THE PROBLEM OF HINDSIGHT BIAS IN FRAUDULENT CONVEYANCE CASES: A REVIEW OF POSSIBLE "MARKET-BASED" SOLUTIONS

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ABSTRACT

Purpose – *In fraudulent conveyance cases, plaintiffs allege that by entering into a complex leverage transaction, such as an LBO, a firm's former owners ensured its subsequent collapse. Proving that the transaction rendered the firm insolvent may allow debtors (or their proxies) to claw back transfers made to former shareholders and others as part of the transaction.*

Courts have recently questioned the robustness of the solvency evidence traditionally provided in such cases, claiming that traditional expert analyses (e.g., a discounted flow analysis) may suffer from hindsight (and other forms of) bias, and thus not reflect an accurate view of the firm's insolvency prospects at the time of the challenged transfers. To address

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the issue, courts have recently suggested that experts should consider market evidence, such as the firm's stock, bond, or credit default swap prices at the time of the challenged transaction. We review market-evidence-based approaches for determination of solvency in fraudulent conveyance cases.

Methodology/approach – *We compare different methods of solvency determination that rely on market data. We discuss the pros and cons of these methods and illustrate the use of credit default swap spreads with a numerical example. Finally, we highlight the limitations of these methods.*

Findings – *If securities trade in efficient markets in which security prices quickly impound all available information, then such security prices provide an objective assessment of investors' views of the firm's future insolvency prospects at the time of challenged transfer, given contemporaneously available information. As we explain, using market data to analyze fraudulent conveyance claims or assess a firm's solvency prospects is not as straightforward as some courts argue. To do so, an expert must first pick a particular credit risk model from a host of choices which links the market evidence (or security price) to the likelihood of future default. Then, to implement his chosen model, the expert must estimate various parameter input values at the time of the alleged fraudulent transfer. In this connection, it is important to note that each credit risk model rests on particular assumptions, and there are typically several ways in which a model's key parameters may be empirically estimated. Such choices critically affect any conclusion about a firm's future default prospects as of the date of an alleged fraudulent conveyance.*

Practical implications – *Simply using market evidence does not necessarily eliminate the question of bias in any analysis. The reliability of a plaintiff's claims regarding fraudulent conveyance will depend on the reasonableness of the analysis used to tie the observed market evidence at the time of the alleged fraudulent transfer to default prospects of the firm.*

Originality/value – *There is a large body of literature in financial economics that examines the relationship between market data and the prospects of a firm's future default. However, there is surprisingly little research tying that literature to the analysis of fraudulent conveyance claims. Our paper, in part, attempts to do so. We show that while market-based methods use the information contained in market prices, this* *information must be supplemented with assumptions and the conclusions of these methods critically depend on the assumption made.*

Keywords: Fraudulent conveyance claims; solvency determination; leveraged buyout (LBO)

INTRODUCTION

A bankrupt firm's creditors are typically paid off in a Chapter 11 bankruptcy according to the absolute priority rule (APR). Senior or secured creditors are paid first, with any remaining assets being used to pay unsecured creditors. Current shareholders often receive nothing. Shareholders who sold their equity stake in the company before it went bankrupt bear no loss.

These rules can be overridden, however, if the company is engaged in a complex leveraging transaction, such as a leveraged buyout (LBO), before it went bankrupt. Distributions made to former shareholders may be challenged by unsecured creditors as fraudulently conveyed. If the plaintiffs prevail, distributions are pulled back from the former shareholders, shifting the bankrupt firm's losses from the unsecured creditors to the former equity holders.

An increasing trend in fraudulent conveyance litigation is to rely on market evidence in determining whether a transaction was fraudulent to creditors, rather than other more traditional evaluative tools, such as discounted cash flow models. The underlying argument is that contemporaneous market evidence is more reliable than evaluations prepared by experts which may be tainted, for example, by hindsight bias.

This paper examines some important issues that impact the utility of using market evidence in fraudulent conveyance cases. We do not seek to resolve all such issues. Instead, our objectives are modest; we: (1) describe the key methods of analyzing credit risk that economists have developed over the past four decades, including the use of accounting ratios and prices of securities such as stocks, bonds, and credit default swaps (a type of credit derivative) as forward-looking indicators of financial distress; and (2) identify the potential strengths and weaknesses of approaches that rely on contemporaneous market data.

LBOS AND FRAUDULENT CONVEYANCE LAW

In an LBO, an investor (often a private equity firm) acquires control of a public company by buying out the firm's existing public shareholders at a premium. The private equity firm buyer typically invests some of its own capital in the transaction. However, it funds the acquisition primarily with debt (i.e., bank loans or bonds) which is collateralized by the target firm's own assets and future cash flows.[1] Upon completion of the LBO, the target firm is privately owned by the acquirer, and the acquired firm's capital structure consists of relatively little equity in comparison to its new debt. The benefits of such a transaction have been argued to include a new and motivated management and, in the case of a going private transaction, the ability to operate free of public disclosure requirements. Given the acquired firm's highly leveraged capital structure, however, there is potentially little room for error if plans do not go as anticipated.

If an LBO transaction does go poor and results in bankruptcy, the acquired firm's unsecured creditors may challenge the LBO as a fraudulent conveyance. The typical argument is that the transaction did not benefit the company, saddling the firm with onerous new debt obligations with the only beneficiary being the former shareholders and management, who often also receive payments as part of the LBO for either their stock or additional compensation as a result of the transaction.

There are two types of fraudulent conveyances: intentional or constructive. Whether a company was solvent when a transfer was made (or rendered insolvent by the conveyance) is usually an issue in the subsequent lawsuit under either theory. For example, under the Bankruptcy Code, to prove an intentional fraudulent conveyance, courts often look at the company's financial state at the time the transaction was being consummated. Solvency issues are even more heightened in the case of a constructive claim. To show that a transfer was constructively fraudulent, a plaintiff must show that the debtor: (1) received less than reasonably equivalent value for the transfer and (2)(a) was insolvent, or rendered insolvent, on the date the transfer was made; (b) was left with unreasonably small capital; or (c) intended to incur debts beyond its ability to pay as they became due.[2]

Traditional notions of solvency are clearly at issue in item 2(a), which is typically referred to as the "balance sheet test." Specifically, Section 101 (32) of the Code defines insolvency to mean a financial condition such that the sum of the entity's debts is greater than all such entity's property, at "fair valuation." Items (b) and (c) are viewed as simply being other measures of the company's financial solvency.[3] Test No. 2(b) focuses on whether the transferee was doomed as a result of the challenged transfers or left with the inability to generate "sufficient profits to sustain operations." See *Moody v. Sec. Pac. Bus. Credit, Inc., 971 F.2d 1056, 1070 (3d Cir. 1992)* (determining whether a company is left with unreasonably small capital typically requires an analysis of the debtor's cash flow and AU:2 available operating capital). *In re Taubman, 160 B.R. 964, 986 (Bankr. S.D. Ohio 1993)* (noting that the phrase unreasonably small capital is not defined in the Code and that an appropriate analysis of the phrase involves an examination of the debtor's cash flow and available operating capital). Test No. 2(c) focuses on whether the debtor intended to incur debts, or believed it would incur debts, beyond its ability to pay them. See, for example, *In re WLT Energy Corp., 282 B.R. 343 (Bankr. W.D. La. 2001)* (belief to intend debts beyond the ability to pay when they matured); *In re EBC, Inc., 380 B.R. 348* (solvency existed because debtor was paying debts as they matured). Most courts, when evaluating solvency in connection with an LBO, examine each of these three alternatives, and a case decision rarely addresses only one of these items.

