MARKET SEGMENTATION AND DEFAULT RISK: THE CDS AND LOAN CDS MARKETS

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Abstract

We identify significantly positive pricing-parity deviations from a simulated portfolio that participates in opposite legs of the undervalued and overvalued contracts in the CDS and LCDS markets for exactly the same underlying firm, maturity, currency and restructure clauses. These deviations cannot be accounted for by trading costs, illiquidity, imperfect data about recovery rates in the event of default, or counterparty risk, suggesting segmentation between CDS and LCDS markets. We confirm the existence of potential trading profits using matured one-year contracts and investigate their determinants through panel regressions that show firm-level variables more important than macro factors in explaining the deviations.

Keywords: Credit Default Swap, Loan Credit Default Swap, Market Efficiency, Market Segmentation

JEL Classification: G3, G14, G18, G32

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1. INTRODUCTION

Credit Default Swaps (CDS) and Loan CDS (LCDS) contracts are essentially financial agreements between protection buyers and protection sellers to transfer the credit risk of the underlying assets (respectively, corporate debts and syndicated secured loans). The more recent LCDS market has grown quickly since its inception in 2006, fueled by the rapid growth in its underlying asset market. Compared to traditional CDS contracts, LCDS contracts have higher recovery rates and cancellability options. Unlike the CDS market, the LCDS market has not been studied extensively in the existing literature due to lack of data.

In this paper we study the pricing-parity relation between CDS and non-cancellable LCDS contracts written on the same firm with the same maturity and restructure clauses.[3] This relation assumes market efficiency and no uncertainty of recovery rates but is otherwise model-free. Using the CDS and LCDS datasets provided by the Markit company we construct a simulated portfolio to exploit deviations from current pricing parity[4] by participating simultaneously in both markets. For the observed CDS and LCDS spreads and the reported recovery rates in the case of default for both types of contracts,[5] the current payoffs to these portfolios are persistently positive over most of our time series data.[6] These positive payoffs are large and exist for all credit-rating classes of loans in our data base. We show that the positive payoffs may be a

[3] See Dobranszky (2008) and Ong, Li and Lu (2012) for the discussion of CDS and non-cancellable LCDS parity.

[4] The current pricing-parity deviation should be zero under the no arbitrage and no recovery rate uncertainty assumptions. Deviations from parity imply that we observe positive current payoffs on the simulated portfolio.

[5] We also call them "Estimated Recovery Rates" since these recovery rates are estimated and provided to Markit by its clients who are active participants in these markets and most probably are large financial institutions.

[6] Since the exploitation of these pricing-parity deviations involves simultaneous trading in both CDS and LCDS markets, we avoid the term "arbitrage profits" for these deviations because of lack of intraday data and information on the liquidity of the LCDS contracts.

tradable anomaly, since they cannot be justified by transaction costs, by imperfect information with respect to the recovery rates, by counterparty risk, or by market illiquidity. We confirm these findings by examining available information on actual simultaneous recovery rates of CDS- and LCDS-underlying assets, by fitting a structural model and estimating first passage default probabilities and CDS recovery rates from various data sources, and by examining the realized payoffs of our portfolios for the matured contract pairs in our data base. In most cases we find that the positive current payoffs are augmented by positive *future* expected payoffs for our simulated portfolios. We also find that the realized portfolio payoffs are positive in *all* matured contracts in our data. In analyzing the determinants of the pricing-parity deviations we find that firm-level effects, especially those related to informational asymmetry, are more important than macroeconomic factors in accounting for these deviations.

To our knowledge, this paper is the first to document market segmentation within credit derivative markets.[7] Our paper contributes to the growing literature on integrated studies of stock, bond, option and CDS markets. Earlier studies have focused on information flows between the various markets and on the co-movements of the time series of the observed prices in these markets, but have not uncovered any tradable anomalies that do not involve privileged information.[8] Our results, based on one of the most popular data sources for credit derivatives, also raise questions on the appropriateness of deriving financial asset prices based on frictionless equilibrium among different markets without examining whether the integration of these markets is, in fact, supported by the data.

[7] Ong, Li and Liu (2012, p. 68) mention that the CDS and LCDS operate on "decidedly inconsistent markets" and present the pricing parity relation developed in the next section, but do not provide any evidence in support of their statement.

[8] See, for example, Acharya and Johnson (2007) on insider trading in the CDS and stock markets, Berndt and Ostrovnaya (2008) on information revelation in option, CDS and equity markets, and similar information flow studies by Norden and Weber (2009) and Forte and Pena (2009).

If both CDS and LCDS contracts are written on the same firm, the claims are triggered by the same default events which are defined by the International Swap and Derivatives Association (ISDA). Thus, the default and survival probabilities of these credit derivatives should be exactly the same given the same maturities, restructuring clauses and denominated currencies. However, the syndicated secured loans, which are the underlying assets of the LCDS, are backed by collateral assets and generally have higher priority during the bankruptcy process compared to senior unsecured debts which are the underlying assets of CDS. Based on observed recovery rate estimates in our data base, we identify a CDS and LCDS parity relation under the no arbitrage assumption, which should hold provided these two credit markets are fully integrated. With single name CDS and LCDS daily observations during the period from April 2008 to March 2012, we document time-varying and significantly positive current payoffs on a simulated portfolio that exploits the pricing-parity deviations observed when either the CDS or LCDS is overvalued and the other is undervalued by simultaneously taking the appropriate position in the corresponding markets.

Since these positive current payoffs indicate market segmentation and a possibly tradable anomaly, we verify the anomaly by examining several possible explanatory factors that may justify it or prevent its elimination.[9] Such factors are transaction costs, the unreliability of the recovery rates reported in the databases as estimates of the "true" recovery rates upon default, and the justification of the positive payoffs as rewards for risk arising out of the uncertainty in the recovery rates, the illiquidity of the contracts, or counterparty risk. We also verify whether our simulated portfolios did in fact generate positive arbitrage profits for contracts that matured

[9] Note that this anomaly is emphatically not related to the financial crisis, since it appears throughout the entire period of our data, unlike the violations of arbitrage relations between the CDS and underlying bond markets documented by Alexopoulou, Andersson and Georgescu (2009) and Bai and Collin-Dufresne (2013).

within our study period, after a generous allowance for transaction costs. We find that the positive current payoffs survive the inclusion of transaction costs similar to those reported in earlier studies and in the Bloomberg database, since the spreads are much lower than the estimated pricing-parity deviations. We also find that Markit recovery rate data are in almost all cases unbiased estimates of the realized recovery rates reported in earlier studies and in the Moody's database, even though the latter vary widely between firms and default types. Further, a comparison of Markit CDS recovery estimates to other reported estimates from earlier studies for senior unsecured debts similar to the ones traded in the CDS market shows that the estimates in our database are, if anything, rather conservative with respect to the existence of positive future payoffs from the simulated portfolios in the event of default. We confirm that our results are robust to recovery-rate concerns when we estimate the risk-adjusted default probabilities from the Leland and Toft (1996) structural model estimated using Generalized Method of Moments (GMM) and data from accounting reports and the equity and option markets. Our results are also robust with respect to the illiquidity concern, since we document fewer positive deviations for the less liquid CDS and LCDS contracts with maturities other than five years. We also show that an illiquidity factor cannot be extracted from a principal components analysis of the portfolio payoffs.

Perhaps the most convincing proof that our positive portfolio payoffs are not, in fact, rewards for risk comes from our subsample of one-year maturity contracts that have expired within our data period. There were more than 11,000 such CDS-LCDS contract pairs with identical specifications within the period April 2010-March 2011, after the financial crisis, in our data set. *All of them* showed positive cash flows even after a generous allowance for transaction costs, with an average size of 1.23% that is far too large to be justifiable by counterparty risk.

In the absence of detailed microstructure data that identifies the traders in both markets it is not possible to formulate a conclusive explanation for these observed payoffs of our arbitrage strategy. The market segmentation conjecture arises from the fact that market power exists in both CDS and LCDS markets, and that it is well known from the Industrial Organization (IO) literature that monopolists find it profitable to segment their markets. A recent study[10] documents extensive market power in the CDS market, with a small number of very large financial institutions acting as dealers, while middle-sized and small banks use CDS to hedge their credit exposures.[11] The market power in this instance arises out of barriers to entry in the dealer market due to economies of scale, again a well-known phenomenon in the IO literature. Thus, the positive payoffs of our portfolios may be monopoly rents extracted by market makers by segmenting the two markets, similar to those observed in at least one other financial markets case.[12]

Once the existence of unexplained pricing parity deviations is established, we run panel regressions for current payoffs from violations of the parity relation on firm-specific and macroeconomic variables for the entire sample of firms and for several sub-samples. The independent variables include standard firm-specific variables, while the macroeconomic variables include, in addition to the standard business cycle variables, an important event during our sample period, the simultaneous release of a set of publications to regulate and standardize North American LCDS by ISDA on April 5, 2010.

[10] See Atkeson, Eisfeldt and Weill (2013, pp. 7-8).

[11] Market power on the dealer side in the CDS market has also been documented by Gunduz, Nasev and Trapp (2013), who use microstructure data that identifies traders by type, and by Gupta and Sundaram (2013), who study CDS settlement auctions.

[12] See Knoury, Perrakis and Savor (2011).

The results for the firm-specific variables are consistent with expectations based on the findings of earlier studies about the determinants of the level and changes in CDS spreads[13] and their effects on information asymmetry, one of the probable sources of the positive current pricing-parity deviations. Specifically, we find that leverage is always positively correlated with current deviations, while its effect on recovery rates is primarily on the CDS market. Idiosyncratic risk, estimated from the residuals of a Fama-French three-factor model, is strongly and positively associated with current pricing-parity deviations as expected, since this risk is an indicator of information asymmetry. Several macroeconomic variables are also significant. The ISDA by establishing global standards for LCDS contracts increased market efficiency (or lowered market segmentation) in all the samples, but its effect was significantly different from zero only for the not-rated firms, which experience less information transparency. Several variables associated with the business cycle have strongly significant effects on current deviations for almost all samples.

The rest of the paper is organized as follows. In Section 2 we briefly describe the CDS and LCDS markets, present the CDS and LCDS parity and construct the simulated portfolio strategy. In Section 3 we describe our sample datasets. In Section 4 we report and analyze the empirical evidence for current payoffs (pricing-parity deviations) of the portfolios and examine their robustness with respect to transaction costs, recovery rate estimates, counterparty risk and illiquidity. In Section 5 we present the results of the panel regressions of the realized current payoffs from our simulated portfolios from cross-market pricing-parity violations on the macroeconomic and firm-specific variables. Section 6 concludes the paper.

[13] See Collin-Dufresne, Goldstein and Martin (2001), Ericsson, Jacobs and Oviedo (2009) and Cao, Yu and Zhong (2010).

2. CDS AND LCDS PARITY

2.1 CDS and LCDS Markets

The CDS market has existed for a long time but the LCDS market is relatively new and was launched in 2006 in both the US and Europe.[14,15] It has grown very quickly since its inception because of the rapid growth in the underlying asset, itself driven by a surge in leveraged buy-outs, and also because of the introduction of industry-wide documentation published by the International Derivative and Swap Association (ISDA) to standardize and regulate the LCDS contract. While the reference obligations of CDS contracts are usually corporate debts, the reference obligations of LCDS contracts are syndicated secured loans.

Based on their cancellability, LCDS contracts can be divided into Cancellable LCDS (European LCDS) and non-cancellable LCDS (US LCDS) contracts.[16] The European LCDS contract is created as a hedging product since it incorporates the prepayment risk of the reference obligation and the contract is cancelled automatically once the underlying syndicated loans are repaid. Nevertheless, the US LCDS contract is designed as a trading product that can be used to generate marginal profits by creating a synthetic credit position where one commits to make (receive) payment in the case of default.[17]

Similar to an ordinary swap contract, there are physical and cash settlements for both CDS and LCDS contracts once the settlement is triggered by a credit event. The default settlement mechanism for European and US LCDS is physical settlement under which the protection seller pays an amount equal to the notional amount of the reference obligation covered by the LCDS

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[14] See "Pricing Cancellable LCDS" on Merrill Lynch's Credit Derivatives Strategy (Global, February 2007).
[15] See "Loan-Only Credit Default Swap" prepared by Orrick, Herrington & Sutcliffe. The template forms of LCDS documentation were published by International Derivative and Swap Association (ISDA) for the US and European LCDS market on 8th, June 2006 and 2nd, May 2006, respectively.
[16] See Shek, Shunichiro and Zhen (2007) and Liang and Zhou (2010) for the valuation of cancellable LCDS.
[17] Minton, Stulz and Williamson (2009) find that the use of credit derivatives by US banks is very limited and most of the credit derivatives are held for dealer activities rather than for the hedging of loans.

multiplied by the reference price which is usually 100%.[18] Under cash settlement, there is no delivery of the reference obligation and the protection seller only pays to the protection buyer the difference between par value and the market price after a credit event. Especially after the Great Recession, cash settlement has become more popular because the physical delivery of a loan is cumbersome and time consuming. One of the common difficulties for cash settlement is how to determine the market price (real recovery rate) in the illiquid market that often exists after a credit event. In the cash settlement of a LCDS contract, the final price of the underlying syndicated loan is determined by an auction methodology.[19]

Short selling constraints are always a major concern when executing trading strategies for traditional investment instruments, especially for parallel trading in the corporate bond market. CDS and LCDS are essentially swap agreements between two counterparties to transfer the exposure to the default risk of the underlying asset. Thus, there is no requirement to hold the underlying assets,[20] especially under cash settlement, which makes an arbitrage position feasible.[21] In the following analysis, we focus on the US LCDS and assume cash settlement for both CDS and LCDS contracts.

2.2 CDS and LCDS Parity Without and With Transaction Costs

According to the specifications of CDS and US (or Non-cancellable) LCDS contracts, which are essentially financial agreements between the protection buyers and protection sellers, the premium of such contracts (denoted by c) received by the protection seller (or paid by the protection buyer) must equalize the present value of the expected premium leg to the present

[18] See "Loan-only Credit Default Swaps" prepared by Bartlam and Artmann (2006) in Orrickon, page 5.
[19] See the link: http://www.creditfixings.com/CreditEventAuctions/fixings.jsp for the details of CDS Auctions.
[20] This is the so-called "naked" or "synthetic" contract.
[21] See Mengle (2007).

value of the expected default leg in order to rule out an arbitrage opportunity. This can be expressed mathematically as follows under continuous time,

$$c = \frac{\int_t^T (1-R(\tau))P^D(\tau\,|\,t)e^{-\int_t^\tau r(u)du}d\tau}{\int_t^T P^S(\tau\,|\,t)e^{-\int_t^\tau r(u)du}d\tau}\,. \tag{2.1}$$

$R(\tau)$ denotes the time-varying recovery rate; $r(u)$ denotes the time-varying instantaneous interest rate; $P^D(\tau\,|\,t)$ denotes the probability that a default event occurs at time τ for the first time conditional on the information at time t; and $P^S(\tau\,|\,t) = 1 - \int_t^\tau P^D(s|t)ds$ denotes the probability that a firm survives until time τ conditional on the information at time t. Assume a constant interest rate, r , and let

$$\int_t^T P^D(\tau\,|\,t)e^{-r\tau}d\tau \equiv G(T|t),\ \int_t^T P^D(s|t)ds \equiv F(T|t) \tag{2.2}$$

Integrating by parts, we find that the denominator of (2.1) with a constant interest rate is given by

$$\int_t^T P^S(\tau\,|\,t)e^{-r(\tau)\tau}d\tau = \frac{e^{-rt}}{r} - \frac{e^{-rT}}{r}[1-F(T|t)] + \frac{G(T|t)}{r} \tag{2.3}$$

The expressions in (2.2) and (2.3) are given in particular structural models of the firm in terms of the parameters of the asset dynamics process.[22] The estimation of the parameters could be done by calibrating the particular model to the observed spreads and to other observable variables of the model, as shown in our online appendix.

