CREDIT RISK MODELING:

AN EMPIRICAL ANALYSIS ON PRICING, PROCYCLICALITY AND DEPENDENCE

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Abstract

Credit Risk Modeling:

An empirical analysis on Pricing, Procyclicality and Dependence

By Fouad Ayari

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Credit risk modeling has grown significantly over the past few years; driven by explosive growth in the credit derivatives market and the outlook of more quantitatively sophisticated bank capital regulations under the upcoming Basel II Accord which makes credit risk capital requirement more risk-sensitive. Thus credit risk is attracting strong interest from all market participants, financial institutions (commercial banks, investment banks, hedge funds), regulators (US Federal Reserve, FDIC, Bank of International Settlements) and investors.

Credit risk modeling relies mainly on three parameters, namely the probability of default (PD), the recovery rate (RR) and the correlation structure among borrowers (when computed on portfolios of debt instruments).

This study intends first to explain the implied "correlation skew" using the term structure of the interest rates, particularly the liquidity premium theory, (the "correlation skew is observed because the market implied correlation does not correspond to the single constant correlation assumed by the Single Factor Gaussian Copula, as suggested by David Li[1]). I show that liquidity has some explanatory power on the correlation that can explain the clustering at the lowest and highest tranche. Within Merton[2] model, and given the scarcity in defaulted debt instruments data, the market generally uses equity returns as a proxy for assets returns. The second section analyses the relationship between credit default swap index spread and stock market returns and shows that effectively there is a relationship between both markets.

The third section provides a comprehensive analysis on the cyclicality of default rates, recovery rates and their dependence using financial data

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[1] Li, David (2000),"On default Correlation: A Copula Function Approach", *The Journal of Fixed Income,* March 2000.

[2] Merton, Robert (1974), "On the pricing of corporate debt: the risk structure of interest rates", Journal of Finance, VOL 29, 449-470.

provided by Bank Call Reports[3] from 1991 to 2005 for all US commercial banks with total assets greater than $300 millions. It shows that indeed, default rates[4] and recovery rates are cyclical and inversely related. These findings have important implications in credit risk modeling for both the credit derivatives market and the new Basel II capital requirement proposed rule because not only current market practice assumes constant recovery rate[5] and independence between probability of default and recovery rate, but also regulators are still debating on how banks should include a downturn LGD[6] (loss given default).

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[3] The Federal Financial Institutions Examination Council provides Banks Call Reports to the public on its website www.ffiec.gov.

[4] This dissertation applies a similar approach to that of Georges French by using the charge-off rate as a proxy for default rates. French, George (2003), " Estimating the Capital Impact of Basel II in the United States", *Federal Deposit Insurance Corporation*, December 2003.

[5] Market quotes given by Bloomberg which usually come from several suppliers such as Morgan Stanley are usually based on the assumption of a constant recovery rate of 40%

[6] see Basel II: International Convergence of Capital Measurement and Capital Standards: a Revised Framework, www.bis.org. and also the Quantitative Impact Study at www.ffiec.gov/qis4.

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I would like to dedicate this Doctorate to my mother Naima Ayari and to my father Mouldi Ayari for their continuous support, commitment, encouragements and dreams. I would have never achieved this without their love and affection throughout my life. I would like also to thank my wife Judith for her love, support and patience for all these years and for giving me two wonderful children, Elias and Hannah. A big thank to all my sisters and brothers, Boujemaa, Malika, Zakia, Faycal, Fattah and Khira for their trust, love and support.

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I gratefully acknowledge dissertation support from the Financial Research Unit at the New York State Banking Department, in particular Dr Katherine Wyatt for allowing me to utilize bank Call Report Data at the aggregate level in regards to chapter three and also for awaking my interest in

Basel II and its relation with credit risk modeling. There are plenty of great individuals who indirectly contributed to this dissertation, and I would like to thank all of them from the bottom of my heart.

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CHAPTER I: OVERVIEW OF CREDIT RISK MODELING

I-1 INTRODUCTION

Default risk and recovery risk are the main parameters in determining the credit spread in credit risk. Default risk is the uncertainty about whether or not the entity will fail to meet its obligations and recovery risk is the uncertainty about the amount recovered in case of default.

Credit derivatives are financial instruments that transfer all (or a portion) of the credit risk of an underlying obligation or entity (or group of obligations or entities) from one party to another, without necessarily transferring the underlying asset. Their value is derived from the credit quality of an obligation such as a loan or a bond of a reference entity. They have become a major tool in risk management as market participants (borrowers and lenders) can now assume or distribute credit risk in a customized fashion.

