0.403	0.490	0.333	0.313	**-0.0364**	-0.0374	0.148	-0.374	0.0742	0.0774
	(0.52)	(0.77)	(0.99)	(0.67)	(0.56)	**(-0.16)**	(-0.31)	(0.23)	(-1.20)	(0.39)	(0.44)
						-0.0548	-0.0299	0.0378	-0.295		
Junk Grade	-0.363	0.516	0.890	0.723	1.002	**1.365****	1.163*	2.168	0.449	1.492**	1.501**
	(-0.34)	(0.52)	(0.87)	(0.77)	(0.99)	**(2.29)**	(1.76)	(1.66)	(0.36)	(2.31)	(2.31)
						0.230	0.238	0.300	0.0827		
by CDS DEPTH											
High Depth	-0.130	0.0907	0.434	0.447	0.676	**0.806****	0.395*	1.488*	0.696	0.954***	0.956***
	(-0.17)	(0.19)	(0.96)	(0.98)	(1.11)	**(2.53)**	(1.88)	(1.83)	(1.18)	(2.94)	(2.82)
						0.247	0.226	0.242	0.313		
Low Depth	0.213	0.335	0.529	0.466	0.166	**-0.0473**	-0.0279	0.119	-0.407	0.0146	0.0125
	(0.35)	(0.69)	(1.06)	(0.96)	(0.28)	**(-0.23)**	(-0.12)	(0.24)	(-1.70)	(0.06)	(0.05)
						-0.0448	-0.0149	0.0362	-0.278		

Table 6 *(continued)*

Panel B. Stock Returns of Joint-market Momentum Returns

	Stock Momentum Portfolios sP			Intersection of CDS and Stock (P, sP)			Difference in Joint- and Single-market Strategies			
	sP1	sP5	sP5−sP1	P1, sP1	P5, sP5	P5,sP5−P1,sP1	**Entire Sample**	Pre-Crisis	Crisis	Post-Crisis
ALL FIRMS			*Single-market*			*Joint-market*	*Difference*			
	0.140	0.263	0.124	-0.340	0.820*	1.160***	**1.037***	0.142	2.647	0.565
	(0.13)	(0.41)	(0.16)	(-0.50)	(1.72)	(2.95)	**(1.72)**	(0.29)	(1.63)	(0.81)
n_{up}/N (fraction)	0.0678	0.0901	0.0223***	0.0525	0.181	0.129***	0.107***			
n_{dn}/N (fraction)	0.189	0.103	-0.086***	0.324	0.108	-0.216***	-0.130***			
n_{ant}/N (fraction)	0.189	0.0901		0.324	0.181		Fraction Diff: P1= 0.135***, P5=0.0909***			
by CREDIT RATING										
Investment Grade	0.127	-0.157	-0.284	-0.713	-0.463	0.250	**0.534**	-0.745	2.699**	0.800
	(0.15)	(-0.29)	(-0.43)	(-0.73)	(-1.09)	(0.47)	**(1.17)**	(-1.19)	(2.11)	(0.93)
n_{ant}/N (fraction)	0.158	0.0554		0.290	0.075		Fraction Diff: P1=0.132***, P5=0.0196**			
Junk Grade	-0.284	1.170	1.453	-0.742	1.171	1.913***	**0.460**	0.00444	1.437	1.030
	(-0.19)	(1.22)	(1.40)	(-0.74)	(1.61)	(2.97)	**(0.79)**	(0.01)	(0.67)	(1.23)
n_{ant}/N (fraction)	0.258	0.172		0.417	0.284		Fraction Diff: P1=0.159***, P5=0.112***			
by CDS DEPTH										
High Depth	0.208	0.181	-0.0274	-0.823	1.120*	1.944**	**1.971*****	0.733*	4.029**	1.635**
	(0.20)	(0.29)	(-0.04)	(-0.84)	(1.72)	(2.45)	**(3.22)**	(1.80)	(2.38)	(2.45)
n_{ant}/N (fraction)	0.206	0.0890		0.341	0.182		Fraction Diff: P1=0.135***, P5=0.093***			
Low Depth	0.379	0.456	0.0771	-0.210	0.548	0.758	**0.681**	0.185	0.630	1.599*
	(0.34)	(0.68)	(0.09)	(-0.27)	(1.29)	(1.11)	**(1.27)**	(0.44)	(0.54)	(2.03)
n_{ant}/N (fraction)	0.176	0.100		0.278	0.180		Fraction Diff: P1=0.102***, P5=0.080***			

