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ARTICLE INFO

Sunder Ram Korivi and Akhlaque Ahmad (2012). Uses and abuses of credit default swaps – a critique. *Insurance Markets and Companies*, 3(1)

RELEASED ON

Tuesday, 20 November 2012

JOURNAL

"Insurance Markets and Companies"

FOUNDER

LLC “Consulting Publishing Company “Business Perspectives”



NUMBER OF REFERENCES

0



NUMBER OF FIGURES

0



NUMBER OF TABLES

0

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Uses and abuses of credit default swaps – a critique

Abstract

Credit default swaps (CDS) are of relatively recent vintage, and are first heard about in the 1990s for protection against corporate bond defaults. Being an over-the-counter (OTC) derivative product rather than exchange traded, the CDS remained obscure, gaining popularity when they were mass-applied and misapplied to collateralized debt obligations (CDO) bonds carved out of retail mortgage loan repayments. Until then, CDS contracts were sold by CDO bond holders to off-set prepayment risk, with a greater probability of bond prices staying high. This positive outlook turned negative around 2005, wherein investment banks, being holders of bonds bought CDS for protection against rising defaults. Until 2005, with defaults being a rarity, particularly since rising home prices masked actual defaults, CDS prices were used as a proxy to price CDOs higher and obtain the AAA stamp from rating agencies. Such models were constructed by the quants in investment banks. Severe model risk arose. The suppression of actual default data resulted in low CDS prices and a boom in CDO pricing, issuances and in turn, a fresh round of home financing bubbles. With the collapse in home prices, other variables such as low employment, incomes and higher interest rates, hitherto ignored in the quant models, accentuated the bubble. This was rectified much later by the International Swaps & Derivatives Association.

Keywords: derivative pricing, certificate deposit swaps, CDO.

Introduction

The empirical data of the bubble era until 2006, and an oversimplification of the correlation-based model failed to provide an early warning of the impending crash. Perverse incentives, moral hazards and weak regulation of OTC derivatives exacerbated the systemic failure. This paper critiques the origins of the CDS innovation, the misapplication of financial engineering and offers a fresh perspective on the model risk arising from faulty empirics. The attempt is to bridge theory and practice in the nascent-and-opaque CDS markets, and bring in a real-world perspective, with the wisdom of hindsight for a mature application of financial engineering tools. As regards fresh empirical studies are concerned, it is early days yet. This paper attempts to estimate the *impact of* income, employment and interest rates on Home Loan Defaults for the 36 months from January 2005 through December 2007. It eschews the misuse of David Li's model and brings in actual default-triggering variables into CDS price estimation.

The major feature in pricing CDS would be to separate default probability from home prices and link them to employment and wage levels, as conventional wisdom guides. In other words, home prices cannot be an input to CDS pricing. Turned the other way round, wage and employment levels need to influence CDS pricing, which, in turn, is a determinant of the risk premium in CDO pricing. This is the major attempt of this paper.

The findings lead to a better way of modeling for defaults, based on relevant aforementioned macro-economic variables. From a definitional perspective,

a profitable foreclosure must always be classified as a foreclosure and not as a prepayment, to gauge default levels correctly. The objective of this paper is to provide theoretical insight to practitioners and practical insight to theoreticians, a bridging attempt.

1. Background

Credit default swaps (CDS) are contracts used by bond investors to buy insurance-type protection against bond price declines or defaults. It implies a pessimistic (bearish) view of the protection buyer, on the future prospects of the bond's price performance over the contract period (say, a year). A CDS purchase could also be an exercise of caution. For example, a pension fund or a bank could buy CDS contracts on some of the riskier bonds in its portfolio. Logically, the protection seller has an optimistic (bullish) view on the bond's price prospects, hence ideally serves as a counter-party to the CDS buyer.

The economic exchange that takes place in a CDS contract is similar to that in an insurance contract. The protection buyer pays a fee (premium or spread), to the protection seller. In the event of a decline in the bond price below a pre-defined limit (the trigger limit) the protection seller compensates for the decline in the bond price resulting from a pre-defined credit event (the trigger event). If the credit event does not occur or the bond price stays above the trigger limit, the compensation claim does not arise, but the protection buyer's cost is restricted to the premium paid. Premiums or spreads are usually paid in advance on signing of the contract, giving the CDS seller a 'positive carry', i.e. money to invest elsewhere, from the fees received upfront. The protection seller makes a profit out of the premium if the bond prices do not fall below the trigger limit. The protection seller, in turn, could buy protection from another CDS seller to reduce or unwind

potential claim losses through a netting process. If the CDS seller's view turns bearish, he could turn protection buyer to offset his initial exposure, and then become a protection buyer himself.

The CDS price, or spread is quoted in percentages above the 'London Inter Bank Offer Rate' (LIBOR), depends upon the prospects of declines in bond prices, or an imminent default. Microscopically, it is popular to quote prices in basis points – $1/100^{\text{th}}$ of a percentage point. The riskier the default perception, is the higher is the CDS spread. Price approximations are based on the movements of select bonds that go into a CDO-index, one of which was ABX, which tracked sub-prime CDOs. During sub-prime crisis, the CDS on Fannie Mae rose from 6 basis points in 2006 to 88 basis points in 2008. The spreads on Bear Sterns and Lehman during the crisis was as high as 500 basis points.