THE RECENT SHIFT TO MARKET EVIDENCE IN FRAUDULENT CONVEYANCE CASES

Solvency determinations have traditionally been made based on well-established evaluative tools used by experts. For instance, an expert may compare a firm's debt obligations at some point in the past to the estimated value of its assets at the same point in time. But such historical estimated asset values are often based on an expert's opinion about the asset's *future* cash flows that were purportedly reasonable as of that historical date. Some have argued that such estimates, and consequently, the expert's conclusion about the likelihood of the firm's imminent bankruptcy, may be tainted with hindsight bias or the expert's perceived advocacy role.[4]

Two relatively recent cases [*VFB v. Campbell Soup Co., 482 F.3d 624 (3d Cir. 2007)* ("Campbell") and *In re Iridium Operating LLC*, *333 B.R. 283 (Bankr. S.D.N.Y.)* ("Iridium")] highlight such issues. In *Campbell*, the Third Circuit affirmed the district court's conclusion that the value of a division of Campbell Soup was properly based on its market capitalization as opposed to after-the-fact valuations prepared by experts. The Third Circuit viewed the valuations as tainted by "hindsight bias," *id.* at 629, and complained that, to the extent the experts sought to construct a "reasonable valuation" of the company in light of uncertain future performance, their tools for doing so were "inapt." *Id.* at 633.

Similarly, in *Iridium*, the court found that the experts' conclusions on valuation lacked credibility because, among other things, the experts (1) ignored various financial transactions that may have impacted their conclusions, (2) did not rely on the testimony of witnesses who had knowledge of the company's projections and the relevant capital markets at the time of the transaction, and (3) otherwise substituted their own judgments for those of involved parties. *Id.* at 339 42; 345 52. The court instead relied on market evidence, stating that the capital markets had "synthesized and distilled" what "all the smart people" knew, and that, in light of the "overwhelming weight" of the market evidence, the plaintiff could not prove insolvency. *Id.* at 352. To the extent the plaintiff's expert sought to provide reasons for the company's failure within one year of the transaction or otherwise prove insolvency at the time of the conveyances, the court rejected every one of the stated reasons as being tainted by hindsight or because the expert purportedly wrongfully discounted contemporaneous market evidence. *Id.*

However, exactly how does one infer whether a firm is solvent based on market evidence at some point in time? The three notions of solvency, the balance sheet insolvency, unreasonably small capital, and the inability to pay debts, are interrelated from the perspective of market evidence and all reflect the market's expectations of the cash flows of the firm and of the possibility of future default for the firm's creditors. The definition of the term "default" depends, among other things, on the form of credit and on the specific choice of the issuer's contractual obligations to creditors that are considered in determining whether a default event has occurred or not. For example, the future default event associated with a particular bond issued by a firm could refer to the firm's failure to make coupon or principal payments in a timely manner as specified by the bond contract over the bond's remaining maturity. In this case, what does the fact that a firm's stock price traded at $2 at some point in time tell us about the probability that the firm will default on its debt obligations over the next year, or the next two years? Similarly, what default probability estimate can be derived from the fact that one of the firm's bonds traded at 75% of its face value, or its credit default swap (a type of credit derivative) traded at a particular level.

Inferring a future default probability estimate from an observed security price requires a conceptual link (an empirical or theoretical model) between the security price and the future default event, which may be defined in different ways. We discuss some such "links" or models proposed over the past four decades in the finance literature on credit risk modeling. In addition to the observable security price, these models typically require estimates of several other economic parameters, which may be unobservable or not contemporaneously-available. That means, even when courts rely on market data to infer a future default probability estimate, such an exercise involves the use of some economic model, which in turn, requires expert analyses.[5] In sum, relying on market data may ameliorate but not necessarily eliminate the possible potential problems of hindsight bias in expert analyses suggested by some parties.

A REVIEW OF CREDIT RISK MEASUREMENT APPROACHES IN THE FINANCE LITERATURE

Accounting-Based Credit-Scoring Systems

To decide whether to make a loan, a bank considers a borrower's ability to make the required future interest and principal payments. Decades ago, banks primarily relied on subjective borrower characteristics such as the borrower's "4Cs" in deciding to make a loan: "Character" (reputation), "Capital" (leverage), "Capacity" (earnings volatility), and "Collateral." Banks have discarded these measures, relying on formal *accounting based credit-scoring systems* which perform better (Altman & Saunders, 1998). For instance, banks now access creditworthiness by comparing a borrower's debt-to-asset ratio or his or her total interest−total income (interest coverage) ratio to an industry average. But, as Altman (2000) notes, inferring a firm's financial health based on such ratios is "susceptible to faulty interpretation and … potentially confusing" because the borrower may be superior to the industry average according to one ratio measure but inferior according to another. Therefore, more sophisticated *multivariate* models that assess a firm's credit risk by jointly considering the impact of several key accounting ratios (weighting some more heavily than others) to calculate a single credit risk score or a probability of default measure, are now more commonly used.

The most popular among such models are those that use discriminant analysis, for example, Altman's (1968) original Z-score model, and the ZETA model developed by Altman, Haldeman, and Narayanan (1977) and Altman (2000). These models assess the financial distress of firms based on several variables, including the market value of equity.[6] Simply put, a discriminant analysis identifies a *linear* function of accounting and market variables that can best distinguish between borrowers that repay versus those that do not. This requires an analysis of a set of variables to maximize the between-group variance while minimizing the within-group variance among these variables.[7]

A final credit score depends on the weights assigned to each of these explanatory variables, which is an empirical issue. As Altman (2000) notes, "Over the years many individuals have found that a more convenient specification of the model is of the form: $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$." Use of such ratios has intuitive appeal because the accounting data necessary to compute them are generally available and the credit score can be calculated by combining these ratios using a simple linear formula. Credit-scoring models based on such ratios have performed well over different time periods and in different countries and, at first glance, would seem well-suited to applications in fraudulent conveyance cases. Calculating a firm's credit score at a particular point in time could arguably be accomplished without hindsight bias.