Figure 1. CDS Spreads and S&P Credit Rating Changes

This figure displays average CDS spread movements around S&P credit rating changes. We plot the cumulative percentage change in 5-year CDS spread over the interval $[-90, 90]$ days centered around rating downgrade and upgrade events labelled day-0. Depicted are 1,093 rating downgrade events averaging a 1.32 notch deterioration in credit quality and 739 rating upgrade events averaging a 1.21 notch improvement in quality. A 1 notch change in S&P credit ratings is based on the rating scale that includes sub-ratings at each level between AA and CCC (e.g., AA+, AA, and AA-). CDS data are provided by Markit. The time period is January 2003 to December 2011.

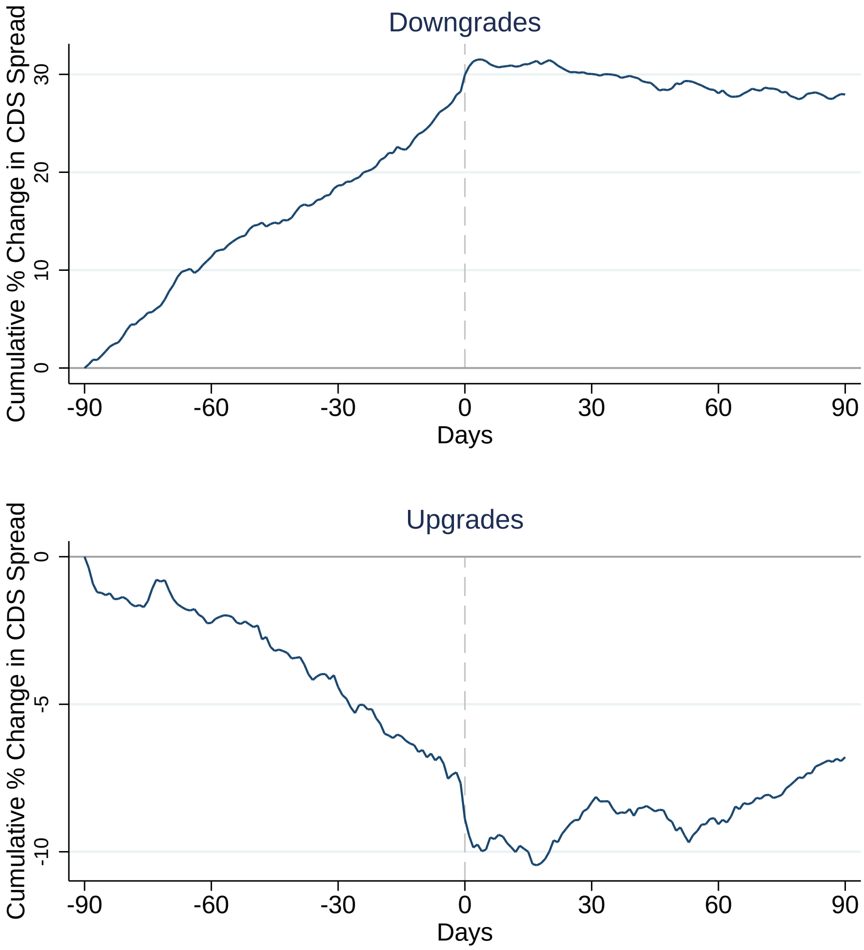
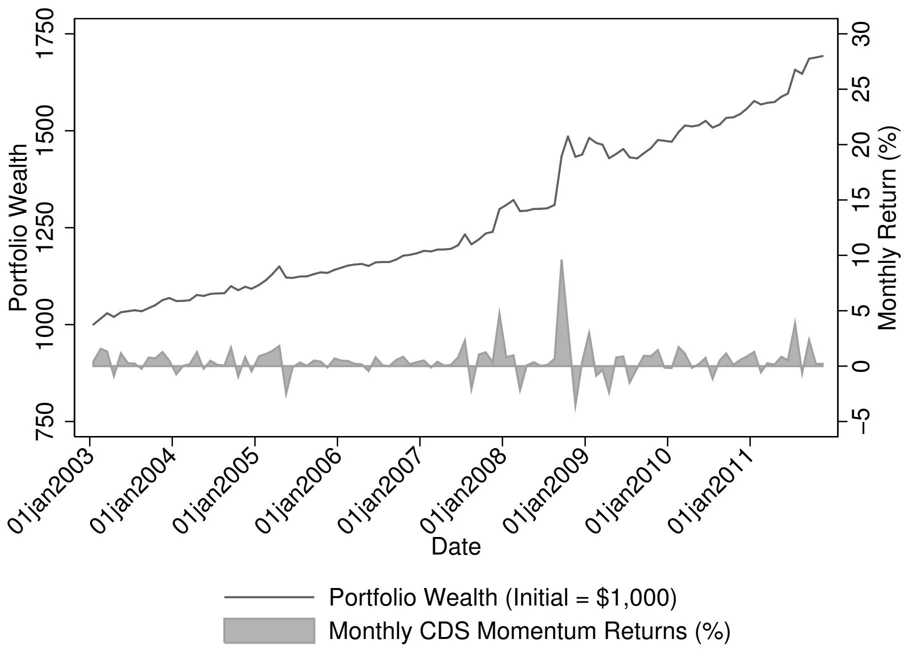