2. Literature

Credit default swaps (CDS) are of relatively recent vintage, and were first heard about in the 1990s for protection against corporate bond defaults. Being an over-the-counter (OTC) derivative product rather than exchange traded, they remained obscure. In 1998, the Chicago Futures Trading Commission, headed by Brooklyn Born, wanted the burgeoning CDS market to be shifted to it (the CFTC) to mitigate counter-party risk, but was discouraged by Alan Greenspan, who cited the superiority of the risk management systems of market participants. At that time, the CFTC was told that it would only add another layer of regulation and stifle market innovation. As a result, CDS markets grew outside the purview and regulation by a stock exchange, creating huge counter-party risks that proved to be systemically threatening.

The credit for inventing the CDS goes to the practitioners at Bankers Trust in the 1990s. At that time, Deutsche Bank wanted to acquire Bankers Trust in its quest to become a derivatives trading powerhouse. The CDS contracts were originally used to provide protection against corporate bonds such as the ones issued by General Electric. Ph.D.s in Mathematics, Physics and Computer Science had joined the ranks of practitioners in Wall Street firms and drove financial innovation in the hitherto staid credit markets. The concept of CDS was perfected by the quant wizards at JP Morgan, and its first product, launched in 1997, was the Broad Indexed Structured Trust Offering (BISTRO). It enabled JP Morgan to lay off some of the credit risk on its corporate bond portfolio to investors who offered credit risk insurance on the said portfolio, for a fee. The first technical paper on the using CDS prices for valuing CDOs was authored by "On Default Corre-

lation: A Copula Function Approach" by David X. Li, as a Working Paper from the Risk Metrics Group at JP Morgan, in September 1999 and a second draft in April 2000, in the Journal of Fixed Income. The Financial Products (FP) division of AIG reverse-engineered this product with their own team of quants. After 2000, CDS contracts were applied for protection against, firstly, prime mortgage bonds. Josh Birnbaum of Goldman Sachs thought about it in 1998.

These CDS contracts were re-invented in 2003 by quants in the mortgage securities department of Morgan Stanley, later on, to the sub-prime markets which were not present when David Li conceived original model.

The main purpose of the CDS contracts, conceived and perfected in the 'derivatives laboratories' at Bankers Trust and JP Morgan was for bankers to lay off credit risk and transfer them to the OTC markets. This provided the resultant capital relief. It is reiterated here, that until that time, CDS contracts were designed for protection on corporate bonds. Default correlations were assumed to be low, especially for a lending bank that did not have geographical or industrial concentrations of risk. David Li's conclusions drawn from the Gaussian Copula are to be viewed in this context.

The credit for popularizing CDS goes to Howard (Howie) Hubler and Mike Edman at Morgan Stanley. The initial application of a CDS in the mortgage markets was born out of betting on more prepayment versus less prepayment. Later, the main purpose of the CDS was to protect proprietary sub-prime portfolios. It was a one-off contract, non-standard, illiquid, opaque and arcane in its nature. The seller's bullishness was justified by early (Pre) payments, holding up the prices of the underlying bonds. In 2003, Morgan Stanley took up David Li's work for a literal application. It was wrongly presumed that default correlations are low in retail mortgage debt. To make matters worse, the copula model was applied to the sub-prime markets that did not exist when David Li's model was conceived. In the absence of actual data due to the short credit history, Home Prices were taken to price CDS risk premiums. This was a flawed approach, because Home Prices themselves were inflated due to the credit bubble and not on account of a rise in the intrinsic value. As time has shown, the prevalent Home Prices failed to sustain the high levels.

CDS contracts, on gaining popularity from year 2005, underwent standardization and approval by the International Swaps and Derivatives Association (ISDA). Greg Lippmann (Deutsche Bank), Mike Edman (Morgan Stanley) and others at GS were

the prime movers behind the standard CDS contract. The year 2005, thus, witnessed a spike in use of CDS. The cost of a CDS rose from on average from 1% to 3%.

Sub-prime lending rose in popularity in 2005, and loan origination standards deteriorated. At that time, Morgan Stanley, which needed default protection for its own mortgage portfolio holdings, found some German investors with a bullish view on mortgages, who sold CDS contracts to it (Morgan Stanley). Apparently, these German investors misread the deteriorated lending standards trusted the credit ratings on the underlying bonds. This is an illustration of how the CDS contracts were and subsequently, mass-applied and mismapped to sub-prime mortgage bonds.

Hedge fund managers such as John Paulson and Michael Burry were prominent buyers of CDS contracts, to monetize their bearish view on bonds, particularly sub-prime mortgages bundled as CDOs. By 2006, the mortgage market machine was roaring. The CDS buying activities of Paulson and Burry caught the attention of Goldman Sachs and Deutsche Bank – these investment banks first unwound the CDS they sold, to convert themselves into buyers of CDS. Subsequently, CDS buyers gained hugely from the sub-prime CDO meltdown, at the expense of CDS sellers such as AIG.