Several pricing models were proposed by academicians and practitioners but, to this date, none of them can accurately calibrate their models inputs to market data. The standard model used in the market is the One Factor Gaussian Copula proposed by David Li[7] (2000), but similar to the

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[7]Li, David (2000),"On default Correlation: A Copula Function Approach", *The Journal of Fixed Income,* March 2000.

implied volatility smile when using the Black & Scholes[8] option pricing model, there is an observed “implied correlation smile” or “correlation skew” from market quotes on multi-name credit derivatives such as synthetic collateralized debt obligations (SCDO) when using the Single Factor Copula Model. This inconsistency can be due to an incorrect model specification (wrong copula), market segmentation (investor preferences in different tranches) or a liquidity problem[9].

Using Li’s model and market data on CDOs , there is a mismatch on the correlation parameters. Whereas Li’s model uses one single flat correlation parameter, the market implies several different correlations at each tranche.

This dissertation tackles this issue by looking at the liquidity effect on the correlation using the Bid-Ask spread as a proxy for liquidity (explanation similar to that of the term structure of the interest rates and Liquidity Premium theory). .In the same chapter (II), this study uses a Vector Autoregression

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[8] Black, F., and M. Scholes. "The Pricing of Options and Corporate Liabilities." Journal of Political Economy, 81 (1973), 637-654.

[9] The observed implied “correlation smile” has been pointed out by most of the market participants and authors cited in the bibliography as well as , Jeffrey D., Jacob Gyntelberg (2005), “CDS Index tranches and the pricing of credit risk correlations”, *BIS Quarterly Review*, March 2005, pp 73-87. This study shows also the correlation skew using its own market data.

analysis to show the relationship between the credit derivatives market and the equity market.

As said initially the explosive growth in the credit derivatives market occurred simultaneously with the BCBS[10] (Basel Committee for Bank Supervision) work on moving from Basel I to a more risk sensitive proposed rules for banks capital requirement, namely Basel II.

Since 1998, the Basel Committee for Bank Supervision is on the working of a new Capital Adequacy framework with new proposed rules called Basel II reflecting a more complex and risk sensitive approach to Credit Risk Management to be implemented mainly by all European Banks and the largest US Banks. The need for Basel II reflects the increased sophistication of risk-management practices and the ways they can be applied to the measurement of capital. Basel II also creates a link between regulatory capital and risk management.

[10] http://www.bis.org/bcbs/index.htm

In the third chapter of this dissertation, I look at the main assumptions underlying Basel II capital rules as cited above and draw on the relationship between bank loan defaults and recovery rates as well as their procyclicality[11].

The sample consists of all US Banks with assets of more than $300 million, with quarterly Call Reports from 1991 to 2005. This study uses the ratio of Charge-Off/Loan Amount as a proxy for Default Rate, similar to a methodology used by George French[12] , at the sector level (Commercial & Industrial, loans to individuals, 1-4 family real estate loans, Construction, Home Equity Line of Credit and Commercial real estate loans) and at the aggregate level.

I find that Default Rates and Recovery Rates are Procyclical, and this study's results confirm Altman, Resti & Sironi (2002[13] and 2003[14]) on the

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[11] There are several interpretations and definitions of procyclicality. This manuscript uses "procyclicality" as a tendency for the variable of interest (probability of default and recovery rate) to fluctuate to fluctuate with the business/economic cycle. The variable of interest could be rising or falling during an economic upturn or downturn.

[12] French, George (2003), "Estimating the Capital Impact of Basel II in the United States", *Federal Deposit Insurance Corporation*, December 2003.

[13] Altman, Edward, Andrea Resti and Andrea Sironi (2002), "The link between default and recovery rates: effects on the procyclicality of regulatory capital ratios", BIS working papers No113, July 2002.

corporate bond default and recovery rates across the business cycles. Using regression analysis (linear and non linear), I also find that Default Rates and Recovery Rates are dependent and inversely related. The implications are of importance within the Basel II framework and it adds evidence to the suggestions of modifications of the current Basel II proposed rules on the estimation of the parameters to be taken into account by regulators and banks into their models, namely cyclicality and dependence (for example using cycle-dependent PD and RR rather than long term averages). There are also implications in credit derivatives pricing because the market assumes a constant recovery rate (usually 40%) and most of the pricing models assume independence between PD & RR (Altman et al, 2002 & 2003).

I-2 Credit Risk Modeling and the Credit Derivatives Market

I-2-1 Market, Instruments and Market Participants

The credit derivatives market includes end-buyers of protection, end-sellers of protection, and intermediaries, who provide liquidity to end-users of CDS. The biggest players are the intermediaries, including investment banking arms of commercial banks and securities houses. End-sellers include commercial banks, insurance companies, collateral managers of CDOs

[14] Altman, Edward, Andrea Resti and Andrea Sironi (2003), "Default Recovery Rates in Credit Risk Modeling: A Review of the Literature and Empirical Evidence", BIS working papers, December 2003.