Figure 2. CDS Momentum Returns

This figure presents various aspects of a CDS momentum strategy using a three-month formation period ($J = 3$) and a one-month holding period ($K = 1$). Panel A presents (*i*) the cumulative wealth of a portfolio invested in the CDS momentum strategy at the beginning of the sample period and (*ii*) individual monthly returns of the momentum strategy. The initial portfolio value is $1,000. The momentum strategy is constructed by purchasing the CDS contracts in the highest quintile of 3-month performance and selling short the CDS contracts in the lowest quintile. The left y-axis tracks the portfolio wealth (in $) and the right y-axis measures the monthly return (in %). Panel B presents the 12-month moving average of monthly CDS momentum returns (in %). CDS data are provided by Markit. The time period is January 2003 to December 2011.

Panel A. Portfolio Wealth of the CDS Momentum Strategy



Panel B. 12-Month Moving Average of CDS Momentum Returns

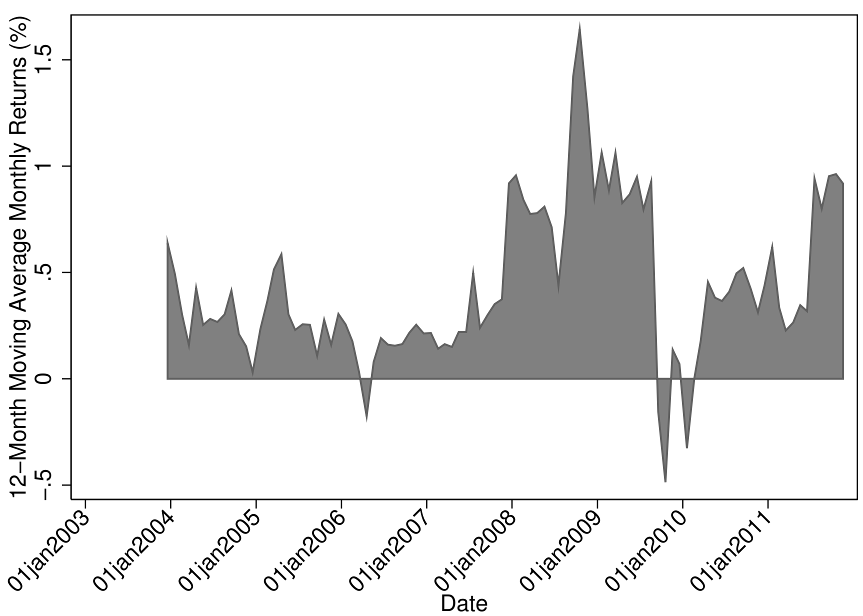
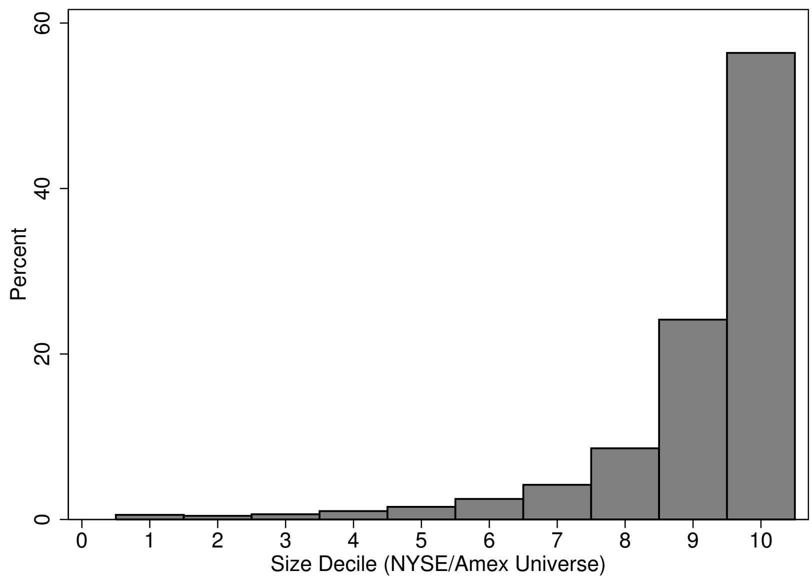


Figure 3. Sample Composition

This figure describes the composition of the sample used in this study. Panel A is a histogram that shows the percentage of the sample in each decile of all NYSE/AMEX listed firms. For example, decile 10 refers to the biggest 10% of firms in the NYSE/AMEX universe. Panel B is a histogram that shows the percentage of the sample in each S&P credit rating category. Panel C is an industry histogram. Panel D is a histogram of CDS depth (i.e., number of contributors to the quoted spread). CDS data are provided by Markit. The time period is January 2003 to December 2011.