The initial CDS contracts were against CDOs created directly from mortgage loans. Subsequently, lower-rated junior and mezzanine CDOs were bundled together as a ‘diversified pool’, paired with CDS insurance, stamped with a AAA from rating agencies and pushed into the markets – originators, investment bankers, rating agencies and insurance writers

all made money during the boom. As the mortgage machine became popular, CDS insurance contracts were also sold to those who merely speculated that a particular series of CDOs would lose value; the reference CDOs (held together by a CDS wrapper, called the ‘synthetic CDO’). Thus, the CDO buyer no longer needed to own CDOs. These are the ‘traded CDS’, where a person could sell a CDS to one side and buy one on the other side, or vice-versa. Not surprisingly, the quantum of CDS contracts far exceeded the CDOs. On declines in the CDO prices, the difference, being the loss in value to the CDS buyer, was cash-settled. With mortgage underwriting standards declining, the quantitative wizards, ‘quants’ who used CDS data for modeling CDO prices, found themselves distanced from reality, as the underlying loans were to witness mounting defaults, even as higher interest and principal payments set in from 2006, in the face of an overall, severe with a decline in home prices.

Apart from the formal paper by David Li in the *Journal of Fixed Income* in 2000, which was more relevant to corporate bond default, there are two others that are specifically relevant to the mortgage bond defaults. The first, by Fabozzi, Cheng and Chen (2007), highlights the key factors that trigger default: interest rates, rating and sector, play a significant explanatory role in default risk pricing. A second paper on the mechanics of the CDS, its widespread application to mortgage loans and consequences are elaborated by Rene Stulz (2010).

3. CDS mechanics

The formal mechanics of the CDS contract are tabulated below.

Table 1. Mechanism and background of the CDS

CDS buyer	Bearish, seeks downside protection for the bond under reference
CDS seller	Bullish, sees no downside, sells protection
Spread	Fee payable by buyer to seller, quoted as % above LIBOR
Reference asset	Bond (say, CDO) for which protection for price declines is covered
Contract period	Period for which price protection is offered (3 to 12 months)
Trigger price	Price of the reference asset that triggers CDS compensation claim
Default (D)	Trigger event that sets off price decline in reference asset (e.g. CDO)
Foreclosure	Event where lender dispossesses defaulting mortgage loan borrower
Prepayment	Event where borrower repays loan ahead of schedule
Home prices (P)	Prices prevailing in respect of homes financed under mortgage loans
Wages (w)	Wage incomes from which mortgage loan payments are met
Employment (e)	Employment levels, that generate wages
Interest (i)	Interest rate levels that result in a cash outgo for the borrower

Table 1 presents the mechanisms and background of the CDS described at the beginning of this paper. An ordinary reading of the above table implies that loan foreclosures, in respect of defaulting borrowers will be dispossessed of their houses and their prop-

erties sold. The proceeds from the foreclosures could either be adequate or inadequate to settle the outstanding loans and interest. Any inadequacy would result in triggering off a default and a short-fall of cash flows into the escrow account, hence a

fall in the value of the CDOs created from the escrow cash flows. Since CDOs were created out of loans to sub-prime borrowers, the presumption is that lower employment rates, income and higher interest rates could jeopardize repayments, hence raise the risk of CDO default – this was the conventional wisdom. However, in 2005-2006, low interest rates and high home prices disguised the actual defaults, since the proceeds in respect of the foreclosures were higher than loan outstandings. Thus, non-repayment of loan installments by mortgage borrowers did not result in triggering CDO defaults. To make matters worse, data-wise, profitable foreclosures were masked as prepayments. Ultimately, the smokescreen of high home prices masked the true default rate and extent of foreclosures.

The term default, therefore, was beset with a deeper, fundamental, definitional problem. From a credit risk perspective, a foreclosure should serve as an early warning system, since fire-sales made on a large scale across the credit market, it should impact declines in home prices. However, for a period of approximately six months in the latter half of 2006, house prices remained higher, covering the outstanding loan amounts with a degree of comfort. It was only later that the flattening or declining of home prices resulted in non-recovery of mortgage loan dues. Lending standards had declined since 2005. The low or zero of incomes of sub-prime borrowers, coupled with rising installments on account of higher interest rates, adjustable rate mortgages and commencement of principal repayments on such loans from 2007, triggered massive defaults and fire-sales of re-possessed houses, and the consequent bursting of the home price bubble from July 2007.

The ‘profitable’ foreclosures in 2006 at higher house price sales were disguised as prepayments, exacerbating the opacity of the data that went into CDO performance assessment and CDS pricing. In other words, the initial ‘profitable’ foreclosures, disguised as prepayments, masked the true extent of the rising trend of defaults. The more the foreclosures were disguised as prepayments, the longer the default rates and probability remained undetected. It was an economic issue that mathematicians missed, in their default-prediction models. Albert Einstein once remarked “What you measure is more important than how you measure it?” The end-result was model risk of the severest kind. These faulty models resulted in higher optimism in CDO pricing, and the low price of CDS sold.

4. Divergence from reality

The popularity and explosive growth of CDS sales (considered easy money in a bull market for CDO)

required a convenient method to price it. Conventional wisdom linked a lower CDS price with a low default rate, being defaults arising from low rates of employment (e), incomes (w) and higher interest payments (i). However, in Wall Street wisdom and lexicon, a low default rate (D) was linked only with a high home price (P). The definitional problem that occurred here did not account for the misreporting of profitable foreclosures as prepayments, a feature that masked a mounting Default probability and resulted in misplaced optimism on the underlying CDOs and the lower pricing of CDS. By linking high home prices directly with low defaults, a spurious correlation was established, based on data from benign periods of low interest rates and high home prices. This convenient and elegant heuristic, a short-cut that seriously overlooked the possibility of decreasing house prices and higher default rates, since sub-prime loan portfolios comprised of borrowers who did not have (regular) incomes to repay from sources other than refinancing – a facility that is unavailable when home prices come down. This is especially true of mortgage loans originated after 2005, which were Alt-A, sub-prime or outright downright NINJA and liar loans.