That said, however, discriminant models have been criticized on several grounds. The primary criticisms of such models are: (1) they are based mainly on book value accounting data which may not fully incorporate market estimates of a firm's future prospects and may also be subject to manipulation; (2) the model's explanatory ratios are measured as discrete time intervals and hence may not properly reflect recent changes in the borrower's condition, which may be better reflected in security prices, assuming such securities trade in efficient markets; (3) a *linear* function of explanatory variables may be overly simplistic; and (4) such models lack a theoretical foundation and are based on empirical analysis that may be sensitive to the choice of variables or sample (for instance, the asset-size of the companies used in the analysis). The weights assigned to particular explanatory variables may depend on the sample and model selected. The relative importance of particular ratios may change over time and differ across firms. Hence, use of the weights from one study in a different context calls for an expert's subjective interpretation, which may be tainted by hindsight bias, as highlighted in *Campbell* and *Iridium*.

Structural Models of Credit Risk

With the exception of the *market value of equity/book value of total liabilities* ratio, none of the explanatory variables in the standard Altman discriminant model directly captures the impact of possible future changes in the firm's financial condition. Instead, they are all based on a snapshot of key accounting ratios taken at particular point in time. Further, such analysis does not begin by defining what triggers default, or the fundamental theoretical relationship between the selected accounting ratios and default.

More recent credit risk models have provided such a theoretical structure by defining default explicitly, and identifying a theoretical relationship between default and particular economic variables, such as the firm's stock price or volatility of the firm's asset values. One well-known class of such "structural" models consists of the option pricing models of Black and Scholes (1973), and Merton (1974).

In the simplest version of such a model, a firm must make a single debt payment at some point in the future which represents the face value of a zero-coupon bond, which is assumed to be the only type of debt the firm has issued. The value of the firm's assets is assumed to change over time, obeying a specific probability distribution. Default occurs at maturity, if the value of the assets is lower than the debt's face value. In such a "default" scenario, the firm's debtholders receive the firm's assets while shareholders get nothing. Otherwise, debtholders are fully paid the promised face value, and the remainder of the value of the assets is paid to shareholders as a liquidating dividend. In option-pricing parlance, the firm's equity is a call option on the firm's assets, with a strike price equal to the face value of debt. The stock's current stock price purportedly reflects the likelihood of future default.

To estimate the implied default probability based on the observed stock price, however, a clear conceptual link between the stock price (an observable parameter) and the implied default probability (an unobservable variable) must be drawn. In the finance literature, several studies have drawn such a link using an option pricing model. To derive empirical estimates of default probability using such a model requires empirical estimates of the parameters which affect whether the firm's asset value will be sufficient to pay off the debt at maturity, for example, the firm's current asset value and future debt obligation, the debt's maturity, and the *volatility* of the asset's returns. Therefore, to estimate bankruptcy (or the probability of default over a particular time horizon) using an option pricing model, simply knowing the company's stock price is not enough. For example, asset volatility is unobservable because the firm's assets, unlike its equity (or shares) are not traded daily. Estimating the *volatility* of the firm's assets requires relying on an additional theoretical link which allows one to infer the unobserved asset volatility level based on the observed volatility of the stock's price (or returns), provided the firm is publicly traded. Financial institutions and firms such as KMV use this approach to estimate the firm's probability of default in some future time period.[8]

Such an approach may be well-suited for use in fraudulent conveyance cases as it can be applied retroactively based on then-contemporaneous information about the firm's equity and debt values, and equity volatility. Such analyses may be less sensitive to an expert's subjective opinions. Moreover, such an analysis would include market data other than security prices and be grounded in a well-established option pricing methodology for which a Nobel prize was awarded.

However, despite these strengths, the approach has weaknesses too. An option pricing model-based estimate of future default probability depends critically on the model's assumptions which may not be realistic,[9] and on empirical estimates of parameters that are unobservable. For example, a critical parameter in such option pricing models is the volatility of the firm's asset values. As the firm's assets, which may consist of real assets such as plant and machinery and intangible assets such as patents, employee talent, and industry expertise, do not trade regularly, changes in the value of such assets (the asset's "returns"), or changes in such returns (the asset's volatility"), are generally unobservable. Further, the model assumes that the asset value changes in small increments smoothly over time.[10] Such a model, therefore, fails to capture sudden large changes in the asset value, which could result in default as the recent collapse of the storied investment bank, Lehman Brothers, in mid-September 2008 dramatically illustrated. An option pricing model also generally fails to take into consideration the uncertainty associated with credit rating changes (Altman et al, 2003). Accordingly, refinements such as endogenous default and other features, have been introduced in more recent structural models.[11] AU:3

The academic literature remains somewhat divided about whether structural models are better at predicting default than accounting ratio-based models. According to some, structural models are better because they include historical accounting information as well as security prices that reflect investors' contemporaneous expectations about future cash flows.[12] Others studies refute this claim.[13,14] A recent study by Agarwal and Taffler (2008) finds that both approaches convey significant information about failure, but neither method subsumes the other. This result suggests that both approaches could be considered in fraudulent conveyance cases, provided that the potential issues associated with both approaches (including potential hindsight bias) are properly addressed.

Finally, it is worth noting that another class of models use bond pricing data to assess default probabilities. Such models are referred to as "reduced-form" models because they do not explicitly model a structural relationship between default and the firm's value. Instead such models estimate implied forward rates on risk-free and risky bonds and use the difference in these rates to infer the market's expectation of the risky bond's default at different times in the future. While inferring a firm's default prospect based on the market price of the firm's debt in this way has an obvious intuitive appeal, it is important to note that bond prices also reflect a host of other economic parameters, for example, the term structure of default-free interest rates, the bond's recovery rate given default, and time variation in the probability that a firm may default on its obligation. Consequently, models used to infer default probabilities from bond prices may rest on assumptions about parameters that may have limited empirical support.

Estimating Default Probabilities using Credit Default Swap Spreads

Market data related to credit default swaps ("CDS") can be used as an alternative to stock or bond prices for the purpose of estimating credit risk with a structural model. Credit derivatives (such as total return swaps, spread options, and CDS) are contingent claims with payoffs that are linked to the creditworthiness of a given firm or sovereign entity.[15] Such derivatives have become increasingly common. For instance, the volume (measured by notional amount) of CDS first developed in 1990s peaked at $62 trillion in 2007. Although volume declined in the aftermath of the 2007 financial crisis, according to the Bank of International Settlement, the notional amount of credit default swaps outstanding in June 2014 was $19.5 trillion.

The most common credit derivative is a single-name CDS, whose payoff depends on whether a defined "credit event" related to a particular reference entity (country or company) occurs during the CDS's life (typically five years). Such a credit event could be the reference entity failing to make promised interest or principal payments on a particular bond ("reference obligation") when due, or the reference entity declaring bankruptcy (or some kind of financial restructuring).