[22] See, for instance, Leland and Toft (1996, p. 990).

Nonetheless, the availability of the CDS and LCDS data sets allows the examination of market integration and efficiency between these two markets. Following the underlying logic of a structural model, the first passage default probability and the survival probability should only be driven by the distance between the firm's asset level and default boundary so that default risk and distance are inversely related. Thus, the US LCDS and traditional CDS issued on the same firm with the same default clause and maturity should share exactly the same first passage default probability and survival probability. If we denote the traditional CDS and US LCDS premiums by c_{CDS}, c_{LCDS} and constant recovery rates by R_{CDS}, R_{LCDS},[23] respectively, it follows that,

$$c_{CDS} = \frac{(1-R_{CDS})\int_t^T P^D(\tau \mid t) e^{-\int_t^\tau r(u)du} d\tau}{\int_t^T P^S(\tau \mid t) e^{-\int_t^\tau r(u)du} d\tau}, c_{LCDS} = \frac{(1-R_{LCDS})\int_t^T P^D(\tau \mid t) e^{-\int_t^\tau r(u)du} d\tau}{\int_t^T P^S(\tau \mid t) e^{-\int_t^\tau r(u)du} d\tau} \qquad (2.4)$$

Thus, the following equality must be satisfied in order to rule out arbitrage opportunities given no market frictions and no errors in the recovery rate estimates,[24]

$$c_{CDS} = c_{LCDS} \frac{1-R_{CDS}}{1-R_{LCDS}} \qquad (2.5)$$

In order to test whether the equality (2.5) holds, we can construct simulated portfolios with zero expected future payoffs when one contract is overvalued and the other is undervalued (a deviation from pricing parity) by simultaneously taking the appropriate positions in CDS and LCDS where one receives and makes payment in the case of default, with the proper amount

[23] We cannot observe the real recovery rates until default. We assume constant recovery rates for a given pair of contracts over time, an assumption used extensively in the literature. See Leland (1994), Leland and Toft (1996), Collin-Dufresne and Goldstein (2001), Huang and Huang (2012), Huang and Zhou (2008), amongst others. The assumption that the recovery rates estimated at contracting time are equal to the actual recovery rates upon default is relaxed and discussed extensively in Section 4.

[24] Also in Ong, Li and Lu (2012).

based on (2.5). If the current payoffs[25] of such portfolios deviate from zero extensively to cover the transaction costs then our simulated portfolios may lead to profitable trading strategies.

Since both the CDS and LCDS markets are relatively illiquid compared to the traditional stock market,[26] we generalize the parity relationship (2.5) by incorporating transaction costs. In the presence of two-way transaction costs which are proportional to the nominal amount of the CDS and LCDS contracts,[27] denoted by k_{CDS} and k_{LCDS}, respectively, there is a non-trading zone on the CDS leg, denoted by $\mathbb{Z}=\left[\overline{c}_{CDS},\underline{c}_{CDS}\right]$, where,

$$\overline{c}_{CDS}=\left(c_{LCDS}+k_{LCDS}\right)\frac{1-R_{CDS}}{1-R_{LCDS}}+k_{CDS},\underline{c}_{CDS}=\left(c_{LCDS}-k_{LCDS}\right)\frac{1-R_{CDS}}{1-R_{LCDS}}-k_{CDS} \tag{2.6}$$

If the observed CDS spreads fall in the non-trading zone $\mathbb{Z}$ given the corresponding CDS recovery rates, LCDS spreads and recovery rates, there is no trading activity and the current payoffs of the portfolios are equal to zero. Otherwise, we are able to construct a trading strategy to generate non-zero current payoffs. Thus, the set of payoffs (or pricing-parity deviations) are given by,

$$PR\_TC=\begin{cases} c_{CDS}-\left[\left(c_{LCDS}+k_{LCDS}\right)\frac{1-R_{CDS}}{1-R_{LCDS}}+k_{CDS}\right] & if \quad c_{CDS}>\overline{c}_{CDS} \\ \left[\left(c_{LCDS}-k_{LCDS}\right)\frac{1-R_{CDS}}{1-R_{LCDS}}-k_{CDS}\right]-c_{CDS} & if \quad c_{CDS}<\underline{c}_{CDS} \\ 0 & if \quad \underline{c}_{CDS}\le c_{CDS}\le\overline{c}_{CDS} \end{cases} \tag{2.7}$$

[25] "Current payoffs", "Current deviations" and "Current pricing-parity deviations" are used interchangeable in this paper.
[26] See Tang and Yan (2007) for the relative illiquidity of the CDS market.
[27] Given a CDS contract with 1$ notional value and premium c, we have to pay $\left(c+k_{CDS}\right)$ when we buy, and receive $\left(c-k_{CDS}\right)$ when we sell.

Specifically, when the observed CDS spread $c_{CDS} < \underline{c}_{CDS}$, we take a position in one share of the CDS contract with \$1 notional amount where we pay the CDS premium continuously given that no default occurs and we participate in $\frac{1-R_{CDS}}{1-R_{LCDS}}$ shares of the US LCDS contract with \$1 notional amount per contract where we receive the LCDS premium. If a default event occurs, we receive $(1-R_{CDS})$ dollars from the CDS leg contract and pay $\frac{1-R_{CDS}}{1-R_{LCDS}} * (1-R_{LCDS}) = (1-R_{CDS})$ dollars to the holder of the US LCDS leg. Given no estimation risk associated with recovery rates and no further market frictions, the current and expected future payoffs for this portfolio are positive and zero, respectively. When the observed CDS spread $c_{CDS} > \overline{c}_{CDS}$, a similar portfolio with zero expected future payoff and non-zero current payoff can be constructed by receiving the CDS premium and paying the corresponding LCDS premium. In the following sections, we will test the violations of parity between the CDS and LCDS markets using the available empirical data and examine the robustness of our results to the relaxation of our assumptions.

3. SAMPLE AND DATA

We obtain our CDS and LCDS data from Markit who collects the quotes on LCDS spreads from large financial institutions and other high quality data sources and produces the LCDS spread database on a daily basis starting from April 11, 2008. Our sample is from April 11th, 2008 to March 30th, 2012, which encompasses the credit crisis and the Great Recession. We only use US (non-cancellable) LCDS to construct the portfolio.

In the CDS market we select the contracts on senior unsecured debts since this type of contract is the most liquid and is used frequently in the literature. In the LCDS market, we select the contracts on the first-lien syndicated loans since the claims on collateral for the first-lien loans are senior to those of the second-lien loans, which indicate more reliable estimated recovery rates for these loans. In addition, the LCDS contracts on first-lien loans form the majority in our data source and are more liquid than those on the second-lien loans. We restrict our CDS and LCDS contracts to those in the United States and denominated in US dollars. To ensure that the first-passage default and survival probabilities of the CDS contracts are exactly the same as those of the corresponding LCDS, we match the daily LCDS and CDS data based on company name, denominated currency, restructure clauses and time to maturity. We focus on the contracts with a 5-year maturity since they are the most liquid contracts and the most studied in the previous literature.[28] The contracts with 1-year, 3-year, 7-year and 10-year maturities are studied as robustness checks.

As the real recovery rates cannot be observed until the firm defaults, we use the estimated recovery rates to proxy for the real recovery rates. The estimated recovery rates are extracted from our Markit datasets; they are based on the raw data providers' estimates.[29] These recovery rate expectations at time of issue may differ from subsequent recovery-rate expectations and actual recovery rates, especially during bad economic times.[30] Nevertheless, these estimates available from Markit represent the only available proxy for the real recovery rates[31] (especially for LCDS contracts) and have been used repeatedly in previous studies.[32]

Table 1 reports the summary statistics for our full sample and sub-samples. We eliminate the observations whose CDS spreads (or LCDS spreads) are greater than 1 and the single name

[28] See Jorion and Zhang (2009), Cao, Yu and Zhong (2010, 2011), Schweikhard and Tsesmelidakis (2011), Qiu and Yu (2012) and Zhang, Zhou and Zhu (2009).

[29] Based on Markit CDS and Bonds User Guide, their clients can also contribute their recovery rates. Data on recovery rates are denoted throughout the Markit product as Client Recovery.

[30] Jokivuolle and Peura (2003), Altman, Brady, Resti and Sironi (2005), Hu and Perraudin (2002) and Chava, Stefanescu and Turnbull (2006) report that the recovery and default rates are negatively correlated.

[31] The real recovery rates are collected from Moody's Default and Recovery Database and discussed in Section 4.

[32] See Huang and Zhu (2008), Zhang, Zhou and Zhu (2008), and Elkamhi, Ericsson and Jiang (2012). Loon and Zhong (2013, p. 38) give a detailed description of the Markit data collection procedures.

contracts which have less than 120 consecutive daily observations. In addition, we obtain the accounting variables from COMPUSTAT, economic macro variables from Federal Reserve H.15 database and equity trading information from CRSP. After merging all these datasets and removing the missing observations and private firms, the full sample contains 68,147 firm-clause-daily cross-sectional observations for 120 single names during the sample period from April 11, 2008 to March 30, 2012.

[Insert Table 1 about here]

In the full sample, the mean LCDS and CDS spreads are around 3.7% and 4.6%, respectively. Both medians are smaller than their corresponding means which indicate asymmetric distributions and fat tails, especially on the right side. These style factors are also verified by positive skewness for the CDS and LCDS spreads. The distributions of recovery rates for the LCDS and CDS contracts are close to a Gaussian distribution with slightly negative skewness. Both the mean and median of the LCDS recovery rates, around 65% and 70% respectively, are greater than the corresponding statistics for the CDS contracts, around 38% and 40% respectively. The syndicated secured loans (the underlying assets of LCDS) are usually backed up with collateral and have claim priority compared to the senior unsecured debts which are the underlying assets that back the CDS once the default event occurs.[33] The sub-sample of investment grades (includes firms rated greater than or equal to BBB), accounts for more than 60% of the total observations, while junk-rated contracts and not rated contracts share almost equally the rest of the observations, approximately 20% each. As expected, both the mean and median of the CDS and LCDS spreads in the investment grade sub-sample are relatively lower

[33] This implies that the LCDS recovery rate estimates should exceed the corresponding CDS ones. This turns out to be true for all but 265 out of the 68,147 pairs of data points. For more on the priority of the LCDS claims see Section 4.4.

compared to the junk and not rated sub-samples, while the mean and median of the recovery rates are broadly similar in all three sub-samples. There are also differences in the accounting variables among the sub-samples, with the junk firms being smaller and more heavily indebted than the investments grade firms. The not-rated firms are mostly relatively small firms in terms of their total assets, with diverse accounting ratios.

We observe extremely high first-order autocorrelations in the daily spreads for CDS (around 0.98) and LCDS (around 0.97) indicating a spread clustering effect in both markets. The first-order autocorrelation of LCDS recovery rates of approximately 0.93 is much higher than that for CDS recovery rates of around 0.77. This further supports the conjecture that LCDS recovery rates are more persistent and reliable compared to their counterparts for CDS contracts. If we lower the frequency of the data from daily to quarterly, the first-order autocorrelations decrease significantly for all the variables.

The daily idiosyncratic volatilities[34] of the full sample have a mean around 2.4% with positive skewness and extremely high kurtosis. As expected, both the mean and median of daily idiosyncratic volatilities of the investment grade firms are relatively lower than those of junk-rated firms. For the not rated firms, the daily idiosyncratic volatilities are more volatile compared to the other sub-samples.

4. THE EFFICIENCY AND INTEGRATION OF THE CDS AND LCDS MARKETS

In this section we examine the current deviations of CDS and LCDS parity constructed in Section 2 at the index and firm levels, respectively. We verify whether these deviations lead to positive payoff portfolio strategies and, if yes, whether there are factors such as frictions, uncertainty of recovery rates and illiquidity that may account for these positive payoffs. The

[34] The calculation details are provided in Section 5.

results are first presented under the assumptions of no transaction costs, certain recovery rates and liquid markets, and then subsequently extended by relaxing these assumptions.

4.1 Trading Strategies

Following the CDS and LCDS parity in the presence and in the absence of transaction costs discussed in Section 2, we first examine the current payoffs in (2.7) with the observed CDS and LCDS data. Figure I in the online appendix and Figure 1 below report the distribution of simulated portfolio strategies without and with transaction costs, respectively.

[Insert Figure 1 about here]

Without transaction costs the CDS and LCDS parity in (2.5) does not hold at all. Generally, buying CDS contracts (receiving the CDS premium) and selling corresponding LCDS contracts (paying the LCDS premium) generates positive current payoffs, which indicates that the LCDS spreads are overpriced compared to the corresponding CDS spreads, especially for the not-rated single name contracts. Nonetheless, there are still around 23% of the portfolios with positive current payoffs from selling the CDS contracts and buying corresponding LCDS contracts in the full sample.

In the presence of transaction costs estimated from actual CDS data (see below) we observe that only approximately 19% of the cross-sectional observations in the full sample cannot generate positive current payoffs. There are still a large number of opportunities to make positive current payoffs, especially for the not-rated single name contracts. As in the case without transaction costs, buying CDS contracts and selling the corresponding LCDS contracts dominates the reverse trading strategy.

4.2 Current Payoffs of Liquid Portfolios without and with Transaction Costs but without Uncertainty of Recovery Rates

In this subsection we analyze the current payoffs of our portfolio strategies assuming that the recovery rates reported by the Markit database are the "real recovery rates" once the default events occur. For the frictionless markets, we construct the simulated portfolio by checking the equality of equation (2.5). There is an arbitrage opportunity if the equality does not hold. We simultaneously buy the CDS contract and sell the weighted LCDS contract provided $c_{CDS} < c_{LCDS} \frac{1-R_{CDS}}{1-R_{LCDS}}$ and *vice versa*.

We build simulated portfolios for each single name contract on a daily basis and analyze the payoffs based on the entire set of observations. The summary statistics are presented in Table I of the online appendix. The average of current payoffs across all observations is approximately a daily 3.75%, implying that the portfolios constructed from the contracts that violate the parity relation (2.5) are able to generate a 3.75% current payoff per day per single name contract on average over the whole sample period. This is very large compared to the average daily returns in the traditional equity and bond markets. Although the high standard deviation, 7.5%, and high kurtosis, 117.53, suggest that the mean may be driven by outliers, the 1.6% median return which is not affected by extreme values is still noticeably large and positive on a daily basis.

[Insert Table 2 about here]

For the transaction costs, estimates from the earlier literature are not very helpful, since their time span does not overlap with our sample period, which covers the Great Recession and afterwards.[35] Since the Markit database only provides the composite quotes for the CDS and

[35] See Table 1 in Acharya and Johnson (2007, p. 117), as well as the summary statistics results in Table 1 and Table 3 in Tang and Yang (2007), who report estimates around 20 or 22 basis points.

LCDS spreads, we match the single names in our sample with the Bloomberg database and find that 61 out of 120 firms are quoted in the Bloomberg historical CDS dataset.[36] The bid-ask quote information is retrieved during the period from January 2nd, 2008 to November 23rd, 2012, which covers the time span of our study. Table 2 reports the summary statistics of both firm average and daily average bid-ask spreads.[37] The median of the daily average bid-ask spreads at around 18 basis points is a little lower than but close to the numbers documented by Acharya and Johnson (2007) and Tang and Yan (2007). The positive skewness and extremely high kurtosis imply fat tails, especially on the right. This turns into a mean of around 35 basis points, relatively high compared to the median.

Intuitively, the one way transaction cost represented by one-half of the quoted bid-ask spread in the LCDS market should be greater in relative terms than its counterpart in the CDS market since the LCDS market is relatively smaller and less liquid. On the other hand, the lower credit spreads for the LCDS contracts would normally imply at equal liquidity lower absolute bid-ask spreads for LCDS. Since there is no data for the real bid-ask spreads in the LCDS market, we use the CDS numbers for the LCDS market as well. Table 3 presents the numerical results of our portfolio strategies based on (2.7) in the presence of time-varying bid-ask spreads, assumed the same for every firm in our sample and equal to the daily average of the Bloomberg sample.[38]

[Insert Table 3 about here]

[36] As Bloomberg does not provide the information about restructuring clauses, we can only match with firm name and we need to assume that the restructure clauses are the same as for the single name contracts in the Markit database.