A representation of the inter-relationships is stated below:

1. D is negatively related to P .
2. D is negatively related to w and e .
3. D is positively related to i .
4. P is negatively linked to i .

These inter-relationships give rise to two possible scenarios, as stated below.

Scenario 1. When w and e fall, D rises, but more than offset when P rises and i falls (profitable foreclosure), typical in time of home price bubbles

Scenario 2. When P declines, D rises; D further rises when i rises and w and e fall (loss-making foreclosure), typical in times of home price bubble collapses.

It seems that Scenario 1 was the basic premise made by the financial sector, at the expense of totally ignoring Scenario 2. The use of P as a predictor for D broke when the economic conditions that supported Scenario 1 did not prevail in Scenario 2. In this article, frequent references will be made to Scenarios 1 and 2 outlined above.

Such a de-link of modeling from realism was confirmed by Alan Greenspan in his testimony to the Congress in the post-sub-prime meltdown enquiry. He stated that he had never factored for a lowering in home prices in the future, as they had only gone higher in the past.

On hindsight, it appears that some of the business realities were assumed away in the mortgage modeling reduction, a fact over-looked by Wall Street which enthusiastically embraced quantitative models.

5. David Li's gaussian copula function: the elegant heuristic

Firstly, it needs to be clarified that David Li's model for default correlations were applied to corporate bonds, using the copula model from actuarial science practice in life insurance (insurance for the joint life of couples). This analogy itself could lead to model risk. The mis-application and heightened model risk arise when the same analog is extended to individual mortgage loans, where defaults can occur in cascades.

Actual defaults in the corporate bond sector in the USA, across the period under observation (2000 to 2004) were few and far between. Traded CDS contracts were more numerous than the actual mortgages or the CDOs carved from them. Li used a large sample of historical CDS prices as proxies for defaults to compensate for sparse historical data on actual defaults on individual home loan mortgages. He assumed that since the volumes of CDS are large (several times the CDO markets), all relevant economic information was embedded within the CDS prices. This, according to him, obviated the need for going through the actual historical default data on mortgage home loans. He also subdivided the CDS portfolios into several sub-groups and found low correlations of CDS prices across each paired sub-subgroup. He concluded that these paired sub-subgroups exhibited correlations readings were normally distributed. The loan portfolios were assumed to sufficiently diversified to absorb default shocks from individual loans. In other words, the left tail losses were adequately capitalized.

In essence, Li's line of thinking may be summarized as follows:

CDS prices → Sub-groups → Low correlation across sub-groups → Low default concentrations, high diversification → High AAA credit ratings → High CDO prices → Low CDS claim losses.

Like catastrophe (CAT) bonds, the premiums (spreads) were seen as easy pickings for funding contingent losses on low-probability events. Elegant and simple as the reduction appeared, it was applied blindly to the retail mortgage loan markets, based on Scenario 1 which turned out to be out of tune with reality. As explained under Scenario 2, there was no scope for examining the effects of low house prices, and under such a scenario, the adverse impact of low wages, employment levels and high interest

costs. The correlations experienced in benign periods would not hold, as time would tell. When the comfort of high prices was blown away, correlations were so high that even genuine AAA rated mortgage-backed securities saw steep declines, resulting in CDS claims being deep in the money.

Li would explain in post-2005, that his models were used too literally, which was not what he meant. Perhaps, the realization that profitable foreclosures were treated as prepayments would dawn upon the market participants much later. A copula model based on actuarial science, for joint insuring joint lives of a married couple, was transplanted into the examination of defaults and home prices, and the underlying portfolios of home loan receivables. Foreclosures were disguised as prepayments, contaminating the value of CDS as a reliable proxy for measuring morbidity. This realism was not reflected in the CDS pricing, until it dawned upon the credit markets in 2006-2007. Those who realized this early enough were Paulson, Burry, Deutsche Bank and Goldman Sachs. Correlations of benign periods had broken down as factors other than home prices turned out to be greater causal factors. Experts, both academicians as well as practitioners, concurred that models based on correlation cannot be blindly taken as robust relationships for all time to come. Over time, relationships need not maintain the Gaussian normal distribution pattern.

6. Eugene Xu's real(i)ty check and counterviews

From 2005, Eugene Xu of Deutsche Bank identified correlations between high Home Prices and low Defaults, but correctly suspected that these correlations were based on data of benign periods. These correlations would not hold from 2007 when home prices fall, exacerbated when higher mortgage payments commence, together with low incomes and employment levels and higher interest.