A CDS, by definition, is an agreement between two parties: the buyer and the seller of the credit protection. In exchange for promising to periodically pay the seller a fixed sum (defined as a percentage of the CDS's notional value) over the CDS's tenor, the buyer receives credit protection from the seller. If the credit event occurs, the seller is obliged to compensate the buyer, who may stop making payments on a going forward basis.[16] Thus, a CDS is similar to an insurance contract that the buyer holds to protect itself against loss related to a defined credit event.[17]

Originally, CDS contracts traded at par – that is they were designed to have a zero cost of entry, and neither the buyer nor seller was required to make a payment to their counterparty when the CDS contract was initiated. The fixed payment ("coupon" or "par spread") that the buyer agreed to pay the seller over the life of the CDS contract was determined at the CDS contract's inception, based on the market's view of the reference obligation's credit risk. Over the CDS's *subsequent* life, while the coupon remained fixed, the mark-to-market value of the CDS could increase or decrease (from the viewpoint of the buyer) as the market's assessment of the reference obligation's credit risk changed. Thus, the market's view at the inception of the CDS contract about the likelihood of the default event occurring over the CDS's life can be inferred from the par spread, as we discuss next.[18]

USE OF CDS SPREADS IN FRAUDULENT CONVEYANCE CASES

To see how CDS spreads can be used to estimate default probabilities, let us consider the following hypothetical example in which a CDS with a notional principal of $1 and 3-year tenor referencing a particular bond issued by company XYZ is offered today at a par spread of S per annum. This means that by agreeing to pay S per year to the seller, the CDS buyer receives protection of up to $1 of firm XYZ's reference debt obligation's face value.

Estimating the default probabilities over the CDS's tenor, given this market-determined spread requires several assumptions about, among other factors, the following: (i) the recovery rate expected upon default, (ii) the timing of the CDS spread payment the buyer must make each year, (iii) the timing of the default in a particular year, if default were to occur, and (iv) the "hazard rate" or the probability of default in a particular year, assuming default has not previously occurred.

The following hypothetical example clarifies how these factors are related and relevant in determining the relationship between the quoted spread and the "market-implied" default probabilities over the life of the CDS. In this example, we assume the following:

1. The recovery rate is fixed at RR percent of the underlying reference obligation's face value, that is, company's creditors are expected to collect RR percent of the face value of debt upon default, or conversely lose $(1-RR)$ percent of the promised \$1 notional value if default occurs. This is the loss for which the CDS buyer would be compensated by the CDS seller.
2. The CDS spread is paid annually at year end up to the earlier of the maturity of the contract or a default.
3. Default, if it were to occur, would occur at the end of the year. In that case, the protection seller pays the buyer is $(1-RR)$, which equals the notional amount net of the recovery rate.

Let h denote the default probability (or the "hazard rate") over a year. It follows that the probability of surviving to the end of the first year is $(1-h)$, to the end of the second year (which requires surviving the first year) is $(1-h)^2$, and the end of the third year is $(1-h)^3$. The buyer must make the first CDS payment of S at the end of the first year. The CDS payment at the end of the second year is made conditional on the reference entity surviving the first year so its expected value is the payment of S multiplied by the probability $(1-h)$ that the firm survives the first year. Similarly, the expected value of the CDS payment the buyer must make at the end of the third year is $S(1-h)^2$. The *present value* of these three expected payments is calculated by discounting them at the risk-free rate, r_f, for one, two, and three years, respectively. The sum of the present values of the three expected payments the CDS Buyer makes, P_{Buyer}, is:

$$P_{\text{Buyer}} = \left[\frac{1}{(1+r_f)} + \frac{1-h}{(1+r_f)^2} + \frac{(1-h)^2}{(1+r_f)^3}\right] S$$

We next calculate the present values of the payoffs that the CDS seller is expected to make each year over the CDS's tenor. To do so we must calculate the probability of default for *that* year. As discussed above, the probability of defaulting in *year* 1 is h. The probability of surviving beyond year 1 is thus $(1-h)$ and the probability of surviving beyond year 2 is $(1-h)^2$. The probability of defaulting *in* year 2 is calculated as the probability of surviving beyond year 1 minus the probability of surviving beyond year 2, or $[(1-h)-(1-h)^2]$. Similarly, the probability of defaulting *in* year 3 is $[(1-h)^2-(1-h)^3]$.

The expected payoffs by the CDS seller at the end of the first, second, and third years from today can be expressed as $(1-RR)$ times the probability of default in each of these years, that is, $(1-RR)h$, $(1-RR)[(1-h)-(1-h)^2]$ and $(1-RR)[(1-h)^2-(1-h)^3]$, respectively. The sum of the *present value* of each of these three expected payments, P_{Seller}, is:

$$P_{\text{Seller}}=(1-RR)\left[\frac{h}{(1+r_f)}+\frac{(1-h)-(1-h)^2}{(1+r_f)^2}+\frac{(1-h)^2-(1-h)^3}{(1+r_f)^3}\right]$$

If the spread S is correctly priced (i.e., properly reflects the market's view of the hazard rate h and the recovery rate, RR) then the P_{Buyer} must equal P_{Seller}. That is,

$$S\left[\frac{1}{(1+r_f)}+\frac{1-h}{(1+r_f)^2}+\frac{(1-h)^2}{(1+r_f)^3}\right]$$
$$=(1-RR)\left[\frac{h}{(1+r_f)}+\frac{(1-h)-(1-h)^2}{(1+r_f)^2}+\frac{(1-h)^2-(1-h)^3}{(1+r_f)^3}\right]$$

So, given the observed value of the spread S and the risk-free rate, r_f, to calculate the implied hazard rate, h, one must assume a fixed value for the recovery rate RR. Then, given the values of S, RR, and r_f, one can solve the equation for h.

For instance, if the hazard rate is 2% per annum and the risk-free rate is 5% per annum, then the sum of the present value of the CDS's buyer's expected payments over three years (the value of square bracket term on the *left* hand side of the above equation) is 2.6709 times the annual spread (S). Further assuming that recovery rate $RR = 40\%$, the sum of the present value of the CDS's seller's expected payoffs, (the value of square bracket term on the right hand side of the above equation) is 0.0321.

Therefore, for the implied hazard rate to be 2%, the spread S must be such that: $2.6709S = 0.0321$, That is, the equilibrium spread, $S = 0.0321/2.6709$, or 120 basis points. Conversely, if the spread is observed to be 120 basis points, then for the CDS to be correctly priced, the implied hazard rate must be 2% per annum (assuming the recovery rate is 40% and the discount rate is 5%). If the observed spread was actually higher, the implied hazard rate too would have to be higher, holding other parameters (such as the recovery rate) constant, assuming that the CDS contract was correctly priced.