[37] Summary statistics for proportional transaction costs are reported in Table II of our online appendix.

[38] The results summarized in Panel A of Table III of our online appendix are very similar if the daily average proportional bid-ask spread is used to calculate the transaction costs in (2.7). Note that, in view of the highly skewed distribution of the bid-ask spreads, the use of the average overestimates the impact of the transaction costs in (2.7) and understates the payoffs of our portfolio strategies. In addition, we show that the current payoffs of the simulated portfolios with real bid-ask spreads for our Bloomberg sub-sample are also very positive (see Table IV in our online appendix).

The table shows results for the full sample and for three sub-samples based on rating status. Compared to the scenarios in the absence of transaction costs in Table I in the online appendix, both the mean and median of the current payoffs decrease for all samples but are still significantly positive, with the mean decreasing only from 3.75% to 3.38%. Therefore, the significantly positive current payoffs survive the introduction of transaction costs.[39] In Table 3 the returns increase in terms of both the mean and median as the rating status deteriorates, with the not-rated contracts generating the highest current payoffs among all the sub-samples. Compared to the rated firms, the not-rated firms are likely to have higher asymmetric information effects since they release less information to the markets. In turn, this can be expected to reduce the efficiency of the CDS and LCDS markets and increase the segmentation of these two markets, resulting in the large positive current payoffs for the simulated portfolios.

As the time span of the single name contracts varies, the cross-sectional average puts more weight on the firms with a longer life. In order to remove this bias, we first calculate the daily average current payoffs for each single name across the life of the contract and then present the statistical properties of the sample reported as “Firm Daily Average Current Payoffs”. The distribution has a 4.5% mean and 2.5% median daily return, which are even greater than those based on the cross-sectional observations.

In order to check the time trend of the current payoffs, we aggregate the value of current payoffs per day across all the available paired single name contracts and then divide by the total number of single name contracts per day to construct a payoff index. Suppose there are N_t pairs

[39] Since the cancellable feature is still embedded slightly in a “non-cancellable” LCDS, a US LCDS can be terminated before expiry under some special circumstances. The ISDA authored a publication on NA LCDS on April 5, 2010 which made the US LCDS truly non-cancellable. In order to rule out the impact of such an embedded option, we perform the same exercise with data after April 5, 2010 only and still document daily abnormal deviations of 1.63% and 0.85% in terms of the mean and median, respectively.

of single name contracts on day t. The payoff of each pair i on day t is denoted by r_{it}. The payoff index return R_t on day t is then expressed by,

$$R_t = \frac{1}{N_t} \sum_{i}^{N_t} r_{it} \tag{4.1}$$

As expected, the distribution of index returns is almost Gaussian for all the samples. As in the cross-sectional results, the average current payoff increases as the rating deteriorates, and the not-rated sub-sample dominates in terms of the mean and median all the rated sub-samples but also has the highest standard deviation, 3.16%. The time trend of daily average current payoffs of the different samples can be observed in Figure 2, both with and without transaction costs, with the two cases being very close to each other. In the full and investment grade samples we note that the current payoffs are relatively higher during the Great Recession period from mid-2008 to late 2009 compared to the other time periods, and gradually decrease in recent years. The junk-rated and not-rated samples have significantly higher volatilities than the investment grade firms. Both junk-rated and not-rated firms sub-samples are small firms in terms of total assets and have relatively lower tangible ratios which make them more vulnerable, especially in turbulent financial market environments. These style factors turn into the higher volatilities for these two sub-samples compared to the investment grade firms.

[Insert Figure 2 and Table 4 about here]

If we now assume that all the positive current payoffs are caused by transaction costs, we can calculate the value of implied transaction costs which makes the current payoffs equal to zero. The computation is straightforward and can be expressed as,

$$\hat{k}_{it} = \begin{cases} \dfrac{c_{LCDS}\left(1-R_{CDS}\right)-c_{CDS}\left(1-R_{LCDS}\right)}{2-R_{CDS}-R_{LCDS}} & if, c_{CDS} < \dfrac{c_{LCDS}\left(1-R_{CDS}\right)}{\left(1-R_{LCDS}\right)} \\ \dfrac{c_{CDS}\left(1-R_{LCDS}\right)-c_{LCDS}\left(1-R_{CDS}\right)}{2-R_{CDS}-R_{LCDS}} & if, c_{CDS} > \dfrac{c_{LCDS}\left(1-R_{CDS}\right)}{\left(1-R_{LCDS}\right)} \end{cases} \tag{4.2}$$

The summary statistics for the implied round-trip transaction cost, $2\hat{k}_{it}$, are reported in Table 4. The average implied transaction cost for the cross-sectional observations of around 200 basis points is more than ten times the realized bid-ask spreads documented for the same sample period. These results show that transaction costs can only explain a small portion (approximately 10%) of the observed abnormal positive current payoffs generated by the portfolios.

4.3 Uncertainty of Recovery Rates: Quality and Bias of the Markit Estimates

After the introduction of transaction costs there are still about 90% of the abnormal positive current payoffs that remain unexplained. One possible explanation is the quality of the recovery rate data, since we have assumed that the recovery rates reported in the Markit datasets are reasonable estimates of the “real recovery rates” in the presence of default events. Note also that the real recovery rates depend on the type of default events and can only be observed once the default events occur. For instance, if a default event is triggered by missing an interest payment, the real recovery rate is usually higher than if the default event is triggered by the filing of Chapter 11 or Chapter 7. Hence, the uncertainty of the real recovery rates, in addition to the quality of the recovery rate estimates, could be an additional source of risk that may explain the observed abnormal current payoffs from a simulated portfolio between the CDS and LCDS markets.[40]

[40] In our analysis we assume that the variability of the recovery rates is unsystematic and not related to macro variables and, thus, the observed spreads do not include a risk premium. This is the most conservative assumption, since such a premium should obviously be higher for CDS than for LCDS. In turn, this strengthens our results for

a. Real Recovery Rates versus the Markit-estimated LCDS and CDS Recovery Rates

A key issue in assessing real recovery rates for the loans and debts underlying the LCDS and CDS contracts is the priority of the former in the event of bankruptcy. This can only be assessed in cases where both types of recoveries are reported simultaneously in bankruptcy data for a given firm. There are very few such simultaneous recovery cases, which we examine in detail in the next subsection. Here we assess the quality of the Markit data as unbiased estimates of real recovery rates based on past data of actual default events reported independently for LCDS- and CDS-underlying assets.

If the priority rule is ignored then there are 25 reported instances of default events due to bankruptcy for first lien secured loan contracts documented by Moody's ultimate recovery database[41] during the period from 1987 to 2012, as shown in Panel A of Table V of our online appendix. These undoubtedly include also firms with no other debt liabilities and, thus, are not relevant to our estimates. Ignoring the two distressed exchange default events that do not trigger default swaps contracts after April 2009, we observe real recovery rates for first lien secured loans of 65.77% on average. The comparable Markit estimate from our Table V is virtually the same at 65.23%. Since these loans are generally backed by collateral whose value is easier to estimate and incorporate into the estimation of the LCDS recovery rates than total firm asset value, the accuracy of the estimate is not surprising. For these reasons we shall assume initially

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the immense majority of our cases, for which the CDS spreads are too low. Models assuming systematic recovery rate risk belong to the reduced form model class and incorporate the priority rule that strengthens our results even further; see, for instance, Boudreault, Gauthier and Thomassin (2013).

[41] Compared to Moody's Recovery and Default database in which the recovery rate is equal to the trading price 30 days after a default event, Moody's ultimate recovery database provides the real recovery rates under the settlement method, long-term trading price method and liquidity method. Since the bankruptcy procedure usually takes a long time, around 15 months on average, the ultimate recovery rates are much closer to the long term true recovery rates. In addition, the ultimate recovery rates are generally higher than the recovery rates expressed by the 30-day trading price after the default events because the assets of default firms are generally very illiquid and the 30-day trading prices may suffer from a fire-sale effect. They are relatively lower in value than their long-term recovery rates counterparts.

that the estimated recovery rates R_{LCDS} are a good proxy for the "real recovery rates" for the LCDS contracts.

We also compare the Markit CDS recovery estimates to observed real recovery rates of senior unsecured bonds. Such real recovery rates for the 1987-2012 period are reported in Panel B of Table II of our online appendix.[42] Ignoring again all the defaults that may not trigger swap payments, we observe that there were 1053 default events due to bankruptcy during the period, with mean and median recoveries of 41.4% and 31.04%, respectively. Given the very large standard deviations of these observed real recovery rates, the Markit-estimated CDS recovery rates shown in Table 1 are very close to these numbers, well within one standard deviation. This implies that for the overwhelming majority of our portfolios these estimates are relatively unbiased estimates of actual CDS recovery rates. In fact, for the April 11th, 2008 to March 30th, 2012 time span of our data Moody's Default and Recovery Database reports a total of 1535 default events in total and 736 events that are not distressed exchanges, as shown in detail in Table VI of our online appendix. The mean and median recovery rates of these 736 events are 17.85% and 10.0% respectively,[43] significantly lower than the Markit estimates reported in Table 1. If these lower numbers are substituted for the Markit estimates then the current payoffs of the overwhelming majority of our portfolios will increase even further.

A similar picture arises out of a comparison of the Markit recovery rate estimates with the actual recovery rates reported in the literature. Acharya, Bharath and Srinivasan (2007)[44] provide recovery rate data from a sample of defaulted firms for the 18-year period ending in 1999. They

[42] There are only four firms in our sample that defaulted during the study period, of which three were of the "Distressed Exchanges" type and are not reliable for our purposes for the reasons given below. For the fourth firm, the CDS real recovery rate is lower than the median Markit estimate in the pre-default days.
[43] These recovery rates are based on the 30-day trading prices.
[44] See pages 797-798.

report median rates of 91.55%, 61.99% and 54.63% for bank loans, senior secured debt and senior unsecured debt, respectively. The first two recovery rates correspond to our LCDS and the last one to our CDS. Again, the very large standard deviations of these data place the Markit estimates well within one standard deviation of the actual recoveries.

b. Impact of the Absolute Priority Rule

The priority of the LCDS over the CDS claims in the event of default is a key issue in assessing the *future* payoffs of our portfolios in case a default event occurs. As a rule, syndicated secured loans have claim priority compared to the senior unsecured debts which are the underlying assets of the CDS markets in bankruptcy. This implies a 100% recovery for LCDS-underlying loans before the recovery for CDS debts can become positive. To understand the role of such priority in the profitability of our pricing parity violations portfolios, we denote by R^r_{CDS} and R^r_{LCDS} the realized (as distinct from the Markit estimates) recovery rates at default and consider the future payoffs of portfolios such that $c_{CDS} < \underline{c}_{CDS}$ in (2.8), which form the overwhelming majority of the cases. The payoff to that portfolio in the event of default is

$$1 - R^r_{CDS} - \frac{1 - R_{CDS}}{1 - R_{LCDS}}(1 - R^r_{LCDS}) = 1 - R^r_{CDS} - (1 - R_{CDS})\frac{1 - R^r_{LCDS}}{1 - R_{LCDS}} \tag{4.3}$$

If there is no error in the estimate R_{LCDS} then the payoff is equal to $R_{CDS} - R^r_{CDS}$. Similarly, the payoff is always nonnegative whenever $R^r_{LCDS} = 100\%$ and strictly positive if $R^r_{CDS} = 0$ and $R^r_{LCDS} \geq R_{LCDS}$. In other words, these portfolios, in addition to the current positive payoffs, have *always* nonnegative future payoffs under LCDS priority and full recovery. They also have positive payoffs in the absence of priority if the estimated recovery exceeds the actual recovery in the CDS but not in the LCDS market.[45]

[Insert Table 5 about here]

We may evaluate the impact of LCDS priority in the event of default if we relax the assumption that R_{LCDS} is an accurate estimate of the real recovery rates for the LCDS-underlying assets. The evidence for the priority rule effect comes from six actual concurrent defaults of senior unsecured bonds and first-lien syndicated secured loans in Moody's ultimate recovery database.[46] Their details are reported in Table 5. The default type for all the firms is bankruptcy which triggers payments on both the CDS and LCDS contracts provided there are credit derivative contracts on the underlying bonds and loans. All the bank loans have collateral backing (generally on all assets).

Panels A and B show the trading price discounted recoveries, settlement discounted recoveries and 30-day trading prices for the syndicated secured loans and senior unsecured debts, respectively.[47] As expected, the real recovery rates of the syndicated secured loans are significantly higher than those of the senior unsecured debts across all the types of recovery rates. Based on the settlement discounted recovery rates, the recovery rate of senior unsecured debts cannot be greater than zero unless the corresponding syndicated secured loans are fully recovered, indicating that the "absolute priority rule" is respected.[48] Based on the trading price discounted and 30-day trading price recovery rates, we observe positive recovery rates for senior

[45] This is true when we pay the CDS premium and receive the corresponding LCDS premium. According to Figure 1, this accounts for around 66% of the total observations in the full sample.
[46] Moody's ultimate recovery database documents the real default event for both bonds and bank loans during the period from 1987 to 2012 in the U.S.
[47] The details of each recovery rate are reported in the appendix.
[48] A syndicated bank loan has priority over a senior unsecured bond for the same issuer.

unsecured bonds in some cases where the syndicated secured loans are not fully recovered, although the recoveries are quite high in all but one of these cases as well. As the trading price discounted recoveries and 30-day trading price recoveries depend on the market value of the defaulted instruments in the long- and short-run after bankruptcy, respectively, pricing errors will occur due to the illiquidity of the default instruments.

Nonetheless, the data in Table 5 strongly suggests that our potential payoffs from pricing parity deviations which are based on the Markit data base estimates of both CDS and LCDS recovery rates are, if anything, highly conservative. Recall that when concurrent default occurs, we receive in the overwhelming majority of pricing parity violations cases the loss given default on the CDS leg and pay the loss given default on the LCDS leg, as in relation (4.3). On the other hand, Table 5 suggests that because of LCDS priority the Markit data seriously underestimates R^r_{LCDS} and overestimates R^r_{CDS}. Comparing the Table 1 and Table 5 data, we see that 4 out of the 13 R^r_{LCDS} values and 13 out of the 18 R^r_{CDS} values exceed and lie below, respectively, the maximum and minimum estimates observed in the 68,147 observations of our entire sample. Further, the payoffs upon default of the pricing parity violations portfolios that pay the CDS and receive the LCDS premium are positive in 3 of the 14 Table 5 cases for which sufficient data exists, while most of the others are positive for all but the highest estimated LCDS recovery rates that lie within the limits of our data shown in Table 1.

If the absolute priority rule is respected, which is true for all the six real concurrent default cases documented in Table 5, we can calculate the implied real recovery rates for the LCDS contracts, denoted as $\hat{R}^r_{LCDS}$, by using the Markit-estimated recovery rates for R_{CDS} and R_{LCDS}, and setting equation (4.3) equal to zero.[49] The full results are shown in Figure II and Table VII of our online appendix, in which $\hat{R}^{r}_{LCDS} = 43.43\%$ on average for the whole sample. This means that the average future payoffs of the portfolio given default will become negative only if the average of R^{r}_{LCDS} is less than 43.43% whenever default occurs. According to the real recovery rates of first lien bank loans for the six concurrent default cases in Table 5, the lowest real recovery rate among all the types, around 51.08%, is still greater than average $\hat{R}^{r}_{LCDS}$, indicating that the expected future payoffs of the portfolio given default are always positive. We assess the unconditional distributions of these future payoffs in the context of a structural model in a future subsection.