Xu then carried out empirical research across geographies in the US sub-prime mortgage markets. He divided the CDS data into quartiles. He found that low defaults were primarily linked with the prevailing high home prices. Little else mattered, during data from benign periods. So long as home prices remained high, loans were above water, i.e. home prices were above the loan outstanding. In the event of loss of employment or lower incomes, or higher interest or installments, owners with high home prices could obtain re-finance, and the extant loans were treated as prepayments, although, in spirit, they were foreclosures. California, with high home prices experienced low defaults, compared to Nevada, Arizona and Florida. Californian employment rates were at

the same level as the rest of the country, though. Florida, in turn, had lower defaults because home prices had appreciated in Florida at a faster rate than Georgia. North Dakota and South Dakota both had the same employment and wage rates, but North Dakota had lower defaults; it turned out that home prices had appreciated faster in North Dakota, though employment and wage rates were the same in both North and South Dakota. All these conclusions were based on data from benign periods up to 2005. Realizing that the loans arising from lax credit standards had been made after 2005, it was only a matter of time until home prices began to flatten or decline, for the true default rates to show up. Since the way business was done had changed (i.e. decline in loan appraisal standards), the old correlation patterns as suggested by David Li were bound to give way to higher default correlations. For, when home prices decline and refinancing alternatives are cut off, the full impact of low wages, employment rate and higher interest would begin to kick in.

Eugene Xu's research prepared Deutsche Bank to be alert to bearish signals and sensitize its actions to prepare for the bear market in CDOs ahead. Deutsche was one of the first banks to start buying CDS contracts and short the market. The team led by Greg Lippman made profits for Deutsche using their newly-acquired bearish outlook. For all other market participants, the old models of the David Li vintage failed to provide timely signals of CDO credit-quality deterioration.

7. Quant brigade – others

The quants who originally designed the CDS contracts on corporate bonds, in the 1990s were from JP Morgan. These ideas were reverse-engineered by a team of quants from AIG-FP. Other quantitative research analysts who distinguished themselves during the sub-prime mortgage meltdown are also mentioned here. Jeremy Primer of Goldman Sachs, who worked under Josh Birnbaum at the trading desk of Goldman Sachs, was one who would constantly work out the IRR of the cash flows into the escrow accounts in respect of CDOs and work out the over-valuation. The same formed the basis of Goldman's lower marks-to-market that led to short selling as

well as making claims on AIG against CDS contracts purchased. Paolo Pelligrini of John Paulson, the hedge fund managers, also, much like Eugene Xu, found that the most sub-standard of mortgages were originated in the period of 2005-2006, and those were the very ones selected for shorting and purchase of CDS contracts.

8. Model risk

A model is as good as the conditions that support it, the data that goes into it. These conditions and the data may change over time due to fundamental reasons and need to be re-visited before any serious application is attempted. The quant community has a mastery over model-building and seek applications. The practitioner community also takes quick-fix solutions to attain business targets, in an attempt to stay with or ahead of the competition. As a result, the gulf between theory and practice gets wider. The widening gulf is exacerbated in the following ways:

- ◆ quants may not be in tune with real world situations and the subtle changes over time;
- ◆ practitioners use quant tools as a black box, to stay safe with the herd.

Quants created models, but asset allocation was done by practitioners who used these models as a black box. Quants may over-simplify problems by assuming away factors that are troublesome to model. The use of past data to model the future may work well most of the time, but the little bits of time during which they do not work, is sufficient to blow up all cumulative gains from use of the models. It so happens that the quant models are critically examined only on an ex-post factor basis, after severe damage has been inflicted. In other words, the black-box models were distant from the common-sense smell test, which Eugene Xu and Paolo Pelligrini figured out, along with Michael Burry and other small hedge fund managers. Loans sanctioned in the post 2005 were simply not creditworthy, rendering the data incomparable to those in the pre-2003 era when the data that went into modeling were markedly different.

Candid admissions by various experts on *model risk* are tabulated below.

Table 2. Opinions and quant brigade

David Li (2005)	Very few people understand the essence of the model
Darrell Duffie	The corporate world almost exclusively relied on the copula-based correlation model. It was not suitable for risk management or valuation.
Janet Tavakoli (2006)	Correlation trading has spread through the psyche of the financial markets like a highly infectious thought virus.
Kai Gilkes	Everyone was pinning their hopes on house prices continuing to rise. When they stopped rising, everyone was caught on the wrong side. Why didn't the rating agencies build in some cushion for house price depreciation scenario? Because if they had, they wouldn't have rated a single CDO. Li just invented the model, he couldn't be blamed.
Paul Wilmott (1998, 2005)	Correlations between financial assets are notoriously unstable. The relationship between two assets can never be captured by a single scalar quantity. It is impossible to sum up history based on a correlation number, but CDOs were sold on the premise that correlation was more of a constant than a variable.

Table 2 (cont.). Opinions and quant brigade

Nassim Nicholas Taleb	People got very excited because of the Gaussian Copula, because of its mathematical elegance, but the thing never worked. Co-association between securities is not measurable using correlation. History never prepares you for that one day when everything that goes in another direction. Anything that relies on correlation is charlatanism.
George Soros	Financial markets are social settings where human minds are a part of the economic experiment, unlike inanimate objects. The Theory of Reflexivity is all about "what A thinks about what B thinks about A". By the time people realize the invalidity of models, it is too late.
Alan Greenspan (2008)	To the extent I figure out what happened and why, I shall change my views. To exist, you need an ideology. The question is, whether it is accurate or not. Yes, I found a flaw. I don't know how significant of permanent it is. I found a flaw in the model of what I perceived as a critical functioning structure of structure of how the world works. I was shocked. Because I had been going for forty years or more, with considerable evidence that it was working exceptionally well.
Gillian Tett (2006)	The Blythe Masters and the Morgan Mafia changed the world of finance.
Mark Whitehouse (2005)	How a formula ignited markets that burned big investors.