As the preceding discussion highlights, the inferred default probability from CDS data depends critically on the assumptions made, for example, the timing of CDS cash flows and default.[19] Further, the implied hazard rate must be interpreted with caution. Two comments are in order. First, it represents the probability of default over a fixed period (1 year in the above example) conditional on the CDS default event not occurring till the start of that period, whereas the unconditional default probability over each of the years of the CDS's tenor is expected to change over time (and is equal to h, $[(1-h)-(1-h)^2]$ and $[(1-h)^2-(1-h)^3]$ in year 1, 2, and 3, respectively). Second, as we discuss below, the probability inferred from CDS data is referred to as "*risk-neutral*" probability which is not the same as the actual default probability that investors associate with the firm's debt and in which a court may be most interested in a fraudulent conveyance case.

LIMITATIONS TO THE USE OF MARKET-BASED MEASURES OF DEFAULT PROBABILITIES

CDS or Bond Market Prices Yield Risk-Neutral Probability, Not Real-World Probability that is the Relevant Measure for Fraudulent Transfer Cases

According to fundamental financial economics principles, the price of a security that trades in an efficient market (which incorporates all relevant information) must equal the present value of the security's future cash flows discounted for the delay and risk associated with such cash flows. For instance, consider a bond that will mature at the end of one year and has a face value of \$1 million payable at that date, unless the firm is then bankrupt. Assume, for simplicity, that if the firm is bankrupt the bondholder will get nothing (i.e., the "recovery rate" is zero). If p denotes the probability of default, then the bondholder's expected future cash flow is $(1-p)\times\$1$ million. The present value of that expected future cash flow is calculated by discounting it by the rate of return investors expect to earn over the same time period (one year) if they instead invest in an equivalently risky bond. As investors are risk-averse,[20] this expected rate of return equals the risk-free interest rate that investors can earn on a security that has negligible default risk (such as a U.S. Treasury bill) plus a risk premium that reflects the additional return that risk-averse investors would require for investing in a risky security. For instance, if the risk-free rate of return is 5% and the risk premium is 10%, then risk-averse investors require 15% to invest in the bond in our hypothetical example. In turn, this result means that the bond's price today, or its present value, must equal its expected future cash flow, $(1-p)\times\$1$ million/1.15. If the probability of default, p, is 8%, the bond's current price is $0.92\ \times\$1$ million/1.15 or \$800,000. That is, by investing \$800,000 in the bond today, risk-averse investors expect to earn 15% on their investment over the year, after taking into consideration their assessment of the probability that the bond may default (in which case they would lose their entire investment). Conversely, if we observe the bond with a stated face value of \$1 million, trading for \$800,000 *and we know that risk-averse investors require a risk premium of 10% over the risk-free rate of 5% to make such an investment*, we can infer, based on such market data, that the bond's default probability is assessed to be 8% by risk-averse investors.

In practice, such an inference may be difficult to draw because of the difficulty in accurately estimating the risk premium that risk-averse investors require. There is, however, a technique known as "risk-neutral" valuation in valuing derivatives (securities whose values are linked to that of another, more primitive security, e.g., a call option written on a stock, or a CDS contract that references a bond) that allows for the issue to be circumvented. This technique relies on the key insight that as long as investors can buy or sell either the derivative or the underlying security and a risk-free bond freely, then the arbitrage-free price of the derivative can be measured relative to the price of the primitive security (which presumably properly captures investors' degree of risk-aversion as discussed above).[21] As a result, in pricing the derivative further consideration of investors' risk-aversion is irrelevant. Therefore, for mathematical convenience, the derivative can be priced assuming that investors are risk-neutral and do not require any risk premium above the risk-free rate to invest in the risky derivative (as opposed to real-world risk-averse investors) but assign a probability of default, called *risk-neutral probability* of default, that differs from the real-world default probability assigned by risk-averse investors. As the risk-free rate is publicly observable, this considerably simplifies the calculation to infer the bond's *risk-neutral* probability of default. For instance, in the preceding example, if the bond trades at \$800,000, and the risk-free rate of return is 5%, this means that risk-neutral investors expect to earn $1.05\times$

\$800,000 or \$0.84 million by the end of the year. As the face value of the bond is \$1 million (and assuming the recovery rate to be zero as before) this means that risk-neutral investors assign a 16% *risk-neutral* probability of default to the bond,[22] whereas the actual probability of default is assumed to be only 8%.

As the conceptual risk-neutral probability of default may be higher than actual default probability in which the court in a fraudulent conveyance case would be interested, the exact relationship between risk-neutral and actual default probabilities must be empirically estimated.[23] For instance, using U.S. corporate bond price data (rather than CDS data), Driessen (2005) estimated the average ratio of risk-neutral to actual default intensities to be 1.89, that is, actual default probability was estimated to be about half its risk-neutral counterpart.[24] In contrast, using CDS data, Berndt et al. (2008) estimated the median ratio of risk-neutral to actual default probabilities for broadcasting-and-entertainment firms. The study found that the median ratio (a) climbed to above 8 in the third quarter of 2002, before dropping to below 4 by December 2004 *for five-year maturities*; and (b) peaked at 8 in the third quarter of 2002, dropping to 1 by December 2004 *for one-year maturities*.[25] Thus, the estimated relationship between risk-neutral and actual default probabilities varies significantly over time, and by the maturity considered, even if the sample of firms considered and the methodology used for the estimation remains unchanged.

More generally, the above discussion highlights a conceptual issue, namely that the price of a risky bond (or a CDS on such a bond) reflects three influences: the bond's default probability, a recovery rate and the investors' risk premium. For instance, the expected future cash flow of a one-period bond with a face value of \$1 million equals $(1-p)\times\$1$ million $+\ p\times RR\times\$1$ million, where p represents the actual probability of default, and RR the recovery rate (which we previously assumed was zero). The bond's present value equals:

$$p_0^B = \frac{[(1-p)+p(RR)]\$1 \text{ million}}{\left[\left(1+\left(r_f+RP\right)\right)\right]}$$

where r_f and RP denote the risk-free rate and the risk premium, respectively.

It follows that an increase in the probability of default or the risk premium would result in a decline in the bond's present value or price, while an increase in the recovery rate would have the opposite effect, holding other factors constant. Thus, a decline in bond's price could be due to one or some combination of the following reasons: (1) an increase in risk-averse investors' assessment of the bond's default probability, (2) a decrease in investors' assessment of the bond's default recovery rate upon default, or (3) an increase in the risk premium. Hence, any attempt to infer the extent to which investors revised their probability of default assessment at the time of an alleged fraudulent conveyance based on observed changes in bond (or CDS) prices must consider, and control if necessary, for any portion of the observed price change attributable to the other two factors (contemporaneous changes in the risk premium and recovery rate). This may be a difficult task.