(collateralized debt obligations), pension funds and mutual funds. End-buyers include commercial banks but also hedge funds and to a lesser extent non-financial companies.

The Bank for International Settlements[15] (BIS) reported that the notional value for the overall credit derivatives market stood at $8.42 Trillion in 2004(compared with an almost inexistent $40 Billion in 1996), having grown 568% in the last three years. Typical instruments are: Credit Default Swaps (CDS), Total Return Swap (TRS), Credit Spread Options (CSO) and Credit Linked Notes (CLN) but CDS made up most of the market, it accounted for $6.4 Trillion of the total notional amount.

According to the OCC Quarterly Derivatives Report[16] on US banks (Office of the Comptroller of the Currency), trust companies and bank holding companies, the total notional amount of credit derivatives for the top 25 US Commercial banks and trust companies was $3.1 trillion in 2004, up from $1.9 trillion in 2003.

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15 BIS Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity March 2005 http://www.bis.org/publ/rpfx05.htm

16 http://www.occ.treas.gov/deriv/deriv.htm

A Fitch Global Credit Derivative Survey[17] found that the composition of the CDx market by rating had shifted over the past year, with an increase in unrated exposures (18% from 8%) and a decrease in "AAA" exposures (17% down from 22%). The average rating in aggregate was BBB/BBB-, compared A-/BBB+ last year. This shift in ratings may be due to a reduction in demand for senior and super senior protection along with the launch of High Yield CDS indices.

According to a Fitch Credit Derivatives Survey[18] (released in 2005 for the year 2004), there was little change in the degree of counterparty concentration in 2004 compared with 2003. The top ten institutions by volume hardly changed; they represented 69% of total counterparty exposures in 2004.

The top ten Counterparties in 2003 were:

1. *JP Morgan Chase*
2. *Deutsche Bank*
3. *Goldman Sachs*

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[17] http://reports.fitchratings.com/coms2

[18]http://www.fitchratings.com/corporate/login/login.cfm?script_name=%2Fcorporate%2Freports%2Freport%5Fframe%2Ecfm&query_string=rpt%5Fid%3D255748%26sector%5Fflag%3D1%26marketsector%3D6

4. *Morgan Stanley*
5. *Merrill Lynch*
6. *Credit Suisse First Boston*
7. *UBS(Union de Banques Suisse)*
8. *Lehman Brothers*
9. *Citigroup*
10. *Bear Stearns*

The top reference entities in 2003, according to Fitch, were:

Table I-2-1-A Top five reference entities in 2003

	PROTECTION SOLD	PROTECTION BOUGHT
1	Ford Motor/Ford Motor Credit Co	Ford Motor/Ford Motor Credit Co
2	General Motor/GMAC	DaimlerChrysler
3	France Telecom	General Motor/GMAC[19]
4	DaimlerChrysler	France Telecom
5	Deutsche Telekom	Deutsche Telekom

[19] GMAC, General Motors Acceptance Corporation, is a subsidiary of General Motors

Among all reference entities, 65% were corporate, 17% financial institutions, 6% sovereigns, and 12% asset-backed securities and other entities. An End-user survey of top credit derivatives dealers conducted by Risk Magazine[20] in June 2005 gave the following as dominant players: JP Morgan Chase, Deutsche Bank, Goldman Sachs, Morgan Stanley, BNP[21] Paribas, Citigroup, Societe Generale, and Barclays Capital.

Credit derivatives are used to hedge the potential risk that borrowers might fail to repay their outstanding debt obligations (bonds or loans); they allow banks and others to hedge their credit risk in such debt obligations without selling or transferring them. There are several types of credit derivatives, the main instruments are credit default swaps (CDS), Total Return Swaps (TRS), Credit Spread Options (CSO), and Credit Linked Notes (CLN). Defining what constitutes a credit event has always made CDS documentation complex. Credit event definitions are set by ISDA[22] and usually include bankruptcy, failure to pay, and restructuring. However, restructuring is defined differently in different markets, and the high yield market excludes restructuring as a credit event. Since 1991, the International Swap and

[20] www.risk.net June 2005.

[21] BNP, Banque Nationale de Paris

[22] International Swap and Derivatives Association
http://www.isda.org/publications/isdacredit-deri-def-sup-comm.html

Derivatives Association (ISDA) has produced available a standardized letter of Confirmation called ISDA Master Agreement that allows the parties to specify the precise terms of the transaction from a number of defined alternatives. The ISDA has also provided a definition of a Credit Event which is very important for clarity in what should trigger payment, settlement in credit derivatives transactions. Most commonly a Credit Event is defined as either a failure to meet payments obligations when due (after giving effect to the grace period), or Bankruptcy (for non-sovereign entities) or Moratorium (for sovereign) or repudiation or even material adverse restructuring.