Panel A. Histogram of Size Deciles of the NYSE/AMEX Universe



Panel B. Histogram of S&P Credit Rating

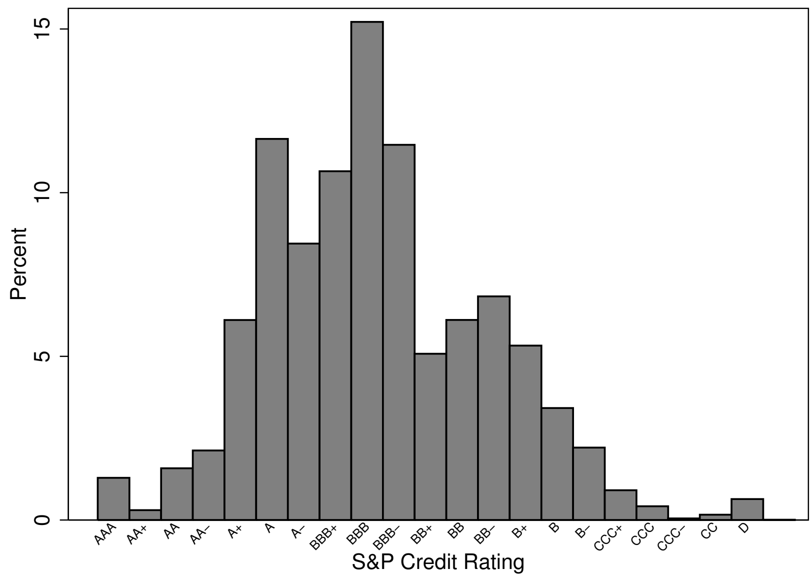
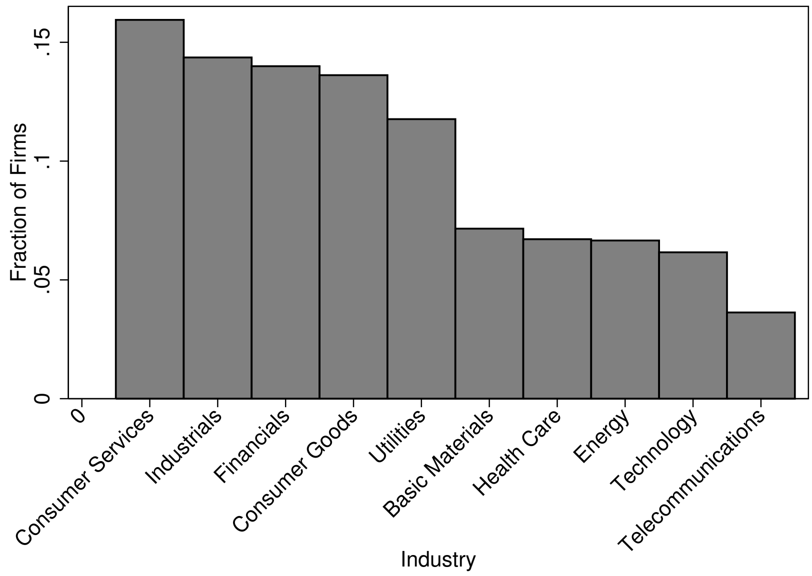


Figure 3 *(continued)*

Panel C. Histogram of Industry Coverage



Panel D. Histogram of CDS Depth

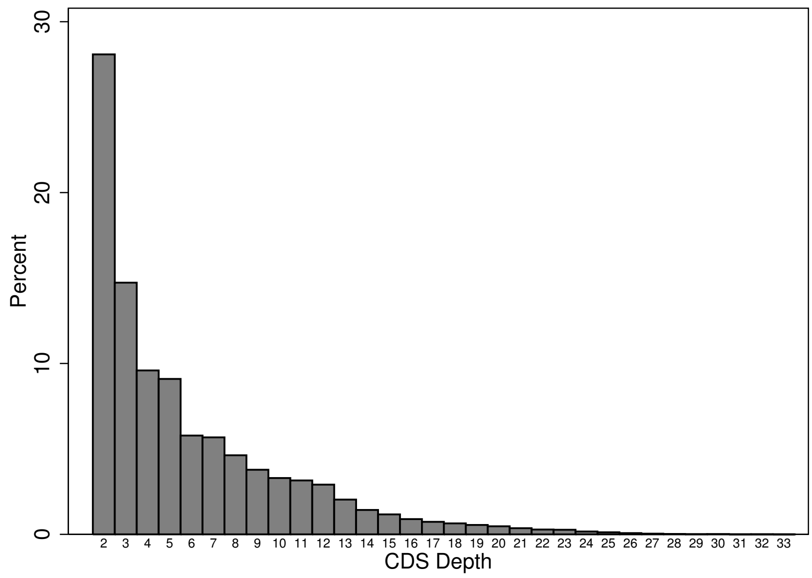


Figure 4. Time Series of CDS Spreads, CDS Returns and Stock Returns

This figure displays the time series of CDS spreads (top graph), CDS returns (bottom graph, solid line) and stock returns (bottom graph, dashed line) for all 1,247 firms in our sample from January 2003 to December 2011. CDS data are provided by Markit, and stock data are acquired from CRSP.