Greenspan's confessions about his model risk, and the fact that they worked well during the boom periods, came too late, in 2008. By then, considerable damage had been done to the investors.

9. Behavioral finance issues

When chasing profits become honorable and the end justifies the means, there is a built-in moral hazard. In these days of regulatory capture where powerful Wall Street investment banks are capable of formulation or dilution of policies, the game is skewed in favor of the banks. Financial incentives drive financial innovation, even where the innovations borders are unethical or illegal. In the context of CDS and CDOs and the manner in which they were modeled and applied, the moral hazard problem arises from the originate-to-hold model to the originate-to-distribute model. Neither the KYC norms of the traditional originate-to-hold banking, nor the insurable interest norm of traditional insurance, nor the capital adequacy standards of regulated capital market entities were available to check the perverse incentive structure. Consequently, the quants created black-box models which were used to by incentive-driven managers to churn profits. Model risk, even of the severest kind was neither recognized by the common sense of business analysis, nor addressed. In behavioral finance studies, this is termed as representation bias, where a modeler fails to recognize the changing natures of variables that explain a phenomenon.

10. Regulation of CDS contracts

Raghuram Rajan pointed out that the failure of AIG, being a large counter-party on CDS transactions, was systemically destabilizing. Nouriel Roubini called for an outright ban on synthetic CDOs where the buyer of CDS protection does not own the CDOs but has every incentive to see or cause their value to decline. There is also an ongoing debate to bring much of the OTC derivatives on to the public domain and make them exchange traded or subject to greater regulatory scrutiny.

11. An attempt at back testing

On the wisdom of hindsight, was it possible to have a better pricing mechanism for CDS and CDO instruments? This would have averted the issuance of CDS and CDO instruments and contained the financial meltdown. This question is examined in the rest of the paper. Conceptually,

$$\text{Price of a CDO} = \frac{\text{Cashflows from borrower}}{(1 + y)},$$

where, $y = \text{RADR Expected Rate of Return from CDO bond} + \text{Risk (CDS) Spread}$.

The risk premium rate needs to be linked to the CDS spread. The higher the default risk, *the higher* the CDS premium, *the lower* the CDO price is. A sound CDS would be the one based on immediately relevant factors. These include: (1) a borrower's credit score; and (2) quantum of interest and principal payments. A deteriorating credit score indicates a lower ability to withstand economic shocks. Rising interest and principal payments further worsen the risk for the lender. These factors assume greater significance during economic downturns, especially the lower income (sub-prime) borrowers. In situations of economic downturn the poor credit quality of loans, especially teaser loans and negative amortization loans, get exposed. Further, they get fully exposed if the proceeds from foreclosed home loans are lower than the unpaid loan principal and interest.

Methodologically, default is a function of credit score and interest payment obligations. The credit score and the interest payment obligations are the two independent variables.

'Credit score' is defined as the credit rating for the individual borrower, rated by the Fair Isaac Company (FICO). Typically, scores above 680 are considered as acceptable, and those below 620 as sub-prime.

'Interest payments' are defined as the actual interest amounts in dollars, as per the individual loan schedules. Typically, in teaser loans, the quantum of interest payments go up. In the case of 'negative

amortization' loans, the initial interest obligations are added to the principal, resulting in higher outflows in subsequent months.

A market participant pricing CDS and CDOs would easily be able to gauge trends in deteriorating FICO scores and rising interest payments in standard loan repayment schedules. Lower FICO scores and higher interest payments translate into higher risk, hence a higher CDS price. CDS prices are quoted in percentage terms (usually basis points). In this paper, an econometric framework is tested with stylized data, from episodic accounts of the sub-prime crisis as mentioned under the references at the end of this paper.

A CDO is a standard financial asset. In a CDO, the numerator is the cash flows from the underlying loans. The denominator is $(1+y)$, where y represents the opportunity rate of return in a given risk class. The additional risk (as captured in the CDS premium) will be added to y to arrive at the risk-adjusted discount rate (RADR).

It would conceptually sound to link the default risk to the creditworthiness of the borrower and the interest outgo. A decline in creditworthiness (lower income or loss of employment) and an increase in interest and loan installments (especially in the case of teaser loans and negative amortization loans) must lead to a higher default risk. Theoretically, a CDS must price this. However, if the CDS is linked only to home prices that were high in boom-time, it will not capture the rising default risk arising from fundamental factors such as creditworthiness and interest payments. In fact, a loan could become sub-prime in nature even before the final default is detected.

A correct approach is attempted, using episodic data from publications that covered the news reportage (in book form, listed in the references at the end of this paper) of the sub-prime meltdown. Although this data is not the actual data, it is representative, as it gives the plausible range of loan default percentages, declining FICO scores of borrowers and interest and loan repayment schedules in respect of adjustable-rate mortgages, teaser loans and interest-only loans. Based on the same, an econometric model is derived, to gauge its efficacy, as a replacement to the David Li model of using CDS prices (which was, in turn, based on home prices in benign periods).