In a Credit Default Swap (CDS), a buyer purchases credit default protection from a seller on a particular obligation(s) of a third party called a reference entity. The protection buyer pays a periodic fee, typically expressed as a percentage of the notional amount, in return for a contingent payment by the protection seller following a credit event of the reference entity, usually a corporation. Payment can be either cash or physical (the underlying bond or note). If there is no credit event, the buyer continues to pay a premium to the seller until the end of the contract. It is worth noting that although the buyer is protected by this ”insurance,” the buyer still faces counterparty risk that the seller does not pay in case of a credit event. The worst case would be “double default” or that both the seller and the reference entity default.

Total Return Swaps: it is also a bilateral financial contract designed to transfer credit risk between parties but a TRS transfers an asset's total economic performance, including but not restricted to its credit related performance.

Credit Options: they are put or call options on the price of a floating rate note, bond, loan or an asset swap package which consists of a credit risky instrument and a corresponding derivative contract that exchanges the cash flows of that instrument for a floating rate cash flow stream.

It is more or less impossible to short sell a bank loan but the economics of a short position can be achieved synthetically by purchasing credit protection using a credit derivative.

CDS being the instrument of the majority of credit derivatives and being the backbone of the Synthetic Collateralized Debt Obligation, this study will deal exclusively with CDS.

I-2-2 Pricing Models[23]

Credit risk models estimate the distribution of possible credit portfolio losses based on the exposure, the expected frequency of default and the loss

[23] For a detailed description of the different credit risk models see Gordy, Michael B. (2000), "A comparative anatomy of credit risk models", *Journal of Banking & Finance* 24 (2000) pp 119-149.

severity. Credit Pricing Models are broadly divided into 2 models, Structural Models and Reduced Form Models. Where historical data on defaults is limited, structural models link the default of an entity to the value of the firm through its equity price (such models only work where the counterparty has a listed equity price). Such models are also known as Merton models (from the seminal paper by Merton in 1974). These Merton based models are popular because data on default is scarce and equity returns are widely available in the market. A number of variation of Merton's followed such as Black & Cox (1976), Geske (1977), Jones, Mason and Rosenfeld(1984), Leland (1994), Shimko, Tejima and Van Deventer(1993), Longstaff and Schwartz(1994), Anderson and Sundaresan (1996), Peter Crosbie and Jeff Bohn (2003). Commercially, Moody's KMV[24] is the most widely known structural model. These models treat equity as an option to buy the company's assets, and use option pricing formulae to link the equity price to likelihood of default. Such models are market based in a sense that they can use the latest market prices to provide a "marked to market" likelihood of default for individual companies. Merton's approach was the first developed framework for modeling default in 1974. His approach is based on the principles of option pricing (Black & Scholes, 1973). The principle is that a default occurs when a company's asset value falls below than that of its liabilities. The default process is therefore

[24] KMV stands for Kealhofer, McQuown and Vasicek, www.moodyskmv.com

driven by the value of a company's asset. At maturity, assuming the firm's debt is entirely represented by a zero-coupon bond, bondholders get the maximum of the face value of bonds or the market value of the firm. Thus it is equivalent to the face value of the bond minus a put option on the value of the firm with a strike price equal to the face value of the bond and a maturity equal to the maturity of the bond. Several Merton based models have been developed after the initial model. The Structural Approach has intuitive appeal, as it is logical to assume that a decline in the stock price is an indication that the firm is becoming riskier (that the probability of default is increasing). But there are some drawbacks to the structural approach: it requires a great deal of data that must be collected and updated frequently; it requires some assumptions about a firm's growth rate and/or about the value of its assets.

An alternative to Structural Models is the "Reduced Form" approach[25]., Reduced Form models take the view that default probabilities may be derived from the market price of risky debt. This is based on the observation that a defaultable bond may be decomposed into a risk-free component and a risky component. Whereas the price of a risk-free bond is the present value of its

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[25] For an empirical study comparing these models, see "Arora, Navneet, Jeffrey R. Bohn and Fanlin Zhu (2005), "Reduced Form vs Structural Models of Credit Risk: A case Study of three models", *Journal of Investment Management,* Vol 3 No 4 (2005), pp 43-67.

risk-free future principal and interest payments, the price of a risky bond is the present value of its future cash flows (these cash flows reflect some PD and an assumed RR in the event of default). Since a risky bond's price will be lower than the price of an otherwise equivalent risk-free bond, a Reduced Form model derives an "implied" default probability from the price difference. Prices or spreads may be used in a Reduced Form model (the growing credit default swap market is an ideal source of data for these models). This approach is much easier to implement than a Structural model. Nevertheless, it is heavily dependent upon the market price of debt, which, particularly for distressed credits, may not be readily available. It is also important to recognize that default probabilities from Reduced Form models are highly dependent upon the assumed recovery rate, which is also difficult to assess in practice.