CDS Spreads Reflect Counterparty Risk (among Other Factors) which Is Not Relevant to the Probability of Default Measure Relevant in Fraudulent Transfer Cases

The protection offered by a credit default swap is only as good as the protection seller's ability to honor its commitment if the credit event occurs. This counterparty risk affects the pricing of CDS contracts. Dealers with higher credit risk charge lower spreads for the same CDS contract compared to other dealers.[26] Such counterparty risk is irrelevant in the context of fraudulent conveyance actions in which courts are interested in the likelihood of default by the debt issuer, not that of an insurer of such debt (i.e., the CDS seller). Therefore, a market-based default probability derived from CDS spreads must be adjusted for such counterparty risk associated with the dealer offering the contract, or other factors also unrelated to the issuer's probability of default, such as tax effects and liquidity.[27] Such factors, which are unrelated to the default probability, may explain differences in the same CDS contract's spread posted by different dealers.[28]

The Default Probability Inferred from One CDS Spread May Be Inappropriate to Assess the Probability of Default for the Class of Debt Claims at Issue in A Fraudulent Transfer Case

Courts may often be interested in evaluating how a particular transfer impacts the solvency of a particular creditor or class of creditors. However, there may be several credit default swaps referencing different classes of debt issued by the same entity (say, a bank). The December 2014 SRO

Published List[29] issued by MarkitSERV, which processes the majority of credit derivative products available to trade today,[30] identifies two classes of standardized CDS contracts[31] for several reference entities or firms.[32] For example, MarkitSERV identified HSBC's senior bond (with a coupon rate of 3.75%, maturing November 30, 2016; ISIN: XS0470370932) as the Standard Reference Obligation (SRO) for all standard CDS contracts that reference HSBC Bank "senior unsecured" debt. Similarly, MarkitSERV identified another HSBC subordinate bond (ISIN: XS0114072423), that pays no coupon interest and matures on July 21, 2020, as the SRO for all standard CDS contracts that reference HSBC Bank "subordinate" debt.

Note, however, that HSBC currently has over 1,400 different debt securities outstanding. Using the default probability implied by the CDS spread which references a particular HSBC bond would clearly not be an appropriate measure of the default risk for other HSBC debt claims which may have different payoff priority in the event of default. Therefore, the court in a fraudulent conveyance matter should recognize the potential for error that may arise in relying on the default measure implied by any CDS spread, given differences in seniority between the CDS' reference obligation and the debt claims at issue in the case.

Two further comments are in order. First, MarkitSERV's SRO Published List does not identify an SRO for all reference entities. For instance, the list only identifies a senior SRO for ING Bank. The default probability implied by that CDS spread would clearly not be an appropriate measure of the default risk for subordinate debt claims against ING Bank. Second, the SRO Published List only covers 88 reference entities at the time of this writing even though CDS contracts related to other firms' debt may be traded through MarkitSERV. In such cases, CDS counterparties are free to choose the CDS contract's reference obligation from a small list provided by MarkitSERV.[33] Once again, the default probability implied by a CDS spread related to some Bank of America bond does not necessarily serve as an appropriate measure of the default risk for other debt claims against the bank. For example, Bank of America has over 1,036 debt securities outstanding, including $8.7 billion *junior* subordinated debt obligations outstanding as of January 2015. Such claims have lower priority than the bank's senior, or even its subordinated debt, in the event of default.[34] Therefore, the default probability implied by a CDS spread related to any Bank of America CDS contract (referencing either its senior or subordinated debt) would under-estimate the default risk for such *junior* subordinated debt.

Further, the SRO identified for a CDS contract may be subsequently substituted if its maturity declines to less than a critical threshold (six months to one year). Hence, the default probability inferred from an observed CDS spread may reflect not just the existing SRO's default likelihood but also that of future substitute SROs.[35]

CONCLUSION

Market prices of shares, bonds, and credit default swaps reflect default probability expectations so, in principle, any of these securities' market prices can be used to infer the probability of default that investors assigned to a particular firm at a particular point in time. Courts have expressed the opinion that such market-based approaches may be more objective compared to ones typically preferred by plaintiffs' experts in fraudulent conveyance actions that may reflect hindsight bias and other identified issues. However, courts should recognize that deriving such a market-based default probability raises several methodological and conceptual questions. In this paper, we summarize some of the well-known methods of inferring probability of default from security prices developed in the finance literature over the past several decades and the issues associated with such methods.

As noted above, in addition to default probability expectations, security prices also reflect information about a host of other value-relevant factors such as tax effects, liquidity, and counterparty risk which may not be relevant in a fraudulent conveyance case. Therefore, to infer the default probability per se, using a security's price, adjustments for the impact of such other value-relevant factors on that security's price may be necessary.

Inferring a default probability from equity prices (which are available only for publicly traded firms) requires the use of some model (such as the option pricing model), which in turn involves assumptions and parameter inputs that are difficult to estimate empirically. The probability of default inferred from CDS premiums, reflects a theoretical *risk-neutral* probability that may be several times higher than the *actual* probability of default which is the relevant measure that courts require in fraudulent conveyance cases. Transforming risk-neutral probabilities to actual default probabilities is an empirical exercise and the relationship between these two measures can vary widely over time, across industry and by the tenor of the CDS instrument selected for the analysis.

Finally, different CDS contracts reference different classes of debt issued by the same firm. Therefore, the probability of default inferred for one class of debt from a CDS contract's spread may over- or under-estimate the default probability of other classes of debt by the firm which may at issue in a fraudulent conveyance case.

In short, there are multiple approaches to assess investors' assessment of the probability of future default by a firm based on market prices. Such market-based approaches may help alleviate the alleged hindsight bias associated with expert opinions in fraudulent conveyance cases, as some courts have noted. However, deriving such market-based default estimates also entails models, assumptions, and empirical estimates of unobservable parameters that require the use of experts. Different experts, using the same market data (but different models and parameter values and assumptions), could thus reach widely different conclusions about the probability of default associated with a particular firm at some point in time in the past. Courts should thus recognize that an expert's opinion about a firm's likelihood of going bankrupt following an allegedly fraudulent transfer that is based on market evidence may remain subject to many of the same concerns expressed by the *Campbell* and *Iridium* courts.

NOTES

1. http://www.nasdaq.com/investing/glossary/l/leveraged-buyout
2. See Simkovic and Kaminetzky (2011).
3. The concept of solvency found in item 2(a) itself may raise a concern. A firm's debt and asset values at a particular point in time do not necessarily inform one about when (if ever) the firm would go bankrupt. Even if the firm's asset values exceeded that of its debt at a point in time, the firm may eventually default on some debt payment. The converse is also true. Even if the book value of a firm's assets is lower than its debt, it does not mean that the firm will certainly default on its debt in the future. Market evidence can be useful in such situations. If a firm's securities trade in an informationally "efficient" market (in which security prices such as the firm's stock or bond prices reflect all relevant contemporaneously-available information), then one may be able to infer investors' assessment of the likelihood of future default by the firm at the time using such security prices. Such an estimate would be based on information that was available to investors at the time, and thus not tainted with hindsight bias.
4. Simkovic and Kaminetzky (2011).
5. Moreover, once a default probability is derived based on historical market data, a fact-finder would have to ascertain whether the default probability was sufficiently high to render a particular transaction "fraudulent." To our knowledge, such parameters are not firmly developed in the case law.
6. See Altman (1968), Altman et al. (1977), and Altman (2000).