Hence, the available empirical evidence about the real recovery rates implies that in the overwhelming majority of cases the current payoffs on the simulated portfolio will be augmented by future payoffs when default occurs, thus increasing the profitability of our portfolio strategy. Such a conclusion implies, in turn, that in the absence of liquidity considerations the observed structure of the premiums in the CDS and LCDS markets indicate that the two markets are segmented and trading takes place without taking into account the LCDS priority rule in the event of default.[50]

On the other hand, the future payoffs upon default will be negative for the portfolios that pay the LCDS and receive the CDS premium. Apart from the fact that these cases are relatively few, they do not necessarily negate the observed abnormal current payoffs. The reason is that all one has to do is refrain from trading in these cases if the evidence from Table 5 is confirmed with

[49] We set $R^{r}_{CDS} = 0$ since the absolute priority rule is respected.

[50] Similar anomalous relations have been observed in the index and equity option markets by Driessen, Maenhout and Vilkov (2009) and the index futures options and underlying market by Constantinides *et al* (2011).

more extensive data on actual defaults and recoveries. These cases are analyzed further in the following subsections, where it is shown that they offer further supportive evidence of market segmentation.

c. Cross Sectional and Time Series Analysis: CDS Parity Implied Recovery Rates

Although we verified empirically that the median real CDS recovery rates are close on average to the estimated recovery rates, deviations between the real recovery rates and estimated recovery rates of the CDS contracts vary dramatically among the individual cross-sectional observations. To analyze the cross sectional and time series sources of this variability, we assume again that the LCDS recovery rates are correct estimates of the actual ones in the event of default, and we estimate the implied CDS recovery rates in the presence of transaction costs by setting the current payoffs of the simulated portfolios equal to zero. Mathematically, the implied recovery rates can be computed as,

$$\hat{R}_{CDS} = \begin{cases} 1-\dfrac{c_{CDS}-k}{c_{LCDS}+k}\left(1-R_{LCDS}\right) & if \quad c_{CDS} > \overline{c}_{CDS} \\ 1-\dfrac{c_{CDS}+k}{c_{LCDS}-k}\left(1-R_{LCDS}\right) & if \quad c_{CDS} < \underline{c}_{CDS} \\ R_{CDS} & if \quad \underline{c}_{CDS} \le c_{CDS} \le \overline{c}_{CDS} \end{cases} \tag{4.4}$$

Where $\hat{R}_{CDS}$ is the implied recovery rate of a CDS contract. Compared to the daily average of estimated recovery rates, the daily average implied recovery rates that are reported in Panel A of Figure 3 are greater and also more volatile.

[Insert Figure 3 and Table 6 about here]

Theoretically, the recovery rates cannot be negative because of the limited liability of the debt holder. However, we do observe some negative implied recovery rates and some of them even last for periods as long as a couple of months. From (4.4) it is clear that these negative recovery rates can only arise whenever $\bar{c}_{CDS} < c_{CDS}$ and do not affect the 66% of the trading strategies that buy CDS and sell LCDS shown in Figure 1. They are, therefore, a convenient tool to analyze the 34% of remaining cases that do not trade or trade in the opposite direction.

According to (4.4) the observed relative CDS and LCDS spreads and the LCDS recovery rates affect the implied CDS recovery rates directly. In order to identify the most important of these factors in terms of the negative implied recovery rates, we collect all the turning days on which the implied CDS recovery rates become negative (First Day). Thus, each such identified implied CDS recovery rate is positive on the day before the turning day (1 Day Before). Table 6 reports the means and medians of all the variables which might affect or be affected by the implied recovery rates. Based on the two-sided Wilcoxon two sample tests, we observe that the negative CDS recovery rates are driven by the significant decreases of the LCDS recovery rates and the equally significant increases in the spread ratios on the turning days. On the other hand, the estimated CDS recovery rates remain virtually unchanged, a striking result in view of the priority of the LCDS claims in the event of default. Such counter-intuitive market behavior supports the segmentation of the LCDS market, since the reduction in the LCDS recovery rate estimates is not reflected in simultaneous reductions of the equivalent CDS estimates.

Both CDS spreads and recovery rates increase but not significantly at conventional levels. Since the CDS spreads depend on both default probabilities and recovery rates (see (2.1)), we compare the changes in the spread ratios (defined as c_{CDS}/c_{LCDS}) to those of the recovery rates ratios defined as $(1-R_{CDS})/(1-R_{LCDS})$, which should be equal by the frictionless parity relation and certainly move in the same direction in the presence of frictions in integrated markets. As already noted, the spread ratios significantly increase but the recovery rates ratios decrease, thus indicating market segmentation, assuming unbiased estimates of the recovery ratios as demonstrated in the previous subsections. In the presence of such market segmentation, the mean current payoff on our trading strategy on the first day of about 5.7% is significantly greater (almost double) the mean current payoff on the one day before of approximately 2.9%.[51] We also observe a decrease in equity returns, CDS spreads and an increase of CDS recovery rates, but none of them are significant at conventional significance levels.

d. *Extended Negative Recovery (ENR)*

Given market frictions, negative implied recovery rates could appear occasionally but should disappear after a reasonable period of time because prices should adjust quickly in a well-functioning market. In this section, we define 19 single name contracts in our sample as "ENR" contracts because they have ten or more consecutive days (approximately two weeks) on which their respective implied CDS recovery rates are negative.

Comparison statistics of ENR and non-ENR (NENR) firms are reported in Table VIII of our online appendix. Compared to the NENR firms, the ENR firms are usually small firms in terms of total asset value with relatively higher leverage on average. The idiosyncratic volatilities of the ENR firms are noticeably higher than those of NENR firms. We also note dramatically higher CDS spreads and slightly higher LCDS spreads for the ENR firms compared to the NENR firms, although their CDS and LCDS recovery rates are very similar. Based on the results of the

[51] As noted above, these current payoffs are not necessarily pure profits, since it was argued earlier that the expected future portfolio payoffs in the event of default are negative in these cases.

Wilcoxon paired mean and median tests, all of the means and medians of the differences in these variables between ENR and NENR firms (with the exception of median difference of the LCDS spreads) is significant at the 1% level. Given these differences in firm-specific characteristics, the trading strategy of selling CDS contracts and buying the corresponding LCDS contracts of ENR firms dominates all other strategies for NENR and ENR firms, as depicted in Figure 4. This indicates that the CDS spreads are generally over-priced for the ENR firms compared to their corresponding LCDS spreads. We also note that the ENR behaviors reflected by the negative implied recovery rates are clustered and occur with greater frequency during the 2008 financial crisis, as depicted in Figure 5.

[Insert Figures 4 and 5 about here]

After removing all the ENR firms from the full sample, we find that the implied recovery rates become less volatile and are consistently above the estimated recovery rates with only one (inverted) spike during May 2011, as shown in Panel C of Figure 3.[52] It appears that the uncertainty of the implied CDS recovery rates is mostly contributed by the ENR firms.

4.4 Contract Liquidity and the Term Structure of the Portfolio Current Payoffs

All of the previous analyses focus on the 5-year CDS and LCDS contracts which are the most liquid contracts in these markets. In this section, we expand our sample to other maturities, including 1-year, 3-year, 7-year and 10-year maturities. Due to the illiquidity and data availability of contracts for the other maturities, the total number of cross-sectional observations is reduced from 69,805 to 33,377 after deleting the observations with missing variables. If

[52] The determinants of this spike are unknown. Interestingly, it was preceded by an announcement on April 29, 2011 by the European Commission that it was examining “whether 16 investment banks and Markit, the leading provider of financial information in the CDS market, have colluded and/or may hold and abuse a dominant position in order to control the financial information on CDS” (European Commission, Antitrust: Commission probes Credit Default Swaps market, Brussels, 29 April 2011). The ISDA became a party to the probe in March 2013.

illiquidity of the contracts is the factor responsible for the large current payoffs of the pricing parity violations portfolios then we should observe more of them for these more illiquid contracts than for the 5-year ones.

[Insert Figure 6 and Figure 7 about here]

Figure 6 exhibits both the medians and means of the current payoffs on the portfolios consisting of CDS and LCDS contract pairings across the different maturities in the presence of transaction costs.[53] The distributions of these current payoffs across all the maturities are highly positively skewed since all the means (around 2.8% in average size) are significantly greater than their corresponding medians (around 1% on average). There is a clear upward trend for the median current payoffs as the maturity increases from 1 to 5 years before it becomes flat for the longer maturities. Nevertheless, the mean payoffs exhibit a flat term structure. As the value of current payoffs on the portfolios with zero-expected payoffs measure the deviations from the CDS and LCDS parity described in Section 1, we expect to observe fewer violations of the parity relation for short-term contracts because of the reduced probability of the default event during contract life.

Figure 7 shows the distribution of the trading strategies across all the maturities we considered. We document that for the shortest (1-year) maturity approximately 35% of the observations, the highest percentage among all the maturities, do not violate the CDS and LCDS parity, as expected. The violation percentage increases as the maturity increases from 1 to 5 years and stays approximately constant thereafter. Since the contracts with 5-year maturity are

[53] The transaction cost information represented by the bid-ask spreads is collected from Bloomberg for the different maturities.

the most liquid ones in our sample, these results suggest that contract illiquidity is not a factor in the incidence of parity violations.

Across all the maturities, paying the CDS premium and receiving the corresponding LCDS premium dominates the other trading strategies. This confirms our earlier findings that the observed CDS premiums are too cheap given the corresponding LCDS premiums, and expected CDS and LCDS recovery rates. We also note that the percentage of receiving CDS premiums and paying corresponding LCD premiums slightly increases as the maturity increases from 1 to 7 years.

4.5 Counterparty Risk

Counterparty risk is the risk associated with a counterparty failing to honor its obligations. For a typical CDS contract, the protection provider makes a commitment to pay for the losses given default. Recent empirical work finds that the CDS premium that a protection provider charges is lower (i.e., priced) if the credit risk of the protection buyer is higher.[54] Since in our trading strategy the investor generally pays the CDS premium and receives the corresponding LCDS premium, he is exposed to the counterparty risk of the CDS protection provider in the event of default. Similarly, the protection buyer of the corresponding LCDS contract generally is exposed to the counterparty risk of the investor when default occurs. Since such an investor acts as a pass through party who receives payment from the CDS protection provider and makes payment to the LCDS protection buyer, the counterparty risk exposure of the investor has been transferred to the LCDS protection buyer. If such an investor has a lower credit risk compared to the CDS protection provider, the counterparty risk will be mitigated through this passing through channel because of the credit enhancement. We now argue that this may explain some small part

[54] See Arora, Gandhi and Longstaff (2012).

of the abnormal current deviations documented in the previous sections of this paper under some relative credit-risk scenarios. Since Arora, Gandhi and Longstaff (2012) find that the magnitude of the counterparty risk that is priced is vanishingly small,[55] the counterparty risk premium might be able to explain a very small portion of the abnormal current deviations only when the intermediate investor has lower credit risk than the CDS (LCDS) protection seller.[56] Otherwise, the counterparty risk should have no impact on CDS and LCDS parity due to the nature of the risk transfer. Thus, the documented abnormal current deviations should be available to an investor whose credit risk is no lower than the CDS (LCDS) protection seller.

4.6 Robustness Checks

a. Structural Model Implied Recovery Rates

Compared to reduced-form models,[57] the structural models treat corporate debt and equity as contingent claims on the firm's assets and link the default risk and firm characteristics. Within this framework, we are able to combine the information from different financial markets, including equity and option markets, with accounting information to calculate the model implied recovery rates. We then verify whether the pricing-parity violations persist with these new recovery rate estimates. We also obtain estimates of the expected future payoffs upon default, analyzed in the next subsection.

For this end, we use the structural model presented in Leland and Toft (1996). Although this model's capital structure differs from the structure of the firms in our sample, it is the most

[55] Arora, Gandhi and Longstaff (2012) find an increase in the dealer's credit spread of 645 basis points only translates into a one basis-point decrease in the CDS premium.

[56] The impact of the central clearing counterparty (CCP) on the CDS market's counterparty risk is unclear. For instance, Duffie and Zhu (2011) show an increase of counterpart risk in the presence of CCP while Loon and Zhong (2013) document a decrease. Due to the nature of counterparty risk transfer under our trading strategy, the presence of CCP should not be able to explain the documented abnormal current deviations documented herein.

[57] For the reduced form models, see Jarrow and Turnbull (1995), Duffie and Singleton (1999) and Duffie and Lando (2001).

popular bond pricing structural model in the literature and has two important advantages. First, Leland and Toft (1996) use the endogenous default boundary that is chosen by the firm itself, and second it presents closed form expressions for all the variables of interest, which provide significant computational convenience for the estimation. The details of data description and Generalized Method of Moments (GMM) procedures are reported in our online appendix.

[Insert Table 7 about Here]

Table 7 reports the results of the GMM estimations and the new current payoffs using the implied CDS recovery rates from the structural model. In Panel A, the implied CDS recovery rates on average are very close to the estimates provided by the Markit datasets, especially the results (around 35%) using put option implied equity volatilities. The high standard deviation of 25.34% and 24.22% for results with option implied volatilities and realized volatilities respectively, across all the firms indicates that the cross-sectional effect is very important. The asset volatilities are approximately 10% under both option implied and realized volatilities and are very persistent across all the firms as indicated by the low standard deviations.

Using the model implied CDS recovery rates as being constant across the whole time period for each firm,[58] we redo the exercise to compute the current payoffs and report the results in Panels B and C for option implied and realized equity volatilities, respectively. Compared to the current payoffs under the estimated recovery rates (see Panel B of Table 2), the means of the current payoffs under the structural model implied CDS recovery rates are much lower at 2.74% and 2.83% for option implied and realized equity volatilities, respectively, but the corresponding medians are much higher at 1.35% and 1.44%, respectively, for the cross-sectional daily

[58] We use estimated LCDS recovery rates provided by Markit. As the underlying asset of LCDS is syndicated secured loans which usually have collateral backing and are senior to the senior unsecured debts, the recovery rates are much easier to estimate.

observations. In addition, the results are very similar for both the firm average and daily average samples. These positive and large abnormal current payoffs on the portfolios, evaluated under two very different methods that use partly different data sets, suggest strong market inefficiency due to segmentation, and the failure of arbitrage to equalize the spreads in the CDS and LCDS markets.

b. NPV of the Portfolio Under the Structural Model

Since the structural model allows us to calculate the first passage time to default under the risk-adjusted measure within the maturity of the debt, we can calculate model-dependent statistics of the net present value (NPV) of our portfolios which is equal to the sum of current payoffs and the present value of expected future payoffs. The current payoffs are calculated by the CDS and LCDS spreads and Markit-estimated recovery rates. As we cannot observe the real recovery rates until the default events occur, we consider the worst default events documented by the concurrent default record reported in Table 5. For all portfolio strategies the NPV is given by

$$NPV = \begin{cases} c_{CDS} - \left[\left(c_{LCDS} + k_{LCDS} \right) \dfrac{1 - R_{CDS}}{1 - R_{LCDS}} + k_{CDS} \right] & \\ - \left[1 - R^{r}_{CDS} - \dfrac{1 - R_{CDS}}{1 - R_{LCDS}} (1 - R^{r}_{LCDS}) \right] \displaystyle\int_{\tau=0}^{T} e^{-r\tau} f\left(\tau, V, K \right) d\tau & if \quad c_{CDS} > \overline{c}_{CDS} \\ 0 & if \quad \underline{c}_{CDS} \le c_{CDS} \le \overline{c}_{CDS} \\ \left[\left(c_{LCDS} - k_{LCDS} \right) \dfrac{1 - R_{CDS}}{1 - R_{LCDS}} - k_{CDS} \right] - c_{CDS} & \\ + \left[1 - R^{r}_{CDS} - \dfrac{1 - R_{CDS}}{1 - R_{LCDS}} (1 - R^{r}_{LCDS}) \right] \displaystyle\int_{\tau=0}^{T} e^{-r\tau} f\left(\tau, V, K \right) d\tau & if \quad c_{CDS} < \underline{c}_{CDS} \end{cases} \quad (4.5)$$

where $G(T) = \int_{\tau=0}^{T} e^{-r\tau} f\left(\tau, V, K \right) d\tau$ is the expected present value under the risk-adjusted distribution of one dollar payment when the default event occurs. It is calculated using the

Leland and Toft (1996) model for each observation.[59] The real recovery rates of CDS and LCDS contracts under the worst case scenarios are $\{R_{CDS}^r = 0, R_{LCDS}^r = 100\%\}$ and $\{R_{CDS}^r = 0,$ $R_{LCDS}^r = 51\%\}$ for the strategies corresponding to the top and the middle lines of equation (4.5), respectively. Since the latter strategies, corresponding to paying the CDS and receiving the LCDS premium, contain by far the largest number of cases, we report their results in Table 8 and leave the others for the online appendix.