Reduced-form models are generally used in areas such as bond and derivative pricing, and rather than producing likelihood of default measures, reduced-form models are generally used to calculate prices of such assets. The reduced-form model assumes that the price of such assets follows stochastic processes, and there are two sets of difficulties: firstly the correct process has to be developed, and secondly the process needs calibrating to market data.

Reduced form models do not condition default on asset value of the firm. These models find the probability of default from the term structure of yield spreads between risk-free and risky corporate securities. The implied forward rates on risk-free and risky corporate bonds are derived and these rates are then used to estimate market expectations of default for that category. The main work on that has been done by Schonbucher (1996), Jarrow, Kando and Turnbull (1997), Duffie and Singleton (1998) and Blauer and Wilmott (1998).

The main commercial credit risk models[26] are KMV's Portfolio Manager (1993), JP Morgan's CreditMetrics (1997), Credit Suisse Financial Product's CreditRisk+ (1997) and McKinsey's CreditPortfolioView (1998). Portfolio Manager and CreditMetrics are Merton based models. KMV's Portfolio Manager focuses on the obligor's distance to default whereas CreditMetrics relies on credit ratings and migration determined by the obligor's asset value. Recovery rates are less subject to research than Default Probabilities, most models use fixed recovery rates (example CreditRisk+) or make simple assumption (Beta distribution) thus allowing recognition of cyclicality in LGD. All these credit risk models treat recovery rate and probability of default as

[26] See footnote 19 for reference.

Independent[27]. Most credit risk models treat recovery rates as not being function of macroeconomic variables, rather, it is treated as a stochastic variable independent of the PD.

I-2-3 Operational Risks and Financial stability concerns

Operational risks are also unusually high in the credit derivatives market given its size. The New York Federal Reserve Bank hosted a meeting on September 15th, 2005 with 14 major participants in the credit derivatives market[28]. A recent report by the Counterparty Risk Management Policy Group[29], which addressed steps the private sector could take to promote the stability of the global financial system, called particular attention to serious "back office" and potential settlement problems in the credit default swap market. Financial regulators and market participants have also pointed to enormous growth in the credit derivative markets, and accompanying operational, legal, and reputational risks.

Processing and Settlement

[27] See footnote 13 for reference on Altman, Edward, Andrea Resti and Andrea Sironi (2003).

[28] For a description of the meeting and its participants, see http://www.newyorkfed.org/newsevents/news/markets/2005/DerivativesParticipants.doc

[29] The report of the counterparty risk management policy group II, July 27, 2005, www.crmpolicygroup.org

Most trades are still manually confirmed, although, with recent progress in automation, about a third of credit derivative trades are confirmed automatically with the Depository Trust Clearing Corporation[30] (DTCC). ISDA reported recently that about 60% of credit derivatives trades are still confirmed manually, with a backlog average of over 10 days. They reported backlog still averages 11.6 business days (down from 21.1 in 2004) with 9% error rates in front office processing, down from 18% in 2004 and 20% in 2003.

Processing in the past was almost entirely manual, which tends to be slow, labor intensive and present difficulties in terms of tracking the location and status of documents. The increase in unconfirmed transactions , a result of growth in the number of trades , combined with the frequency with which credit default swaps (CDS) are traded has resulted in some swap assignments occurring prior to the confirmation of the trade. The level of unsigned confirmations is often caused by confusion over exactly what entity firms have bought or sold credit protection on. large corporations often comprise a series of business entities with complex hierarchies and interrelationships. Getting the reference entity wrong in a credit derivatives trade where there is subsequent credit event can lead to a dispute and end up in court.

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[30] www.dtcc.com

The buy side's increased presence in the market has contributed to an unprecedented volume, which, combined with a still-developing settlement process, could result in uncertain legal obligations if a major credit event were to occur (see example of disputes in next section). Back-office operations need to keep up with ever increasing front-office business.

ISDA produced a standardized confirmation letter in 1992. This was amended in 2002 to make the contract definition of a credit event more precise[31]. Smoothing this documentation process has made trading in CDS more appealing to hedge funds, which previously had to buy corporate and U.S. Treasury bonds to hedge their risk in purchasing credit derivatives.

Credit Events and Legal Risk

However, operational issues, occurring as they do in a rapidly growing market, could set the stage for significant market disturbances if important reference entities were to experience a credit event. The increased market share held by unregulated hedge funds also heightens concerns about possible financial instability. Almost every contributor to a recent report on credit derivatives by the British Bankers Association[32] had experienced a

[31] ISDA credit derivative definition, and confirmation letter are available on its website, http://www.isda.org/publications/isdacredit-deri-def-sup-comm.html

[32] www.bba.org.uk

credit event in the past two years, including defaults by Enron, WorldCom, Parmalat, Marconi, Railtrack, British Energy, Swissair, and Argentina.