12. An alternate econometric approach to estimate defaults

Appendices A and B present data and analysis. Sample period is from January 2005 to December 2007, 36 months data.

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \xi, \quad (1)$$

where Y are the default levels; X_1 is the GDP, reflecting income levels; X_2 is the employment, reflecting ability to repay mortgage loans; X_3 are the interest rates on BBB rated loans, reflecting cash outflow levels of borrowers; ξ is the error term, the residual.

David Li's Gaussian Copula function misguided the markets until the sub-prime loan losses exploded. CDOs created out of the underlying mortgages lost as much as 85% of their value, triggering claims on CDS writers. This, in turn, led to the collapse of AIG, one of the major CDS writers, until its nationalization with US taxpayers' money.

The Gaussian Copula function written about by David Li was from actuarial science. It studied the longevity of the surviving member of married couples. The important application area was insurance policies of joint lives. Low correlations were found across couples studied. Li's study was on defaults in the corporate bond market. The objective was to establish as to whether corporations default en masse i.e. the probability of one defaulting in the event of a default by another. The default correlations identified across bonds were low. They followed a Gaussian normal distribution. CDS contracts on corporate bonds were invented in JP Morgan in the 1990s. Since actual defaults were rare, Li used prices of a large number of traded CDS prices as inputs to compute correlations. During 2004, CDS contracts were sold by Morgan Stanley to earn premium incomes from the CDS spreads, since, in those days, prepayment risk actually kept the CDO prices high. However, lax underwriting standards in the form of increasing Alt-A, sub-prime and NINJA loans turned Morgan Stanley's views bearish, making them buyers of CDS contracts. This was meant to provide default insurance against the proprietary holdings of their mortgage and CDO holdings.

The problem arose when, after 2004, the CDS prices on CDOs were used to value the prices of CDOs and rate them. Although the term CDS implies a relation to the creditworthiness of the underlying borrowers, neither creditworthiness nor default probabilities were assessed seriously. The CDS contracts themselves were assumed to be embed all information relevant to credit markets. David Li's correlation redux became a black-box, although it was faithfully used as a quantitatively rigorous tool. To exacerbate matters, the boom years of mortgage credit and high home prices masked actual default data, as low interest rates fuelled refinancing. This is particularly true from 2005, the turning point for the worsening of credit appraisal standards. As Nassim Nicholas Taleb commented, correlation is charlatanism. Ironically, CDS, an insurance-type cover, was offered on a

capital market instrument (CDO) with the underlying credit being a banking product. The quantitative models were far removed from the dynamics and reality of cash flows.

Correlations across various loan schemes are perfectly positive (+0.99). This implies a huge concentration risk, and there was in effect no diversification; the CDO pools, doomed to default, were not insurable, and should never have been covered by CDS insurance! Eventually, AIG's capital was wiped out. Further, the low creditworthiness implies that rating agencies should never have provided an AAA rating.

Taleb also warned against the blind acceptance of empiricism, particularly if the underlying assumptions are far removed from reality. The conclusions induced could be false, and devastating, as they actually turned out post the sub-prime meltdown. In this paper, it is shown that simple empirical data, anchored to realism, could have been used to model default more realistically. The regression equation is summed up in the section below.

To proceed with the econometric approach, let:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \xi \quad (2)$$

Accordingly, there are two hypotheses.

H_o : Credit scores and magnitude of loan repayments are not significant in influencing defaults.

H_a : Credit scores and magnitude of loan repayments are significant in influencing defaults.

Under the OLS method for BLUE, this is to be tested for the following:

$$Y = [\alpha + \beta_1 X_1 + \beta_2 X_2] + \xi \quad (3)$$

<i>SST</i>	<i>SSE</i>	<i>SSR</i>
Totals	Explanatory	Residuals

The FICO credit score is determined at the time of screening the loan application. On sanction, the applicant picks the scheme: Adjustable Rate Mortgage (ARM) or Interest Only Negative Amortization or Teaser Rate, which determine cash outflow commitments. These two independent variables are presumed to be independent of each other, so as to minimize the effect of multicollinearity. Macroeconomic factors such as GDP, employment, wages etc. are all assumed to be embedded into the FICO scores.

The *a priori* reasoning supporting the hypothesis is that the credit history and the quantum loan repayments constitute the major causal factors for default. These should constitute the major factors for pricing CDS contracts. Data for the dependent variable and the independent variables are available in the public domain. Gaps in the data are fitted

with insights from published versions of the sub-prime crisis. The period covered is from January 2005 to December 2006, constituting 36 months. Data are summarized as Annexures 1 (Regression Data and Cash Outflows under various Loan Repayment Schemes).

The regression output is as follows:

$$Y = 180.25898 - 0.27163X_1 + 0.04695X_2 + \xi \quad (4)$$

With t values: (-3.414) (2.978)

The t values for both the independent variables are found to be significant.

Based on the above, the adjusted R^2 is 0.8127, which shows an 81% explanatory power of the variables, in estimating default.

The model shows that there are more robust, yet simple ways to estimate default risk and to price CDOs than the Gaussian Copula function. This approach links CDS pricing to creditworthiness, rather than treat default as an inverse function of higher home prices. It also reinforces the axiom that correlation need not coincide with causation.