7. The following five explanatory variables for predicting financial distress are included in the model in Altman (2000):

(1) Working Capital/Total Assets – measuring the firm's "net liquid assets … relative to the total capitalization";
(2) Retained earnings/total assets – measuring "total amount of reinvested earnings and/or losses of a firm over its entire life" relative to its total capitalization;
(3) Earnings before interest and taxes/total assets – measuring the "true productivity of the firm's assets, independent of any tax or leverage factors";
(4) *Market value* equity/book value of total liabilities – measuring how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent"; and
(5) Sales/total assets or capital-turnover ratio – measuring the "sales generating ability of the firm's assets" and reflects "management's capacity in dealing with competitive conditions."

8. More precisely, KMV empirically estimates a "distance from default" measure based on the number of standard deviations by which the firm's asset values currently exceeds its outstanding debt obligations, and the percent of firms that actually went bankrupt within one year that also had asset values that exceeded their debt obligations by the same number of standard deviations (Altman & Saunders, 1998). KMV was acquired by Moody's in 2002.

9. For instance, the model assumes that the firm has a single class of debt which can default only at maturity, not earlier. To instead incorporate multiple classes of debt, the priority of each debt class in bankruptcy must be specified. Further, as Franks and Torous (1994) discuss, such priority rules may not be followed upon default. Default may not be exogenous as the model discussed above assumes. Instead, if default entails a cost (a fraction of the firm value that is lost when default occurs), in order to maximize shareholder value, management may optimally choose when to default.

10. That is, such option pricing models generally assume that the firm's value "is continuous in time" and therefore "time of default can be predicted just before it happens," that is, there are no "sudden surprises." Further, the Merton model also assumes that the firm's assets future returns are lognormally distributed; a technical assumption that tends to overstate recovery rates (compared to a model in which the asset returns are assumed to obey a "more fat tailed distribution" (Altman, Resti, & Sironi, 2003).

11. According to Leland (2004), structural models with endogenous default boundary or appropriately chosen exogenous default boundary predict the general shape and level of default probabilities for A, Baa, and B rated debt quite well for horizons exceeding 5 years.

12. See Hillegeist, Keating, Cram, and Lundstedt (2004). Kealhofer (2003) and Oderda, Dacorogna, and Jung (2003) also find that structural models outperform credit ratings.

13. See Reisz and Perlich (2004). Campbell et al. (2006) find such market-based models have little forecasting power after controlling for other variables.

14. This could occur if accounting information incorporated into accounting-based models is incrementally informative over stock and bond prices. This could

happen if asset values are difficult to assess and if debt covenants are based on accounting information. See Core and Schrand (1999) and Duffie and Lando (2001).

15. The description of credit derivatives and credit default swaps is based on Longstaff, Mithal, and Neis (2005).

16. If the CDS is physically settled, the protection seller agrees to buy the reference issue at its face value from the protection buyer in the event of a default by the reference entity. If the CDS is cash settled, the protection seller agrees to pay to the protection buyer cash equal to the difference between the notional value and the market value of the reference obligation following a credit event. This market value is determined through auction in a predetermined manner.

17. The protection buyer in a CDS contract faces the risk that the protection seller will not honor its CDS obligations in case of a credit event. To reduce this risk, the CDS contract may require the protection seller to post collateral. The details of the collateral requirement are specified in the ISDA Master agreement associated with the CDS contract. The collateral amount is usually contingent on the credit rating of the protection seller. A highly rated protection seller may not need to provide any collateral but the collateral amount increases as the rating of the protection seller falls.

18. Following the credit crisis, in 2009, ISDA issued the "Big Bang" protocol to standardize CDS contracts and increase the liquidity of such derivatives (Markit, 2009). Now the standardized coupon for all North American CDS contracts is either 1% or 5% (100 or 500 basis points), regardless of the market's view of the underlying reference obligation's credit risk at the time the CDS contract is initialized. The market's view of such risk, which used to be captured by the spread before Big Bang, is now captured in an up-front charge (known as the "Points Up-Front (PUF)," quoted as a percentage of the notional), which the protection buyer must pay the seller at inception. However, the PUF can be negative, in which case the seller must make this payment up-front to the buyer (in addition to compensating the buyer later in the event of default). (White, 2014).

The PUF can thus be considered to be the present value of the difference between the contractual coupon payments and the par spread the buyer would have been expected to pay instead under the prior convention over the CDS' life ("Standard Corporate CDS Handbook," Barclays Capital, February 2010, page 18). Given this equivalence between PUFs and par spreads, our following discussion of inferring the default probability associated with a CDS' reference obligation from its par spread (hereafter "spread") can be modified for standardized contracts following the Big Bang protocol to be based on the observed PUF rather than the par spread.

19. In practice, CDS premiums may be paid quarterly and default could occur any time during a year. If for instance, one assumed that default were to occur mid-year, then the calculations would be more complicated, and involve, in the event of default, accrued premium for six months, from the end of the previous year to the date of default, which the CDS buyer would have to pay to the seller upon default. Of course, this would be netted against the notional amount less the recovery rate the seller in turn would have to pay the buyer upon default (Hull, 2015). CDS features the "day convention" used to determine the timing of CDS-related cash flows change over time (White, 2014).

Hence, the calculation of the hazard rate from observed CDS market data too must change to reflect changes in contractual features. Further, CDS transactions in practice work somewhat differently from the hypothetical example discussed above given the PUF (Pay up-front) convention discussed earlier. CDS contracts now have a stated coupon and the buyer must pay the seller up-front for the present value of the difference between the par spread and the stated coupon (Hull, 2015, Chapter 15).

20. A "risk-averse" investor is one who, if faced with a choice between two risky investments with the same expected return, prefers the one with the lower risk.

21. In other words, to price a derivative, its cash flows are not directly estimated. Instead, it is assumed that the price of the underlying security (such as stock or bond) properly reflects the underlying security's expected future cash flows, and risk-averse investors' estimated probabilities associated with such cash flows. The derivative is then valued from the perspective of a derivative trader who takes positions in two securities such as a stock and a derivative based on the stock to completely eliminate risk. Since the trader faces no risk, in an efficient market world without arbitrage possibilities, the derivative investors would earn the risk-free rate of return. That is, the value of the derivative is assumed to equal its expected cash flows, measured using the risk-neutral probability of default, discounted by the risk-free rate of return. It follows that the default probability inferred from a derivatives price, using the same risk-neutral valuation model yields a risk-neutral probability estimate.