According to a September 2004 report by Fitch Ratings[33], about 14% of credit events captured in a recent Fitch survey were reported to involve some form of legal dispute. Although the majority of them have been resolved privately, some have resulted in litigation.

The claims were related to:

1) The identity of the reference entity.
2) Whether a particular event qualified as restructuring or as repudiation, i.e., if it triggered a credit event under the transaction.
3) The timeliness of notices delivered under the transaction.
4) The nature of assets that may be delivered.
5) The timeliness of deliveries of assets in connection with the settlement of the transaction.

As well as leading to legal disputes, credit events can put the existence of some market participants at risk. The latest major credit event (April 2005) occurred when ratings agencies downgraded Ford and General Motors credit

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[33] See footnote 17

to BB+ and BB respectively, and the holdings of hedge funds took a major dive. A California hedge fund, Marin Capital, which specialized in credit derivatives related to convertible bonds, was one of the funds affected. Marin, founded in 1999 with $1.7 billion, had to liquidate the fund this past June, after GM bonds were downgraded. Following the drastic earnings revisions at GM, the Dow Jones iTraxx Autos index widened to more than 60bp from 44bp (basis point) at the beginning of the year.

Legal Disputes Involving Credit Derivatives [34]

- In 2000 and 2001, Bank of America and the Italian bank Banca Popolare di Intra (BPI) were parties to over €62 Million of collateralized debt obligations (CDOs), which included Enron and WorldCom in the reference portfolio. Enron defaulted in December 2001 and WorldCom filed for bankruptcy protection in July 2002. BPI sued BoA after a €40 Million loss for mis-selling in the pricing of CDO tranches. BoA settled with BPI and paid €15.5 Million. Tranches above the equity tranche are rated and priced at Libor or Euribor, plus some spread, and the mis-selling claim arose from the fact that BPI was given Euribor +150bp.

[34] These examples of legal disputes involving credit derivatives were available in Risk Magazine in its archives section www.risk.net

According to market observers, the price should have been at least Euribor +2000 bp.

- UBS sued Deutsche Bank for more than $10 million in a credit derivatives deal designed to pay if Armstrong World Industries Inc. defaulted on its debt. The firm later changed its corporate structure and transferred ownership of its stock to its holding company (Armstrong Holding, Inc), before the holding company filed for bankruptcy under Chapter 11. A similar dispute arose between Swiss Re Financial Product and XL Insurance Ltd. concerning Armstrong. Both were settled out of court. The dispute centered on whether the reference entity was the holding company, the operating unit, or both, since restructuring is considered a credit event.

Growth in Credit Derivatives Market Heightens Concerns

Credit derivatives now constitute the fastest growing sector in the derivatives market. London is the dominant center in the global credit derivatives market, according to a recent British Bankers Association (BBA) credit derivatives report; notional amounts are expected to reach $3.5 trillion by the end of 2006 in London (a bit less than half the market). Banks, securities houses, insurance companies and hedge funds (which represent a growing share) constitute the majority of market participants.

According to the OCC quarterly derivatives report on US banks, trust companies and bank holding companies, the total notional amount of credit derivatives for the top 25 US commercial banks and trust companies was $3.1 trillion in 2004, up from $1.9 trillion in 2003 and $800 billion in 2002.

Hedge Fund Participation

One concern in this fast growing market is the increasing market share of hedge funds. Hedge funds activity is now estimated by Fitch to comprise about 20 to 30% of the CDS volume.

Credit-oriented hedge funds have quickly become important sources of capital to the credit markets, promoting liquidity and diffusing credit risk. These credit-oriented funds are growing at a faster pace than the overall hedge fund market. Hedge funds are known to use a lot of leverage and a forced de-leveraging of one or more large credit-oriented hedge funds would likely be felt most immediately in the form of price declines and spread widening across multiple segments of the credit market.

Hedge funds generally play a greater role in holding equity tranches of CDOs and in correlation-related trading than other market participants. Hedge funds have been among the most active market participants in the index-based sector of the credit derivative market. Their strongest activity seems to be on indexes, in particular the DJ CDX and DJ iTraxx.

Industry Studies and Recommendations

The Counterparty Risk Management Policy Group II (CRMPG II), headed by Gerald Corrigan, released a report "Toward Greater Financial Stability: A Private Sector Perspective," on July 27, 2005.The primary purpose of the group is to "examine what additional steps should be taken by the private sector to promote the efficiency, effectiveness, and stability of the global financial system." The report contains specific recommendations and directional guiding principles, as well as discussion of important issues.