Conclusions

The empirical data of the bubble era and an oversimplification of the correlation-based model failed to provide an early warning of the impending crash. Perverse incentives, moral hazards and weak regulation of OTC derivatives exacerbated the systemic failure. This paper critiques the origins of the CDS innovation, the mis-application of financial engineering and offers a fresh perspective on the model risk arising from faulty empirics. The attempt is to bridge theory and practice in the nascent-and-opaque CDS markets, and bring in a real-world perspective, with the wisdom of hindsight for a mature application of financial engineering tools. As regards fresh empirical studies are concerned, it is early days yet. The major correction, however, in pricing CDS would be to separate default probability from home prices and link them to conservatively to employment and wage levels, as conventional wisdom guides. In other words, CDS pricing cannot be an input to CDO pricing. Turned the other way round, wage and employment levels need to influence CDO pricing, which, in turn, is a major determinant of CDS pricing. From a definitional perspective, a profitable foreclosure must always be classified as a foreclosure and not as a prepayment, to gauge default levels correctly. Interestingly, ISDA has now defined the credit trigger event as the actual default (skipping of loan payment) and not the proceeds of the home sale that happens latter, at a gain or loss.

The empirical data of the bubble era and an oversimplification of the correlation-based model failed to provide an early warning of the impending crash. Perverse incentives, moral hazards and weak regulation of OTC derivatives exacerbated the systemic failure. This paper critiques the origins of the CDS innovation, the mis-application of financial engineering and offers a fresh perspective on the model risk arising from faulty empirics. The attempt is to bridge theory and practice in the nascent-and-opaque CDS markets, and bring in a real-world perspective, with the wisdom of hindsight for a mature application of financial engineering tools.

As regards fresh empirical studies are concerned, it is early days yet. The major correction, however, in pricing CDS would be to separate default probability from home prices and link them to conservatively to FICO scores and cash outflows on mortgage loans,

as conventional wisdom guides. In other words, CDS pricing cannot be based on home prices.

From a definitional perspective, a profitable foreclosure must always be classified as a foreclosure and not as a prepayment, to gauge default levels correctly.

CDS contracts continue to be applied in a wide variety of application areas: corporate debt, sovereign debt, retail loan portfolios etc. While the basic idea is of economic use, caution must be taken to understand the workings of the model, with insight from practitioners and relevant, real-world data for designing as well as testing the model. This includes the choice of variables that influence default (income, wages), testing the efficacy of models over various economic cycles and monitoring the true rate of defaults, measured correctly.

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Appendix A

Table 1A. Data

Sr. No	Month/year	Default rate	FICO score	Cashflow
1	Jan-05	1.0	700	134
2	Feb-05	1.1	698	134
3	Mar-05	1.2	696	134
4	Apr-05	1.3	694	134
5	May-05	1.4	692	134
6	Jun-05	1.5	690	134
7	Jul-05	1.6	688	134
8	Aug-05	1.7	686	134
9	Sep-05	1.8	684	134
10	Oct-05	1.9	682	134

Table 1A (cont.). Data

Sr. No	Month/year	Default rate	FICO score	Cashflow
11	Nov-05	2.0	680	134
12	Dec-05	2.1	678	134
13	Jan-06	2.2	676	167
14	Feb-06	2.3	674	167
15	Mar-06	2.4	672	167
16	Apr-06	2.5	670	167
17	May-06	3.0	668	167
18	Jun-06	3.8	666	167
19	Jul-06	4.5	664	167
20	Aug-06	5.3	662	167
21	Sep-06	6.0	660	167
22	Oct-06	7.0	658	167
23	Nov-06	8.5	656	167
24	Dec-06	10.2	654	167
25	Jan-07	11.2	652	376
26	Feb-07	15.6	650	375
27	Mar-07	16.0	648	374
28	Apr-07	16.5	646	373
29	May-07	16.9	644	372
30	June-07	18.7	642	371
31	Jul-07	25.4	640	370
32	Aug-07	28.0	638	369
33	Sep-07	32.0	636	368
34	Oct-07	34.0	634	367
35	Nov-07	36.0	632	366
36	Dec-07	37.7	630	365

Appendix B

```

> lm(DEFAULT.RATE~FICO.SCORE + CFLOW)
Call:
lm(formula = DEFAULT.RATE ~ FICO.SCORE + CFLOW)

Coefficients:
(Intercept)  FICO.SCORE      CFLOW
 180.25898    -0.27163     0.04695

> R<-lm(DEFAULT.RATE~FICO.SCORE + CFLOW)
> summary(R)

Call:
lm(formula = DEFAULT.RATE ~ FICO.SCORE + CFLOW)

Residuals:
    Min       1Q   Median       3Q      Max
-9.5896 -3.2636 -0.2441  2.9537 11.4109

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 180.25898   55.99632   3.219  0.00288 **
FICO.SCORE  -0.27163    0.07956  -3.414  0.00171 **
CFLOW        0.04695    0.01576   2.978  0.00540 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.94 on 33 degrees of freedom
Multiple R-squared:  0.8234,    Adjusted R-squared:  0.8127
F-statistic: 76.91 on 2 and 33 DF,  p-value: 3.774e-13

```

Fig. 1. Data analysis (using R language)