22. Solving the following equation: $(1-p^{\mathrm{RN}})\times\$1$ million = \$0.84 million, yields the risk-neutral probability of default, $p^{\mathrm{RN}}=16\%$.

23. See Hull (2015) for a discussion of risk-neutral and real-world probabilities.

24. Berndt, Douglas, Duffie, Ferguson, and Schranz (2008) explain that "This ratio [of risk-neutral to actual default probabilities] may be viewed as the proportional premium for bearing default risk. For example, if this ratio is 2.0 (for a particular firm, date, and maturity), then market-based insurance that pays one dollar in the event of default would be priced at roughly twice the expected discounted default loss."

25. Berndt et al. (2008), Fig. 2.

26. Arora, Gandhi, and Longstaff (2012).

27. See Driessen (2005), Longstaff et al. (2005), and Berndt et al. (2008).

28. For example, as of January 27, 2015, we found such quotes from 11 dealers on Bloomberg related to a CDS contract with 5-year tenor which referenced Bank of America's "senior unsecured" debt. The minimum and maximum "bids" across these dealers for the same CDS contract were, 69.18 and 71, respectively. The minimum and maximum "asks" across these dealers for the same CDS contract were, 73 and 75, respectively.

29. SRO Published List issued by MarkitSERV on Wednesday, December 31, 2014.

30. MarkitSERV is an electronic trade processing company created by Markit and The Depository Trust & Clearing Corporation in 2009 (https://www.markit.com/product/markitserv).

31. Most CDS contracts are standardized to facilitate trading and follow contractual definitions and reference "Standard Reference Obligations" according to

rules introduced by the International Swaps and Derivatives Association (ISDA) in 2014. See ISDA, "2014 Credit Derivatives Definitions & Standard Reference Obligations" June 30, 2014.

32. SRO Published List issued by MarkitSERV on Wednesday, December 31, 2014.

33. For example, Bank of America, one of the largest banks in the world, is not included in MarkitSERV's SRO Published List as a standardized reference entity. Yet, we found CDS contracts that reference Bank of America's senior and subordinated debt are currently traded. According to Bloomberg, three particular Bank of America senior bonds could be used as the reference obligation for the former CDS contract, while four other Bank of America subordinate bonds could be used as the reference obligation for a CDS contract referencing the bank's subordinate debt. The menu of possible reference obligations are provided by MarkitSERV according to Bloomberg.

34. See HSBC Banks "5.844% Non-cumulative Step-up Perpetual Preferred Securities" dated October 31, 2003.

35. The SRO Published List is revised every quarter. Notably, the SRO identified for a particular reference entity is used as the reference debt obligation for CDS contracts of all tenors related to that entity. Hence, the remaining maturity of an SRO may be shorter (e.g., 1 year) than the CDS contract's tenor (which could be 5 years or more). In such cases, the SRO is substituted with a new SRO with longer remaining maturity. Specifically, when the remaining maturity of an SRO related to a CDS contract referencing an "M(M)R Financial Reference Entity" declines to less than 1 year, it is substituted by MarkitServe on the next quarter's SRO Reference List. The substitute SRO selected is a debt obligation that was obviously issued by the same firm and has the same senior (senior or subordinate) as did the previous SRO. For non-M(M)R reference entities, an SRO must be substituted when its remaining maturity declines to 6 months or less. See "2014 Credit Derivatives Determinations Committees Rules", ISDA, September 16, 2014.

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REFERENCES

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance*, *32*(8), 1541–1551.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*, 589–609.

Altman, E. I. (2000, July). Predicting Financial Distress of Companies: Revisiting The Z-Score and Zeta® Models. New York University, Stern School of Business Working paper.

Altman, E. I., Haldeman, R., & Narayanan, P. P. (1977). Zeta analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, *1*, 29–54.

Altman, E. I., Resti, A., & Sironi, A. (2003). Default recovery rates in credit risk modeling: A review of the literature and empirical evidence. New York University, Stern School of Business Working Paper No. S-CDM-03-11.

Altman, E. I., & Saunders, A. (1998). Credit risk measurement: Developments over the last 20 years. *Journal of Banking and Finance*, *21*, 1721–1742.

Arora, N., Gandhi, P., & Longstaff, F. A. (2012). Counterparty credit risk and the credit default swap market. *Journal of Financial Economics*, *103*(2), 280–293.

Berndt, A., Douglas, R., Duffie, D., Ferguson, M., & Schranz, D. (2008, July). Measuring default risk premia from default swap rates and EDFs. Carnegie Mellon University Working Paper. AU:5

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *7*, 637–654.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives*, *23*(1), 77–100.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. J. (2008). In search of distress risk. *Journal of Finance*, *63*, 2899–2939.

Core, J., & Schrand, C. M. (1999). The effect of accounting-based debt covenants on equity valuation. *Journal of Accounting and Economics*, *27*(1), 1–34.

Duffie, D., & Lando, D. (2001). Term structures of credit spreads with incomplete accounting information. *Econometrica*, *69*, 633–664.

Franks, J. R., & Torous, W. N. (1994). A comparison of financial recontracting in distressed exchanges and chapter 11 reorganizations. *Journal of Financial Economics*, *35*(3), 349–370.

Hillegeist, S., Keating, E., Cram, D., & Lundstedt, K. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies*, *9*, 5–34.

Hull, J. C. (2015). *Options, futures, and other derivatives* (9th ed.). Pearson. AU:6

Kealhofer, S. (2003). Quantifying credit risk I: Default prediction. *Financial Analysts Journal*, *59*(1), 30–44.

Leland, H. E. (2004). Predictions of default probabilities in structural models of debt. *Journal of Investment Management*, *2*, 5–20.

Longstaff, F. A., Mithal, S., & Neis, E. E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. *Journal of Finance*, *40*(5), 2213–2253.

Markit. (2009). *The CDS Big Bang: Understanding the changes to the global CDS contract and North American conventions*. Technical Report, March 13, 2009.

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

Oderda, G., Dacorogna, M., & Jung, T. T. (2003). Credit risk models: Do they deliver their promises? A quantitative assessment. *Review of Banking, Finance and Monetary Economics*, *32*, 177–195.

Reisz, A., & Perlich, C. (2007). A market based framework for bankruptcy prediction. *Journal of Financial Stability*, *3*(2), 85–131.

Simkovic, M., & Kaminetzky, B. (2011). Leveraged buyout bankruptcies, the problem of hindsight bias, and the credit default swap solution. *Columbia Business Law Review*, *1*, 118–221.

White, R. (2014, Octber 3). The pricing and risk management of credit default swaps, with a focus on the ISDA model. OpenGamma Quantitative Research No. 16.

UNCITED REFERENCES

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Brunnermeier (2009); Campbell, Hilscher, and Szilagyi (2008); Reisz and Perlich (2007); White (2014)

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