The CRMPG II report lists fundamental issues whose resolutions are central to anticipating financial shocks and limiting their severity, they include counterparty credit risk, hidden concentration, complexity of models that fail to capture tail events (or default correlations), complexity associated with the recent product innovation[35] (example CDO Square which is a CDO of CDOs), financial risk associated with potential conflict of interest (asymmetric information), and oversight of hedge funds.

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[35] an interesting description of CDOs can be found at http://www.vinodkothari.com/Nomura_cdo_plainenglish.pdf and http://www.mathematik.uni-ulm.de/finmath/ss_05/fe/JPMorganCDOHandbook.pdf

Specific recommendations include:

- Dealers should have an ISDA-endorsed master agreement in place before executing an order and should develop multi-account master agreements for each type of account they represent.

- Market participants should not assign or accept assignments of transactions without the consent of all three parties.

- Market participants should attract widespread acceptance of documentation standard for the treatment of confidential information, and take such risk into account when considering such agreements.

- Market participants should identify portfolio concentrations to a security or a market factor.

- Industry members should be aware that credit derivatives transactions may intentionally or unintentionally give rise to other risks including retained credit risk, counterparty credit risk, legal risk, operational risk and concentration/liquidity risk.

The Joint Forum of the Basel Committee[36] released a study on credit risk transfer in March 2005. Many of their recommendations echo those of the CRMPG.

- It is important for investors in CDOs to seek to develop a sound understanding of the risk involved and not rely solely on rating agency assessments.

- Firms that rely on models should have sufficient staff and expertise to properly understand the assumptions and the limitations of the models.

- Market participants should understand the nature and scope of external ratings assigned to credit risk transfer instruments as well as how ratings methodologies differ across rating agencies.

- Market participants must continue efforts towards standardization of documentation.

- Participants must execute confirmation and any other documentation associated with credit risk transfer transaction promptly after it has been agreed.

[36] www.bis.org/bcbs/jointforum

- Participants must conduct stress test and VaR measures that take account of market liquidity.

The Group of 30[37] recently released recommendation for the securities clearing and settlement in their study “Global Clearing and Settlement: A Plan of Action.” Their recommendations include:

- Promulgate standards of sound legal practice and due diligence and promote the use of standardized contracts.

- Reduce legal risk by not only strengthening due diligence and following best practices guide but also by promoting the creation of an International Legislative Standard prepared by intergovernmental organizations so as to strengthen the enforceability of contracts.

- Recognize and support improved valuation methodologies and closeout netting arrangements.

Finally, the Revised Basel II Framework[38] attempts to improve existing capital requirements by outlining treatment of the risk mitigating effects of

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[37] the report is available at http://www.group30.org/docs/executive_summary.pdf

[38] Basel II: International Convergence of Capital Measurement and Capital Standards: a Revised Framework, www.bis.org.

credit derivatives as well as addressing the counterparty risk and market risk they may carry. The Revised Framework is intended to be more flexible and better able to evolve with advances in markets and risk management practices. To this end, the Framework recognizes double-default effects, updates the treatment of specific risk in the trading book, and includes specific capital treatment for failed transactions and transactions that are not settled through a delivery-versus-payment (non-DVP) framework.

I-3 Credit Risk Management and Measurement under Basel II

Basel II implementation effect on Banking Institutions has initiated a strong debate over the proposed capital rules and the adequacy of Banks' own estimates of the Loss Given Default. To date, this debate is still current and so far the last Quantitative Impact Study[39] (QIS4) has not provided the appropriate answers nor did it lead to a general consensus between regulators and banks. The challenge is how the level of risk and its consequences changes through time and how it is related to the economy. This represents currently a critical issue to banks and regulators to correctly set the level required capital and it should change but also to policy makers and central bankers, given the potential impact on financial stability.

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[39] www.ffiec.gov/qis4

Indeed, stress test performed last year on the proposed rule, Basel II, has resulted in a significant decrease in capital to be held by banks. According to the QIS-4 findings[40] (Quantitative Impact Study), the aggregate minimum risk-based capital requirements would fall by 15.5% for participating banks in moving from Basel I to Basel II.

The skepticism and worries stem from the fact that too little capital can represent a high risk for the banking industry during a severe economic downturn and jeopardize financial stability and resilience. Specifically, the assumptions of the models used by banks on probability of default, recovery Rates and Correlation, if incorrectly specified, can misrepresent the effects of the implementation of Basel II and lead to “underinsured banks”, potentially dangerous for the Economy as a whole.

Basel II lead a renewed interest in the measurement and modeling of parameters in credit risk portfolio models, namely Probability of Default, Recovery Rates and Correlation, and this happen to be in conjunction an explosive growth in the credit derivatives market for which the pricing of its different instruments relies also on the same inputs.