[Insert Table 8 about here]

Table 8 reports the summary statistics of the NPV and Figures III and IV in the online appendix show the distribution of NPV with option implied volatilities and realized volatilities, respectively, for the pay-CDS, receive-LCDS strategies. Table IX of our online appendix shows the relevant statistics for the opposite strategies. Since the results are very similar for both volatility estimation methods, we concentrate our discussion on the option implied equity volatilities case. Both mean and median NPV for the whole sample are significantly positive, around 2.77% and 1.73%, respectively, with similar results for the various sub-samples. The high standard deviation (6.04% for the whole sample) indicates heterogeneity across the observations. For the rated firms, the mean NPV decreases as the ratings decrease. We also note a significantly higher standard deviation of the NPV for the investment-rating class compared to the other sub-samples. For the not-rated firms, both the mean and median NPV are the highest among the sub-samples, with a relatively low standard deviation. A striking result of our estimations is the low probability of a negative NPV, which never rises above 5% for the entire sample and for all sub-samples. As for the Table IX results, they also show positive mean and median NPVs with

[59] The expression is also given in our online appendix. We assume that the asset risk premium is 4% for all the samples following the assumption invoked in Leland (2004).

higher probabilities of losses that are, however, still below 15% at the most for the whole sample. These results should be contrasted with the historical 5% value at risk (VaR) annual rates of return for five key US portfolios, including the "All US" and four of the six Fama-French portfolios, which never rise above -6% over the July 1926-September 2012 period and several sub-periods within it.[60]

Although all the results reported in Table 8 are under the worst-case scenario, the portfolios constructed by CDS and LCDS parity are still able to generate significantly positive NPVs on average in all cases. Since the recovery rates of both CDS and LCDS increase above 0 and 51% respectively as we move away from the worst-case scenarios, the NPV increases for all the types of strategies. The positive NPV is additional evidence under the structural model that the positive current payoffs of our strategies that we documented in the previous subsection are not rewards for risk but further evidence of market segmentation, over and above those presented in the previous subsections.

c. Principal Components Analysis of the Portfolio Payoffs Across all Maturities

In this exercise, we use principal components to identify the latent factors driving the portfolio current payoffs across all the maturities. If the illiquidity of CDS and LCDS contracts is a driver of the documented positive current payoffs, there should be a latent factor that is highly correlated with the illiquidity of the contracts. Specifically, such a latent factor should exhibit a different relationship with the less liquid contracts, such as contracts with 1-year and 10-year maturities, from that with the most liquid contract (i.e., 5-year maturity). The results are shown in Table X of the online appendix.

[60] See Table 5.3 in Bodie, Kane and Marcus, *Investments*, 10th edition, McGraw-Hill, 2013.

Based on the results of Table X, the first principal component (PC1) explains approximately 96% of the total variances across all the maturities, which is inconsistent with the conjecture that illiquidity is a candidate driver of the abnormal current payoffs. We also note that PC1 is highly correlated with the current payoffs for all the maturities and that the values of the correlations are very close to each other. These results rule out the possibility that the documented positive current payoffs are rewards for illiquidity risk and reinforce the segmentation hypothesis for the CDS and LCDS markets.

d. Naïve Trading Strategy

While CDS and LCDS recovery rates are inputs to justify the choice of trading strategy, it is impossible to observe the real recovery rates until a firm defaults. In this robustness test, we rule out this uncertainty from the trading strategy selection process and pursue a naïve trading strategy under which we always pay the CDS premium and receive the corresponding LCDS premium. Interestingly, we are still able to document daily abnormal current deviations in terms of their mean and median of approximately 1.52% and 0.64%, respectively, for the full sample. Such noticeable current deviations under the naïve trading strategy further support segmentation between the CDS and LCDS markets.

e. Realized Portfolio Payoffs for Matured Contracts

Although it is not possible to observe ex post the payoffs of our portfolios for the 5-year CDS-LCDS contract pairs, such verification is feasible for a subset of our 1-year sample, ending on March 19, 2011. For this subset there are 31,493 observations between April 11, 2008 and March 19, 2011, of which 11,425 observations are after April 5, 2010, when the LCDS contracts became fully non-cancellable. Using Moody's default and recovery data base, we find exactly one default event for the firms in our data base, with a recovery rate of 95%. Consequently, all our portfolios have positive cash flows, with an average size of 2.21%, for the full sample and 1.23% for the post April 5, 2010 sample. By contrast, the naïve strategy has average cash flows of 0.96% and 0.6% for the full and reduced sample respectively, but does show several negative cash flows. These results confirm the high profitability of our portfolio strategies in a real setting and confirm the segmentation between the two credit markets.

5. IMPACT OF MACRO AND FIRM-SPECIFIC VARIABLES

In this section, we study the impacts of different macro-economic and firm-specific variables on the current payoffs of the pricing parity portfolios in the presence of transaction costs. The list of variables was chosen from the most important factors explaining the levels and changes of credit spreads reported in the existing literature,[61] and refined based on multicolinearity[62] and data availability. The variables' correlations are reported in Table XI of the online appendix.

a. *Firm specific variables:*

We use logarithm of total asset (*LOGA*),[63] current ratio (*CAL*),[64] leverage ratio (*LEV*),[65] tangible assets (*TANG*)[66] and Idiosyncratic volatilities *(IDIO)* to control for the firm-specific characteristics. To obtain *IDIO*, we first calculate the daily returns by $r_{it} = p_{it} / p_{it-1} - 1$, where p_{it} denotes the daily closing equity price for firm i at day t, and then run the following regression using the Fama-French three-factor model to get the residual ε_{it},

[61] See Collin-Dufresne, Goldstein and Martin (2001), Acharya, Bharath and Srinivasan (2007), Acharya and Johnson (2007), and Cao, Yu and Zhong (2010).
[62] For instance, we use the yields on 5-year US treasury bonds since both CDS and LCDS contracts in our sample have five years to maturity. We use the spread between the yields on Aaa and Baa corporate bonds (CBS) and eliminate the VIX because we find that these two variables are highly correlated and that the CBS has better explanatory power than VIX.
[63] The sum of book value of total liabilities and the market value of total equity (traded and non-traded).
[64] Current assets divided by current liabilities.
[65] Total liabilities divided by total assets.
[66] The total value of property, plant and equipment divided by total assets.

$$r_{it} - rf_t = \alpha_t + \beta_1 (R_t - rf_t) + \beta_2 SMB + \beta_3 HML + \varepsilon_{it} \tag{5.1}$$

The idiosyncratic volatilities, $\sqrt{h_{it}}$, which are the conditional volatilities of the residuals, are filtered by an EGARCH model, given as follows,

$$\begin{aligned} &\varepsilon_{it} = \xi_{it}\sqrt{h}_{it}, \xi_{it} \sim N\left(0, \sqrt{h}_{it}\right) \\ &\ln(h_{it}) = \omega + \beta\left[\theta\xi_{it-1} + \gamma\left(\left|\xi_{it-1}\right| - E\left|\xi_{it-1}\right|\right)\right] + \alpha\ln(h_{it-1}) \end{aligned} \tag{5.2}$$

Idiosyncratic volatility is used as a measure of pricing uncertainty or price informativeness. Although there is some debate about the association between idiosyncratic volatility and price informativeness,[67] we conjecture that higher idiosyncratic volatility is associated with lower market efficiency. Since idiosyncratic noise generally reflects firm-specific factors which indicate increased information asymmetry, we expect that higher idiosyncratic volatilities are associated with increased current payoffs.

b. Macro variables

Publication of ISDA dummy (ISDA): As an administrator of the globally agreed standards of credit default swaps, the International Swaps and Derivative Association (ISDA) became more proactive after the sub-prime financial crisis and released a series of publications providing guidance and standards to try to protect investors and improve the efficiency of the CDS market. We examine the impact of the release on April 5, 2010 of a series of documents published by the ISDA regarding the North American Loan CDS market and described in the appendix. The *ISDA* dummy variable is equal to zero before and including the April 5 2010 ISDA publication day and equals one after this date. Since the LCDS market should become more efficient and deviations

[67] See Brockman and Yan (2009), Chen, Huang and Jha (2012), Krishnaswami and Subramaniam (1999), and Lee and Liu (2011).

from efficiency should decrease with standardization, we expect a negative coefficient for this dummy variable.

Macro variables associated with the business cycle: There are four such variables, the 5-year US treasury bond yield *(TB5Y)*, the slope of the term structure *(SL)*, measured by the difference between the yields on 5- and 1-year US treasury bonds, the yield spread between Aaa and Baa corporate bonds *(CBS)*, and the return of the S&P 500 total return index *(SP)*.

These four variables are leading indicators of the business cycle. With the exception of *CBS*, whose increase is associated with weakening prospects for the economy, increases in the other three factors indicate a stronger economy. The effects of these variables on the current payoffs of our portfolio strategies are by their nature ambiguous, since they affect all four variables on both sides of the parity relation (2.5). They affect the spreads directly because of their obvious impact on the default probabilities, but also affect both recovery rates indirectly, since the latter tend to increase when economic prospects improve. For *CBS* the CDS/LCDS spread ratio effect, which increases almost by definition when *CBS* increases, is likely to dominate the indirect recovery rates ratio, thus increasing the divergence and predicting higher current payoffs when CBS increases and a positive coefficient for this variable.

For the other three, however, no clear a priori prediction about the direction of their impacts can be formulated. Even if we assume that both spread and recovery rate for LCDS are relatively unaffected by the state of the economy, the latter would impact in opposite directions CDS spreads and recovery rates and affect both sides of the parity relation (2.5) in the same direction, with the net effect impossible to predict. All one can conjecture is that these divergent effects will weaken the explanatory power of these variables with respect to the current payoffs in the panel regressions.

The accounting variables, including total assets, book value of total liabilities, market value of equity, current assets, current liabilities and tangible assets, are obtained from the COMPUSTAT database via the WRDS platform. The data are updated quarterly. For our initial regressions, we convert the frequency from quarterly to daily by keeping the value constant within each quarter and then take a one quarter lag. The fixed income macro variables, including the yields on 1- and 5-year US treasury bonds, and Aaa and Baa corporate bond yields are obtained from the US Federal Reserve H15 database. The equity prices and S&P 500 total return index data are obtained from Bloomberg.

c. Regression results

The panel regression results are reported in Table 9.[68] Overall, the combination of the firm specific variables and macro variables is able to explain on average 63.9% of the deviations between the CDS and LCDS markets in the presence of transaction costs. The lowest R-square of 39.20% is observed for the regression for the ENR firm sub-sample followed by an R-square of 46.81% for the regression for the investment grade sub-sample. The R-squares for the junk-rated, not-rated and NENR subsets are all above 79%. The signs of the estimated coefficients that are significant are generally consistent across the subsets.

The leverage ratio consistently increases the current payoffs of the simulated portfolio for all the samples apart from the not-rated firms and exhibits greater sensitivity for ENR firms. A

[68] For the regressions we allow for residual autocorrelation across time and cross-sectional dependence across firms by employing clustered standard errors as in Petersen (2009). We use clustering because the first-order autocorrelation for the current payoffs of the various simulated portfolios examined in this section of the paper exceeds 0.9; see also Wolfson (2011).

higher idiosyncratic volatility increases the current payoffs significantly across most of the samples except for the junk and ENR firms. In particular, for the investment grade firms the current payoffs increase by 0.37% on average for every 1% increase in idiosyncratic volatility. We also note that the impact of idiosyncratic volatility is much greater for the NENR firms compared to that for the ENR firms. Neither the logarithm of asset value nor the current ratio (CAL) have significant coefficients for all samples.

[Insert Table 9 about here]

For the macro factors, the yield on 5-year US treasury bonds (*TB5Y*), the slope of the yield curve for treasury bonds (*SL*) and the spreads between Aaa and Baa corporate bonds (*CBS*) are significant at the conventional level for the full sample. The coefficients of the ISDA publication dummy are not significantly different from zero except for the not-rated sub-sample. According to Table 9, we note that the not-rated sample has the highest volatility for the current payoffs compared to the others. Since the purpose of the ISDA publications is to standardize and regulate the LCDS markets, their effect should be much more important for the samples with the most volatile current payoffs, as in our empirical findings. With the exception of the S&P 500 total returns, whose coefficients are negative but not significant anywhere, the variables associated with the state of the economy generally have significant impacts on current payoffs. The effect of the yield of 5-year US treasury bonds on current payoffs is consistently negative for all sub-samples but not significant for not-rated and ENR samples. The slope of the yield curve for treasury bonds positively affects current payoffs. The spread between the yields on Aaa and Baa corporate bonds (*CBS*) significantly increases the current payoffs on the simulated portfolio for the full sample, consistent with our predictions.

d. Robustness tests

The separate contributions of the macro and firm-specific factors are studied by conducting regressions for restricted models and the results are reported in Table XII of the online appendix. For the restricted model of fixed effects only, the goodness of fit of about 58.18% is slightly lower than that of the unrestricted model of about 63.90%. This implies that the cross sectional effect is much more important than the time series effect.

We also restrict the model with only firm specific variables or only macro variables, respectively. Although more than half of the coefficients of the macro factors are significantly different from zero, their contribution to current payoffs is much smaller compared to that of the firm-specific factors. Numerically, the maximum contribution of all macro factors and firm specific factors are approximately 1.87% and 11.69%, respectively, in terms of R-square.[69] In other words, the marginal contribution of macro variables to the explanation of abnormal current payoffs is very small compared to that of firm specific factors. Further, we note that coefficients of the leverage ratio (*LEV*) and idiosyncratic volatilities (*IDIO*) are significantly different from zero at conventional levels and their signs are consistent with those for the unrestricted model.

Nonetheless, the fact that firm specific effects account for most of the variability of current payoffs should not obscure the fact that macro factors are also extremely important in segmenting the markets and increasing the payoffs, even though the reasons for their effects are hard to interpret. Table XIII in the online appendix presents time series regressions of the payoffs for the payoff daily index calculated by (4.1) for the full sample and all sub-samples. The signs, sizes and levels of significance of the coefficients are very similar to those of Table 9 and are generally consistent across all samples. With the exception of the Junk and ENR sub-samples,

[69] See Carlino, Defina and Sill (2013) for the analysis of marginal contribution of each factor.

the explanatory powers of the regressions are very high, over 80% for the NENR and over 75% for the full sample. There are also significant dummy variable coefficients for the years of the observations.

We also check the robustness of our findings when we reduce the frequency of our time series data. In these exercises, the daily current payoffs are aggregated into weekly, monthly and quarterly time intervals and the panel regressions are repeated for the full sample in each case. The results are reported in Table XII in the online appendix. Both the sign and (most of the times) the significance levels of the coefficients are very robust with respect to the level of aggregation, but their magnitude depends on the frequency of the data.

In summary, the contribution of the cross sectional effect on current payoffs dominates that of the time series effect in the full panel regressions. The firm-specific factors, especially firm size, leverage ratio and idiosyncratic volatility, are much more important than the macro factors in explaining the observed current pricing-parity deviations at the individual firm level. The macro factors play a major role as explanatory variables of the daily payoff index time series. Our findings are confirmed with lower frequency data.