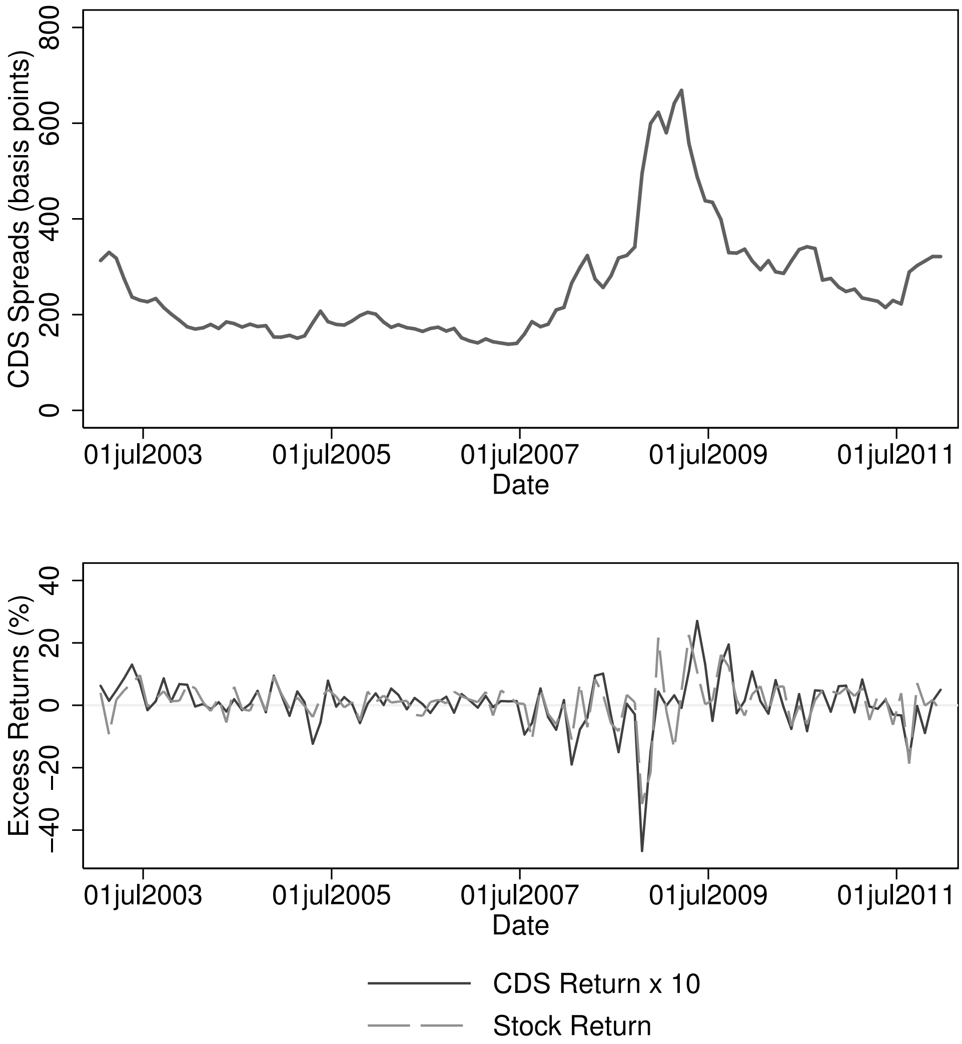


Figure 5. CDS-to-Stock Momentum

This figure portrays the profitability of the CDS-to-stock momentum strategy, the stock momentum strategy using the UMD factor, the stock momentum strategy using our sample of firms, and the joint momentum strategy sorting on both the past CDS return and past stock return. The CDS-to-stock momentum strategy is constructed by purchasing the equity of firms in the highest quintile of 3-month CDS return (*winners*) and selling short the equity of firms in the lowest quintile (*losers*). The y-axis tracks the dollar value of a portfolio that invests in each momentum strategy. The initial portfolio value is $1000. CDS data are provided by Markit. The time period is January 2003 to December 2011.