6. CONCLUSION

We document extensive violations of the CDS and LCDS parity relation (most likely arising from market segmentation), implying a time-varying and significant positive current payoff from simulated portfolios that simultaneously take offsetting positions in CDS and the corresponding LCDS contract, which depend on the direction of the violation of the parity relation. Such abnormal positive current payoffs cannot be explained by data imperfections, risk of future positions or illiquidity of contracts. We confirm these findings with data from matured one-year contracts that show uniformly positive *realized* profits of our simulated portfolios, and with the estimation of a structural model that uses additional unrelated data sources and reaches virtually identical conclusions.

This failure of arbitrage to equalize the spreads in the CDS and LCDS markets is more prevalent in times of financial crisis, but is also present under more normal circumstances. It could be a tradable anomaly, which may be due to the novelty of the LCDS market. It is briefly mentioned as a possibility in a published source that refers to internal financial industry reports,[70] but is formally documented here for the first time. It remains to be seen whether it will persist as the market matures.

An alternative explanation that, however, also implies the segmentation of the CDS and LCDS markets, relies on the "limits to arbitrage" explanation of apparent anomalies.[71] In the absence of intraday data on both markets it is not possible to verify the availability and depth of the contracts necessary to realize the positive current payoffs. Further, the operations involved in establishing the positions are swap agreements that do not involve short sales but may involve margins or collateral.

Market segmentation also can arise if there is market power, either from traders or from the swap dealer side, who participate in both CDS and LCDS markets and behave differently in the two markets in order to maximize their aggregate profits. Such market power for the CDS market has been mentioned in recent studies that note this market's highly concentrated nature.[72]

[70] See Ong, Li and Lu (2012, p. 68). That study, which does not rely on any data, dismisses the CDS-LCDS market segmentation as a potentially tradable anomaly and attributes it to factors such as the ones examined in this paper. As we saw, these factors cannot account for the simulated or observed profits.
[71] See Shleifer and Vishny (1997). This concept underlines explanations of the dramatic violations of an "arbitrage" relationship between bond yield spreads and credit-default swap (CDS) rates during the financial crisis as in Duffie, (2010); Gârleanu and Pedersen, (2011) and Mitchell and Pulvino, (2012).
[72] See Bolton and Oehmke (2013) and Atkeson, Eisfeldt and Weill (2013).

Further, derivatives market segmentation due to market power has been noted in at least one study in a different context (pre-2002 option trading in the Montreal Exchange).[73]

Examination of these factors requires access to microstructure data in the two markets. Given the importance of the CDS markets in the recent financial crisis, such a microstructure study should be the focus of future research.

[73] See Khoury, Perrakis and Savor (2011).

Appendix A: Some Details about the North American Loan CDS Documentation Published on April 5, 2010 by the ISDA[74]

Document Name	Abstract
Bullet Syndicated Secured Loan Credit Default Swap Standard Terms Supplement	*"This template is designed to document credit default swap transactions where the Deliverable Obligations are limited to Syndicated Secured Loans of the Reference Entity. This form is primarily intended for use in the North American market. The contract: (a) has a "bullet" maturity, i.e. not subject to acceleration in the case where the Reference Entity's loans are repaid; (b) is subject to a credit event determination by a Determinations Committee; (c) provides for auction settlement if the Participating Dealers vote to hold an auction under the Bullet LCDS Auction Rules in relation to a Reference Entity and Designated Priority; and (d) contains specific rules and procedures for determining Successors to the Reference Entity (the procedures are contained in the Bullet LCDS Continuity Procedures). If no auction is held or the auction fails or is abandoned, Physical Settlement will apply to LCDS transactions under the most recently-published form of LSTA Physical Settlement Rider, which is available from the LSTA's website."*
Bullet Syndicated Secured Loan Polling Rules	*"This document contains the rules and procedures that apply to determine whether a loan qualifies as a "syndicated secured" loan of the Reference Entity, for purposes of the syndicated secured list."*
Bullet LCDS Auction Rules and LCDS Auction Settlement Terms	*"The Bullet LCDS Auction Rules and LCDS Auction Settlement Terms are designed to facilitate the settlement of Bullet Syndicated Secured Loan Credit Default Swap transactions."*
Bullet LCDS Continuity Procedures	*"The Bullet LCDS Continuity Procedures contain the procedural rules for determination of a Successor under the Bullet LCDS documentation*."

74 The abstracts are quoted from ISDA website: http://www.isda.org/publications/isdacredit-deri-def-sup-comm.aspx#ra

Appendix B: Restructuring Clause[75]

Restructuring Clause	Details
Cum Restructuring (CR) or old restructuring	Any restructuring event is qualified as a credit event and any bond of maturity up to 30 years is deliverable. (1999 ISDA credit derivative definition)
Modified Restructuring (MR)	Restructuring events are considered as a credit event and the bonds with maturity of 30 months or less after the termination date of the CDS contract are deliverable. (2001, ISDA credit derivative definition)
Modified-Modified Restructuring (MM)	Restructuring events are considered as a credit event and the bonds with maturity of 60 months or less for the restructured obligations and 30 months for all the other obligations after the termination date of the CDS contract are deliverable. (2003, ISDA credit derivative definition)
Ex-Restructuring(XR) or without restructuring	All the restructuring events are not considered as a credit event.

Appendix C: Recovery Rate Calculation Approaches[76]

Settlement discount method	The value of the settlement instruments is taken at or close to default.
Trading price discount method	The value of the settlement instruments is based on the trading prices of the defaulted instruments at or post-emergence.
30-day trading price method	The value of the settlement instrument is based on the trading price of the defaulted instruments 30 days after the bankruptcy.

[75] See Packer and Zhu (2005) and Berndt, Jarrow and Kang (2006).
[76] Sources: Moody's Ultimate Recovery Database, Special Comment, April, 2007.

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Table 1: Summary Statistics

This table reports the summary statistics for the full sample and sub-samples during the period from April 11th, 2008 to March 30th, 2012. The idiosyncratic volatilities are the conditional daily volatilities of individual equity return residuals by fitting the Fama-French three-factor model. Total assets equal the sum of book value of total liabilities and market value of total equities. Leverage equals book value of total liabilities divided by the total asset value. Tangible ratio equals the book value of tangible assets divided by the total asset value. The current ratio equals current assets divided by current liabilities.

	CDS Spreads	CDS Recovery Rates	LCDS Spreads	LCDS Recovery Rates	Idiosyncratic Volatility	Total Asset (Thousands)	Leverage	Current Ratio
Full Sample (No. of Observations: 68147)								
minimum	0.0027	0.0125	0.0001	0.0750	0.0053	446.51	0.0834	0.2398
maximum	0.9651	0.7050	0.8984	0.9775	0.8429	295142.56	0.9857	5.8299
mean	0.0461	0.3817	0.0367	0.6523	0.0237	25193.94	0.6045	1.5413
median	0.0311	0.4000	0.0243	0.7000	0.0203	13565.72	0.6126	1.4112
standard deviation	0.0684	0.0567	0.0482	0.1128	0.0172	37329.28	0.1842	0.6878
skewness	6.7356	-1.8116	6.4265	-0.7765	10.8217	4.17	-0.2464	1.3736
1^{st} order serial ρ (Daily)	0.9783	0.7730	0.9690	0.9273	0.8162	0.9904	0.9890	0.9874
1^{st} order serial ρ (Quarter)	0.4535	0.2632	0.4125	0.3724	0.4439	0.5672	0.5450	0.3671
Investment Grades (Above and include BBB, No. of Observations: 41327)								
minimum	0.0027	0.0722	0.0001	0.0750	0.0053	446.5	0.0834	0.2398
maximum	0.9453	0.6750	0.8671	0.8500	0.6991	295142.6	0.9746	5.2277
mean	0.0418	0.3809	0.0331	0.6386	0.0229	31707.0	0.5912	1.4944
median	0.0252	0.4000	0.0210	0.6750	0.0194	17942.9	0.5964	1.3890
standard deviation	0.0614	0.0506	0.0497	0.1152	0.0161	40757.4	0.1834	0.6286
skewness	5.4439	-3.2517	6.7415	-0.6919	8.5820	3.7	-0.2199	1.1164
1^{st} order serial ρ (Daily)	0.9659	0.7369	0.9346	0.8946	0.7962	0.9594	0.9709	0.9748
Junk (Below BBB, No. of Observations: 11665)								
minimum	0.0028	0.0125	0.0001	0.3250	0.0054	446.51	0.0834	0.2398
maximum	0.9651	0.7050	0.6253	0.8500	0.5781	257135.61	0.9794	5.2277
mean	0.0543	0.3750	0.0384	0.6349	0.0240	23330.80	0.6341	1.4500
median	0.0391	0.4000	0.0257	0.6500	0.0215	13154.38	0.6582	1.3259
standard deviation	0.0765	0.0556	0.0416	0.1136	0.0155	38118.25	0.1939	0.6880
skewness	7.5180	-2.3062	3.0163	-0.6069	8.1152	4.50	-0.4206	1.8634
1^{st} order serial ρ (Daily)	0.8493	0.6214	0.8495	0.8364	0.6903	0.8697	0.8719	0.8730
Not Rated (No. of Observations: 15155)								
minimum	0.0037	0.0188	0.0001	0.1000	0.0056	450.51	0.1008	0.2398
maximum	0.9463	0.7050	0.8984	0.9775	0.8429	249734.43	0.9857	5.8299
mean	0.0515	0.3889	0.0449	0.7030	0.0255	8867.08	0.6178	1.7393
median	0.0363	0.4000	0.0349	0.7250	0.0218	5739.02	0.6364	1.6201
standard deviation	0.0781	0.0707	0.0476	0.0882	0.0209	15260.94	0.1746	0.7961
skewness	7.4978	-0.2131	7.5601	-1.0831	13.8551	11.73	-0.1909	1.2968
1^{st} order serial ρ (Daily)	0.7864	0.7350	0.8066	0.8261	0.6336	0.8855	0.8320	0.8339

Table 2: Summary statistics of bid-ask spreads (Unit: basis points)

This table reports the summary statistics of bid-ask spreads. The *Firm Averages* shows the average bid-ask spread for each firm during the period from January, 2nd, 2008 to November 23rd, 2012, depending upon the data availability. The *Daily Average* shows the average bid-ask spread for each day across all the available firms. The unit is basis points.

	Firm Average	Daily Average (Cross Firms)
Minimum	3.76	4.50
Maximum	283.24	93.23
Mean	35.15	26.13
Median	17.68	21.62
Standard Deviation	47.35	14.83
Skewness	3.28	1.89
Kurtosis	13.27	3.31
No. of Observations	61 Firms	1219 Days

Figure 1: Distribution of Trading Strategies with Transaction Costs

This figure depicts the distribution of trading strategies with transaction costs for the cross-sectional daily observations of the full sample during the sample period from April 11th, 2008 to March 30th, 2012.

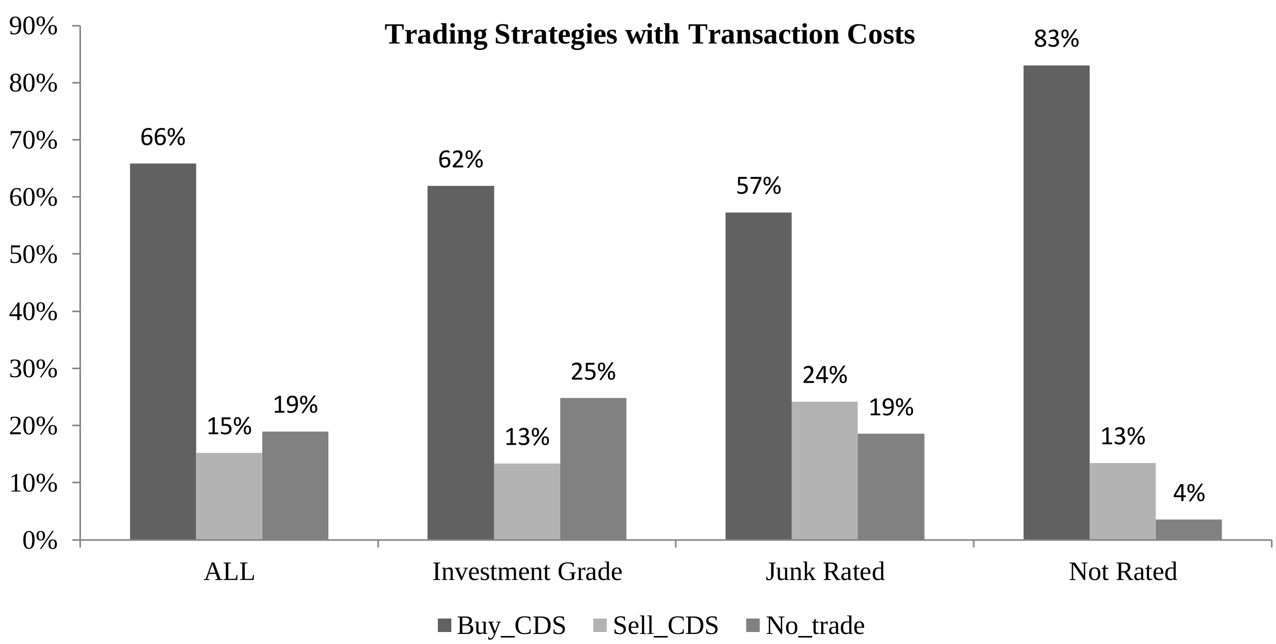


Table 3: Summary Statistics of Current Payoffs with Transaction Costs

This table reports the summary statistics of the current payoffs generated by the simulated portfolios when the CDS and LCDS parity is violated for the cross-sectional daily observations, firm daily average across the time span and index daily across all the available firms during the sample period from April 11th, 2008 to March 30th, 2012. It is assumed that the transaction costs are the same under CDS and LCDS market. The daily transaction costs come from the daily average bid-ask spread observed in the Bloomberg database with the sample firms in Table 2.

	Minimum	Maximum	Mean	Median	Standard Deviation	Skewness	Kurtosis
			Cross-Sectional Daily Observations (68147 Observations)				
Full Sample	0	1.6471	0.0338	0.0124	0.0740	8.5618	123.3978
Investment	0	1.6470	0.0266	0.0079	0.0649	11.6478	238.8615
Junk	0	0.5149	0.0292	0.0106	0.0527	3.8685	19.0626
Not Rated	0	1.2905	0.0568	0.0344	0.1015	5.7636	42.8601
			Firm Daily Average Observations (120 Firm-Clause Contracts)				
Full Sample	0	0.6572	0.0413	0.0210	0.0811	5.4707	35.5509
			Index Daily Observations (959 Daily Observations)				
Full Sample	0.0166	0.0855	0.0332	0.0288	0.0120	1.0370	0.3901
Investment	0.0057	0.0781	0.0257	0.0225	0.0122	1.0986	1.1091
Junk	0.0012	0.1466	0.0315	0.0264	0.0207	1.4661	2.7208
Not Rated	0.0135	0.1386	0.0562	0.0462	0.0316	0.8427	-0.4417

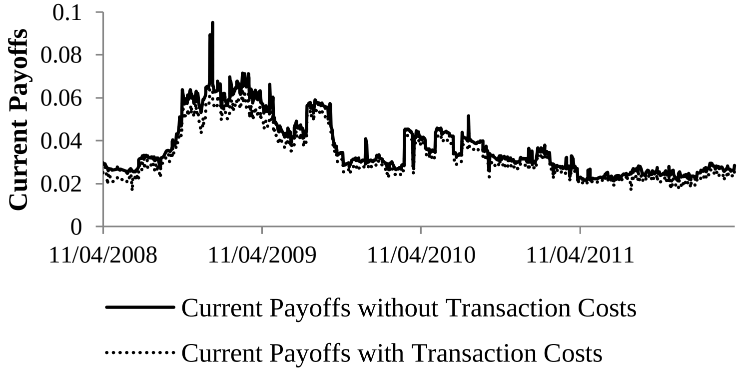
Table 4: Summary Statistics of Implied Transaction Costs in the absence of Current Payoffs

This table reports the summary statistics of the implied transaction costs under which the CDS and LCDS parity is not violated for the cross-sectional daily observations (Panel A), firm daily average across the time span (Panel B) and index daily across all the available firms (Panel C) during the sample period from April 11th, 2008 to March 30th, 2012. It is assumed that the transaction costs are same under CDS and LCDS market. The transaction costs reported in the table are round trip transaction cost (Bid-Ask spread) in basis points.

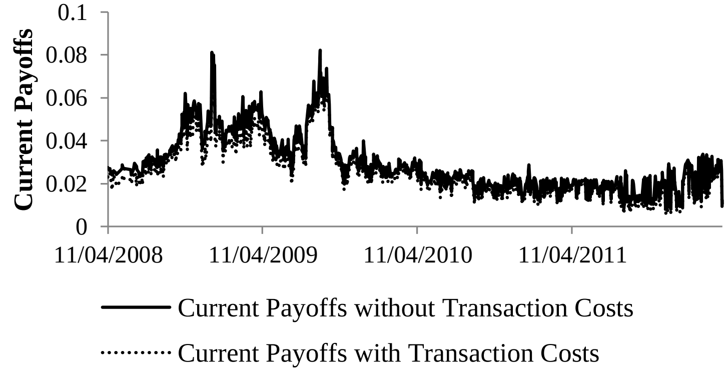
			Panel A: Cross-Sectional Daily Observations (68147 Observations)				
	Maximum	Minimum	Mean	Median	Standard Deviation	Skewness	Kurtosis
Full Sample	10254.70	0.00	199.89	73.49	404.40	8.97	159.88
Investment	10254.70	0.00	175.04	55.08	429.77	10.58	194.06
Junk	2547.22	0.00	172.70	44.46	350.95	3.61	14.41
Not Rated	6401.14	0.00	288.59	227.50	356.07	5.91	71.13
			Panel B: Firm Daily Average Observations (120 Firm-Clause Contracts)				
	Maximum	Minimum	Mean	Median	Standard Deviation	Skewness	Kurtosis
Full Sample	2032.92	0.00	202.52	116.02	288.07	3.46	16.24
			Panel C: Index Daily Observations (959 Daily Observations)				
	Maximum	Minimum	Mean	Median	Standard Deviation	Skewness	Kurtosis
Full Sample	509.57	101.39	196.01	162.59	74.94	1.24	0.49
Investment	513.04	17.46	168.73	156.59	69.85	1.21	2.54
Junk	826.96	19.63	191.45	159.44	119.70	1.25	1.75
Not Rated	1084.12	111.29	283.12	216.36	168.70	1.78	2.53

Figure 2: Daily Average Current Payoffs

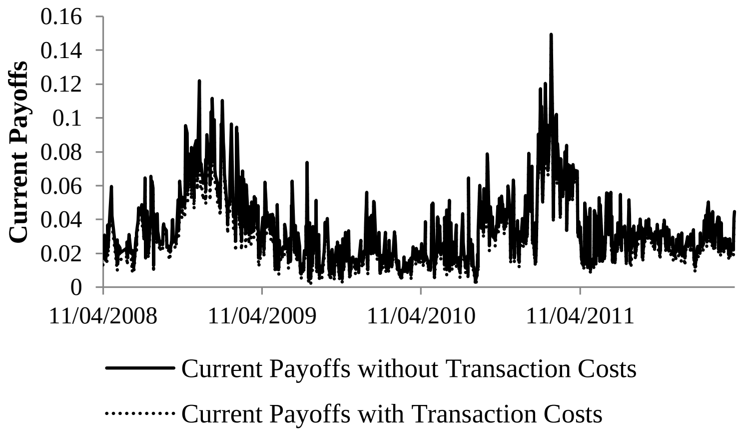
Panel A: Daily Average Current Payoffs of Full Sample



Panel B: Daily Average Current Payoffs of Investment Grades Contracts



Panel C: Daily Average Current Payoffs of Junk Rated Contracts



Panel D: Daily Average Current Payoffs of Not Rated Contracts

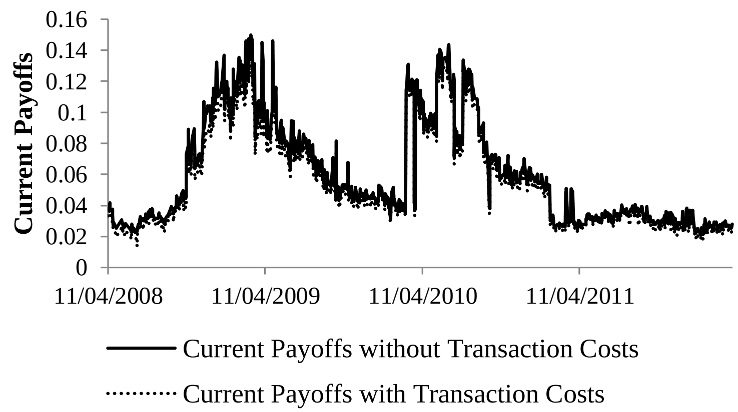


Table 5: Actual Concurrent Defaults of Syndicated Secured Loans and Senior Unsecured Bonds

This table reports actual concurrent defaults of first lien syndicated secured loans and senior unsecured bonds listed in Moody's Ultimate Recovery Database during the period from 1987 to 2012. All the defaults are due to bankruptcy. PP&E is property, plant and equipment. The blank spaces signify that the data are not available. The details of trading price discounts, settlement discounts and 30-day trading price recovery rates are reported in the appendix.

Company Name	Date of Obligor Default	Instrument Type	Instrument Description	Collateral	Trading Price Discounted Recovery	Settlement Discounted Recovery	30 Day Trading Price
Panel A: First Lien Syndicated Secured Loans							
CCS Medical Inc	07/08/2009	Term Loan	First lien term note	All Assets	63.67%	51.08%	
Hilex Poly Corp.	05/06/2008	Term Loan	First Lien Hilex Poly Term Loan B	PP&E	94.16%	100.00%	95.00%
Movie Gallery, Inc.	10/16/2007	Term Loan	March 2007 Credit Facility First Lien Term Loan	All Assets		100.00%	
Quality Home Brands Holdings LLC	12/04/2009	Term Loan	First Lien Term Loan	All Assets	52.84%	58.38%	
Sbarro, Inc.	04/04/2011	Term Loan	First Lien Term Loan	All Assets	72.88%		98.21%
Werner Holding Company	06/12/2006	Term Loan	First Lien Term Loan	All Assets	91.63%	100.00%	96.75%
Panel B: Senior Unsecured Debts							
CCS Medical Inc	07/08/2009	Senior Unsecured Bonds	Unsecured note payable	Unsecured	0.00%	0.00%	0.00%
Hilex Poly Corp.	05/06/2008	Senior Unsecured Bonds	Sonoco Note	Unsecured	0.00%	0.00%	0.00%
Movie Gallery, Inc.	10/16/2007	Senior Unsecured Bonds	11% Senior Notes due 2012	Unsecured	0.00%	19.47%	25.00%
Quality Home Brands Holdings LLC	12/04/2009	Senior Unsecured Bonds	13.50% Senior Adjustable Notes	Unsecured	1.84%	0.00%	0.00%
Sbarro, Inc.	04/04/2011	Senior Unsecured Bonds	Unsecured Senior Notes	Unsecured	0.00%	0.00%	22.00%
Werner Holding Company	06/12/2006	Senior Unsecured Bonds	10% Senior Subordinated Notes due 2007	Unsecured	0.83%	0.00%	19.25%

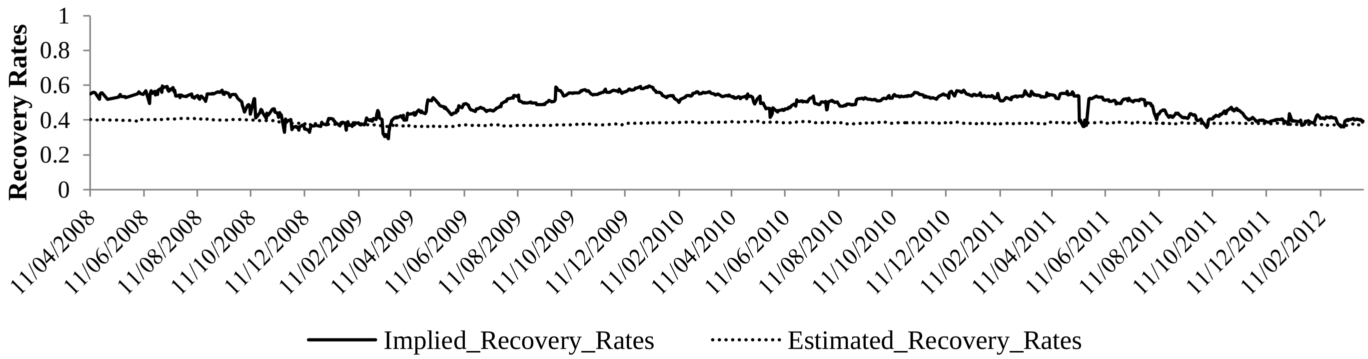
Table 6: Event study of Negative Implied Recovery Rates

This table reports the means and medians of the variables of interest on one day before (*1 Day Before*) and the first day (*First Day*) of the negative implied recovery rates for the full sample. *Spread ratios* are equal to the *CDS spreads*/*LCDS spreads*. *Recovery Rates Ratios* are equal to (1-*CDS Recovery Rates*)/(1-*LCDS Recovery Rates*). For the means, the two-sided two-sample tests with normal and t approximation are conducted and the corresponding *p*-values are reported as the difference test. For the medians, the Wilcoxon median two-sample tests are conducted and the corresponding *p*-values are reported. ***, ** and * indicate the 1%, 5% and 10% significance levels, respectively.

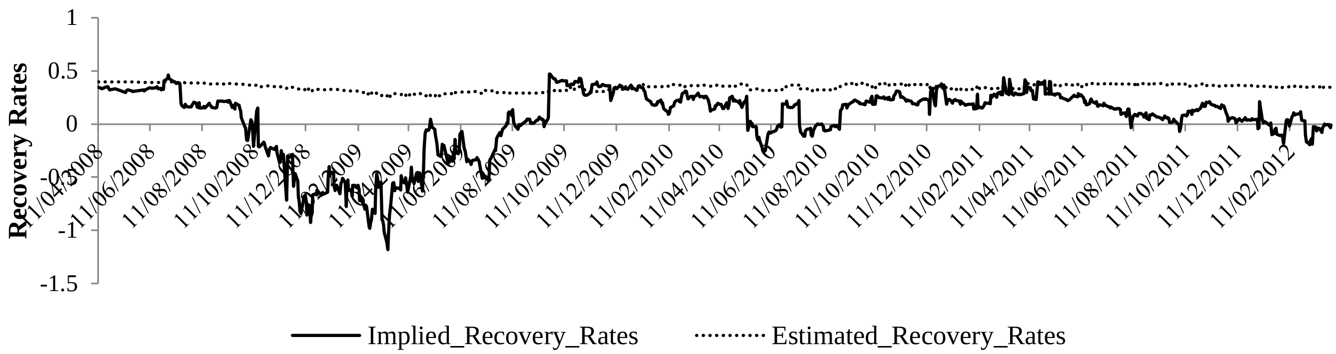
	Mean				Median		
	1 day Before	First Day	Difference Test Student t (p-value)	Difference Test Normal (p-value)	1 day Before	First Day	Wilcoxon Test (p-value)
CDS Spreads	0.1424	0.1582	0.2163	0.2160	0.0918	0.0935	0.2446
LCDS Spreads	0.0728	0.0639	0.1174	0.1169	0.0323	0.0309	0.1245
Spreads Ratios	6.0397	7.9953	<.0001***	<.0001***	2.8469	3.3583	0.019**
CDS Recovery Rates	0.3379	0.3405	0.4852	0.4852	0.3667	0.3667	0.5
LCDS Recovery Rates	0.6277	0.5977	0.0270**	0.0265**	0.7000	0.6708	0.0799*
Recovery Rates Ratios	1.9249	1.7988	0.0191**	0.0187**	2.0000	1.9355	0.0516*
Current Payoffs	0.0293	0.0567	<.0001***	<.0001***	0.0222	0.0347	<.0001***
Equity Returns	-0.0055	-0.0160	0.3304	0.3303	-0.0054	-0.0071	0.3224
Idiosyncratic Volatility	0.0469	0.0405	0.3360	0.3358	0.0305	0.0311	0.2446
Bid-Ask Spreads	0.0035	0.0034	0.3534	0.3532	0.0024	0.0024	0.3224
No. Observations	150	150			150	150	

Figure 3: Index of Implied Recovery Rates

Panel A: Daily Average Recovery Rates of the Full Sample



Panel B: Daily Average Recovery Rates of the ENR Firms



Panel C: Daily Average Recovery Rates of the NENR Firms

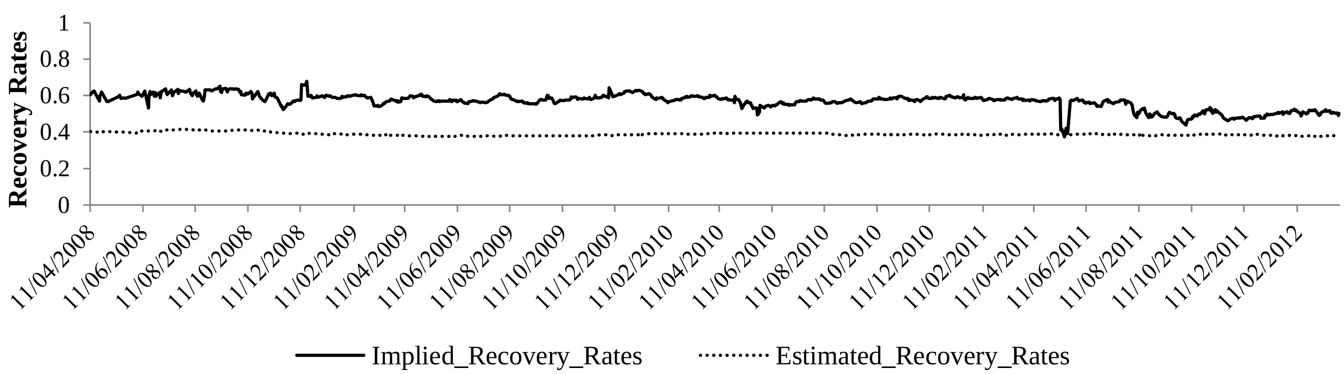


Figure 4: Trading Strategies of ENR and NENR Firms

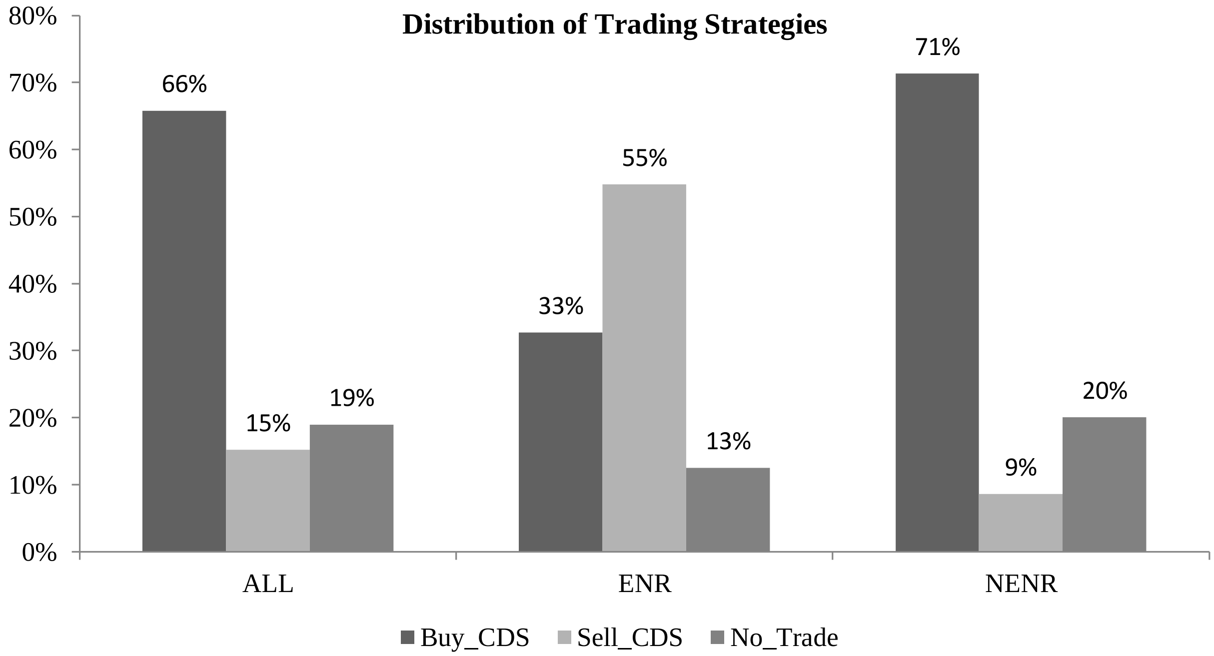


Figure 5: Time Distribution of the Negative Implied Recovery Rates

This figure depicts the percentage of the negative implied recovery rates over the total available observations for the full sample during the sample period from April, 11th . 2008 to March 30th, 2012.

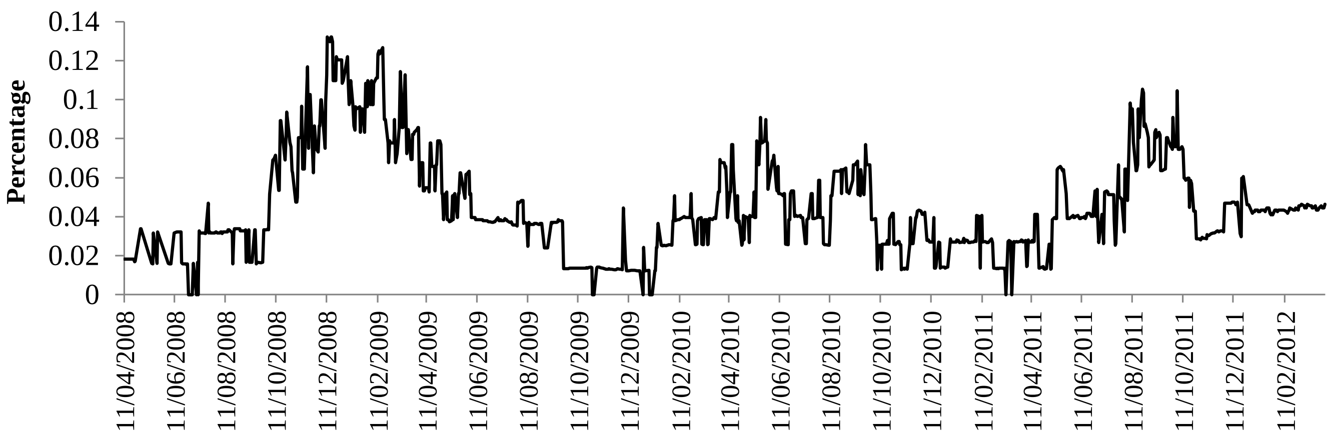


Figure 6: Term Structure of Portfolio Current Payoffs

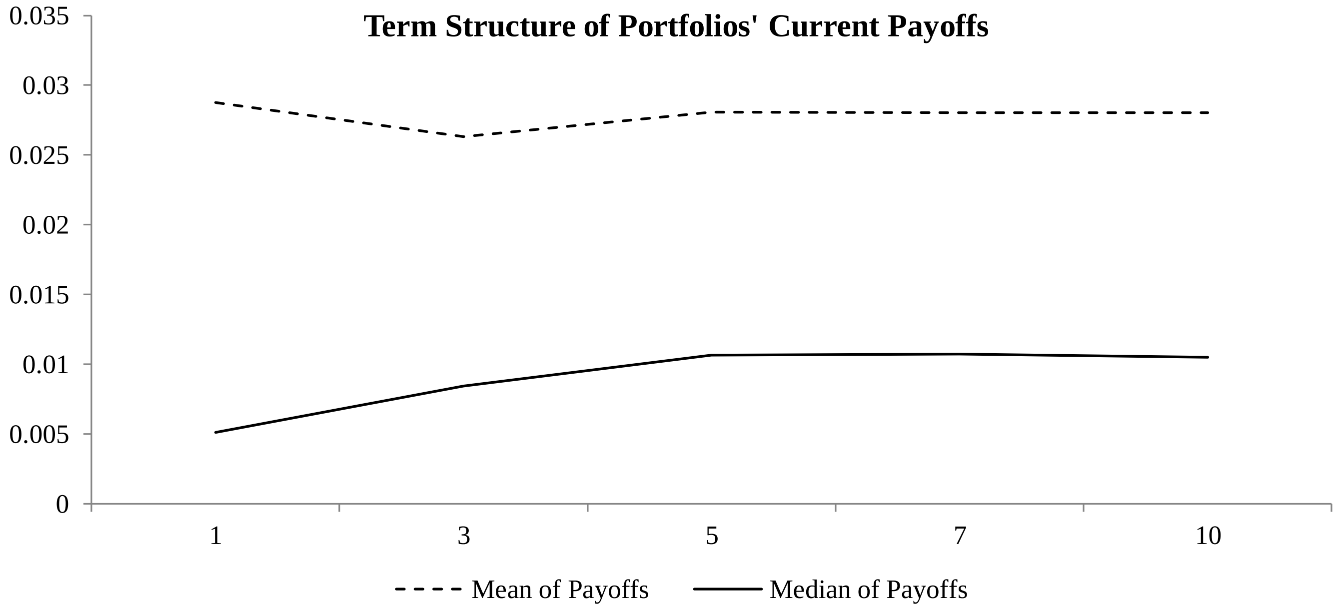


Figure 7: Distribution of Trading Strategies for different Maturities

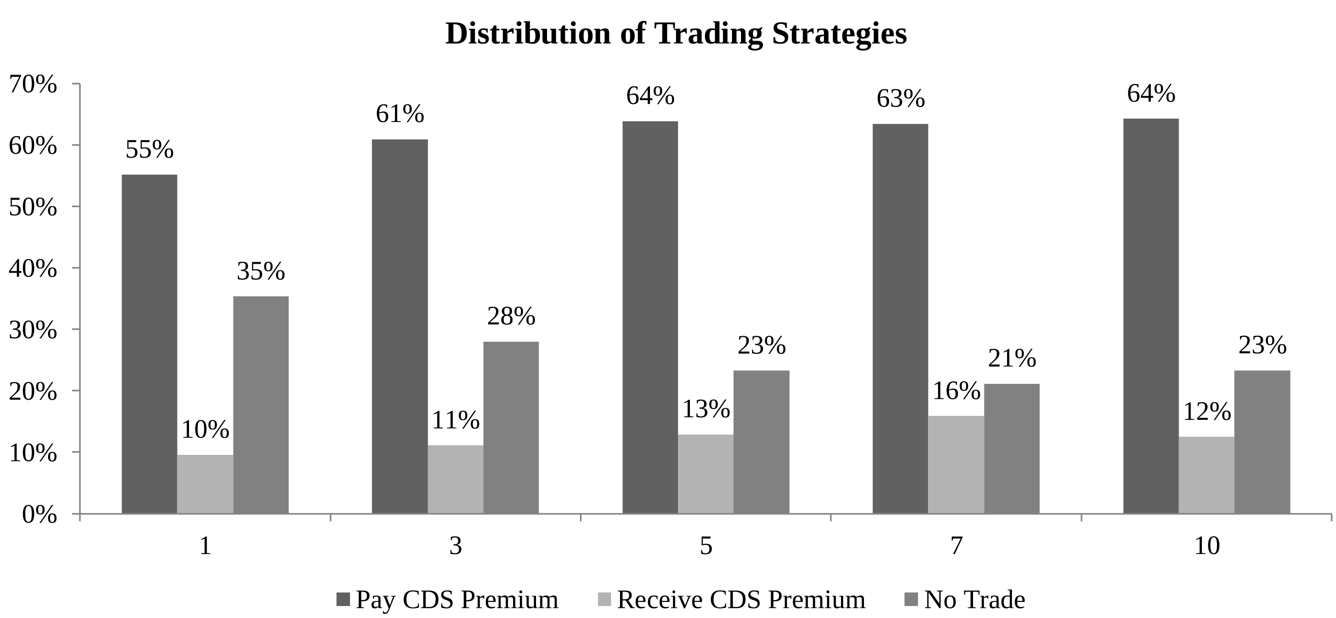


Table 7: Portfolio Current Payoffs with Structural Model Implied CDS Recovery Rates

This table reports the results of the Generalized Method of Moments (GMM) estimation with put option implied volatilities and realized volatilities of equity, respectively, in Panel A. The details of the GMM estimation are reported in the online appendix. The summary statistics of the current payoffs of portfolios in the presence of transaction costs are reported in Panel B and C with different equity volatilities, respectively. The estimated LCDS recovery rates provided by Markit and the structural model-implied CDS recovery rates are used for the calculation of current payoffs in Panels B and C.

Panel A: Results of GMM Estimations

	Results with Put Option Implied Volatilities of Equity			Results with Realized Volatilities of Equity		
	Asset Volatilities	CDS Recovery Rates	Sum of Squared Errors	Asset Volatilities	CDS Recovery Rates	Sum of Squared Errors
Average across firms	0.1093	0.3532	0.0500	0.1019	0.3211	0.0406
Standard Deviation across firms	0.0844	0.2534	0.1078	0.0794	0.2422	0.0341

Panel B: Current Payoffs with Option Implied Equity Volatilities

	Minimum	maximum	Mean	Median	Standard Deviation	Skewness	Kurtosis
Cross-Sectional Daily Observations (50258 Observations)							
Full Sample	0.0000	0.7174	0.0274	0.0135	0.0435	5.4270	53.3188
Firm Daily Average Observations (80 Firm-Clause Contracts)							
Full Sample	0.0001	0.1433	0.0304	0.0187	-0.0323	1.6933	2.7541
Index Daily Observations (878 Daily Observations)							
Full Sample	0.0157	0.0813	0.0274	0.0211	0.0128	1.4296	1.2226

Panel C: Current Payoffs with Realized Equity Volatilities

	Minimum	maximum	Mean	Median	Standard Deviation	Skewness	Kurtosis
Cross-Sectional Daily Observations (50258 Observations)							
Full Sample	0.0000	0.7555	0.0283	0.0144	0.0436	5.1204	49.7035
Firm Daily Average Observations (80 Firm-Clause Contracts)							
Full Sample	0.0002	0.1435	0.0321	0.0240	-0.0323	1.4947	2.1458
Index Daily Observations (878 Daily Observations)							
Full Sample	0.0161	0.0844	0.0284	0.0223	0.0133	1.3764	1.0540

Table 8: Summary Statistics of NPV with Structural Model (Leland and Toft (1996)

This table reports the net present value (NPV) of the trading strategy of paying the CDS and receiving the LCDS premium, based on the CDS and LCDS pricing parity under the worst scenario in which the future real recovery rates of CDS and LCDS contracts are zero and 51%, respectively. The first passage cumulative default probabilities are calculated using Leland and Toft (1996)'s calibration with the Generalized Method of Moment (GMM) technique. Mathematically, the NPV for each observation is given by equation (4.5).

	Mean	Median	Min	Max	Standard Deviation	Less than zero (Percentage)
Panel A: Pay CDS Premium Strategy with Option Implied Volatilities						
Full Sample	0.0277	0.0173	-0.1967	1.6471	0.0604	3.32%
Invest Rating	0.0274	0.0156	-0.1398	1.6471	0.0719	2.77%
Junk Rating	0.0236	0.0154	-0.1426	0.1874	0.0330	3.64%
No Rated	0.0308	0.0251	-0.1967	0.5009	0.0374	4.51%
Panel B: Pay CDS premium Strategy with Realized Volatilities						
Full Sample	0.0274	0.0167	-0.1902	1.6471	0.0602	3.76%
Invest Rating	0.0265	0.0147	-0.1296	1.6471	0.0719	3.56%
Junk Rating	0.0236	0.0150	-0.1331	0.1874	0.0329	4.54%
No Rated	0.0318	0.0259	-0.1902	0.5009	0.0363	3.78%

Table 9: Panel Regression with Important Events and Macro Economic Factors

This table reports panel regression results with single name fixed effects during the sample period from April 11th, 2008 to March 30th, 2012. The variables are the intercept (*INT*), publication of ISDA dummy (*ISDA*), total asset (*LOGA*), current asset over current liability ratio (*CAL*), leverage ratio (*LEV*), tangible assets ratio (*TANG*), idiosyncratic volatility (*IDIO*), 5-year US treasury bond yields (*TB5Y*), slope of the yield term structure (*SL*), the spread between Aaa corporate bonds' yield and Baa corporate bonds' yield (*CBS*) and S&P 500 index returns (*SP*). Clustered standard errors are used to allow for residual autocorrelation and cross-sectional dependence as in Petersen (2009). The statistically significant coefficients are indicated by ***, ** and * for significance at the 1%, 5% and 10% significance levels, respectively. P-values are reported in the parentheses.

Variables	Full Sample	Investment Grades	Junk	Not Rated	NENR Firms	ENR Firms
INT	-0.1465	-0.2019	0.0618	-0.0836	-0.2841	0.0487
	(0.5260)	(0.4530)	(0.6767)	(0.8701)	(0.6363)	(0.7067)
ISDA	-0.0018	-0.0013	-0.0027	-0.0065*	-0.0101	-0.0014
	(0.4162)	(0.6660)	(0.3599)	(0.0825)	(0.4049)	(0.5246)
LOGA	0.0137	0.0197	-0.0041	0.0015	0.0172	-0.0019
	(0.5266)	(0.4374)	(0.7831)	(0.9738)	(0.7487)	(0.8745)
CAL	-0.0049	-0.0045	0.0002	-0.0079	-0.0324	-0.0008
	(0.4120)	(0.4850)	(0.9571)	(0.3768)	(0.1863)	(0.8244)
LEV	0.1018***	0.1314*	0.0811**	0.0631	0.2328*	0.0582**
	(0.0064)	(0.0563)	(0.0190)	(0.3233)	(0.0697)	(0.0248)
TANG	-0.0080	-0.0124	-0.0544**	0.0319	-0.0092	-0.0300*
	(0.7717)	(0.7453)	(0.0408)	(0.6668)	(0.8933)	(0.0576)
IDIO	0.3187***	0.3669**	0.2805	0.1396*	0.1745	0.3882***
	(0.0097)	(0.0291)	(0.1047)	(0.0663)	(0.2708)	(0.0069)
TB5Y	-0.5131**	-0.5193*	-0.9028*	-0.7315	-0.5872	-0.5936***
	(0.0351)	(0.0984)	(0.0568)	(0.1861)	(0.4409)	(0.0083)
SL	1.3424***	0.8423**	1.4500***	2.0243***	1.9844	1.2105***
	(<.0001)	(0.0109)	(0.0047)	(0.0001)	(0.1087)	(<.0001)
CBS	1.0319***	0.3169	0.9649***	2.7882***	1.2291	0.9769***
	(0.0024)	(0.4926)	(0.0012)	(<.0001)	(0.5153)	(<.0001)
SP	-0.0022	0.0110	-0.0138	-0.0112	0.0067	-0.0016
	(0.7171)	(0.1467)	(0.3965)	(0.5405)	(0.7537)	(0.7912)
No. of Observations	68147	41327	11665	15155	9745	58402
Adjusted R^2	63.90%	46.81%	86.16%	81.72%	39.20%	79.35%