[40] The summary can be found at http://www.occ.treas.gov/ftp/release/2006-23a.pdf

Only recently, there has been an abundance of articles, papers and surveys on the procyclicality of default and recovery as well their dependence.

Most of the work, though, has been on corporate bond defaults and to a lesser extent bank loan defaults. The reason is mainly due to the fact that data are hardly available and historically constrained due to nature of the parameter in question, default, which is rare event, even more difficult on a portfolio basis (cross default for correlation estimation are even more scarce).

Banking regulators have been working on Basel II since 1998, representing an update of Basel I that was adopted since 1988. The main reason of this new capital adequacy framework is that regulators through the Basel Committee on Banking Supervision intend to introduce more risk sensitive capital requirement than what was the case in Basel II.

Basel II therefore has pointed a lot of light on credit risk management and measurement.

One can easily understand that the BCBS is to adapt new rule to a different Banking Industry and risk management practice than it was in 1988. Indeed, credit markets have grown, especially credit derivatives markets, we witnessed continuing financial innovations and banking deregulation. This is why Basel I came in, in the first place and surely it worked pretty well by increasing resilience, transparence and homogeneity in banking practices. But Basel II is much more complicated analytically and it also gives some flexibility to Banks. For example Banks are given significant latitude in determining how to incorporate downturn effects. In the US about 20 of the largest banks are expected to adopt Basel II, thus each bank's regulatory capital will be determined by an external complex formula but also by its own internal models, and the European Parliament has already voted the directive for a full compliance by all European banks.

In the proposed rules by the BCBS[41], for banks that do not have sufficiently developed credit risk models, credit risk capital requirements are to be determined using the "standardized" approach which effectively does not require modeling inputs from banks.

However, for banks that are employing more quantitatively oriented techniques of credit risk management, particularly Internal Rating Systems, an internal rating based approach was proposed, the IRB approach which has two tiers.

The first tier known as the foundation approach, permits banks to input their own credit risk assessments of their lending portfolios, but estimation of

[41] The rules are detailed on www.bis.org, see footnote 29 for exact reference.

additional inputs are derived through the application of standardized regulatory rules. This IRB is intended to be used by banks that currently face difficulty in estimating certain risk model parameters due to data limitation or less developed credit risk models. The second tier, known as the “advanced IRB approach” would allow banks to use their own internal credit risk modeling outcomes to establish their regulatory credit risk capital requirement.

Internal Rating Based (IRB) risk weights are calibrated by estimating the capital needed to cover the credit loss on an exposure during times of economic downturn.

Banks use long run average default probabilities to infer an exposure’s default probability. Required to estimate Downturn LGD, banks have differing views on how cyclicality should be taken into account in their models.

Standard ratings-based models for analyzing credit portfolios and pricing credit derivatives assume that defaults and recoveries are statistically independent[42].

But a very simple argument against that assumption could be the following: During periods of economic downturn, default rates are higher, and since there are more defaults, the number of distressed securities supplied to

[42] See footnotes 12 &13.

the secondary market (or in the workout process) increases, making them cheaper, and if it's cheaper compared to their par value then the recovery rate will be lower. That simple argument suggests 2 evidences:

1) Defaults and Recoveries are not statistically independent and are inversely related.

2) Defaults and Recoveries are procyclical (thus presence of systematic risk, non diversifiable away).

Basel II is composed of three pillars[43]: Pillar 1, minimum capital requirements; Pillar 2, supervisory review; and Pillar 3, market discipline. Pillar 1 is supposed to produce a *minimum* level of regulatory capital and that each institution's actual capital held will vary according to its own risk profile and business mix. Explicit assumptions are built into Pillar 1, such as the idea that portfolios are well diversified and do not contain geographic or sector concentrations (Pillar I, represents about 75% of all 3).

Specifically, the capital requirement formula[44] is the following (for corporate exposures):

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[43] See footnote 29

[44] See footnote 29 for document, page 60.

$K=[LGD x \Phi[(\Phi^{-1} (pd) +\sqrt{\rho}. \Phi^{-1}(0.999))/ \sqrt{(\rho-1)}]] x[1+(M-2.5)b]/(1-1.5b)$

With

Φ: Normal Cumulative Distribution Function (CDF)

Φ^{-1} Inverse of Normal CDF

b=maturity adjustment=$(0.11852-0.05478*\ln PD)^2$

ρ: Correlation among borrowers.

$\rho=0.12*[1-\exp(-50PD)]/[1-\exp(-50)] + 0.24*[1 - ((1-\exp(-50PD))/(1-\exp(-50)))$

The correlation structure in Basel II is based on the One Single Factor developed by Vasicek [45](1991). The idea is that conditional on a single factor (representing the risk systemic, for example Real GDP growth or Unemployment), borrowers' PD are independent. And that makes computations easier because the joint probability of default is then the product of their marginal conditional PDs.

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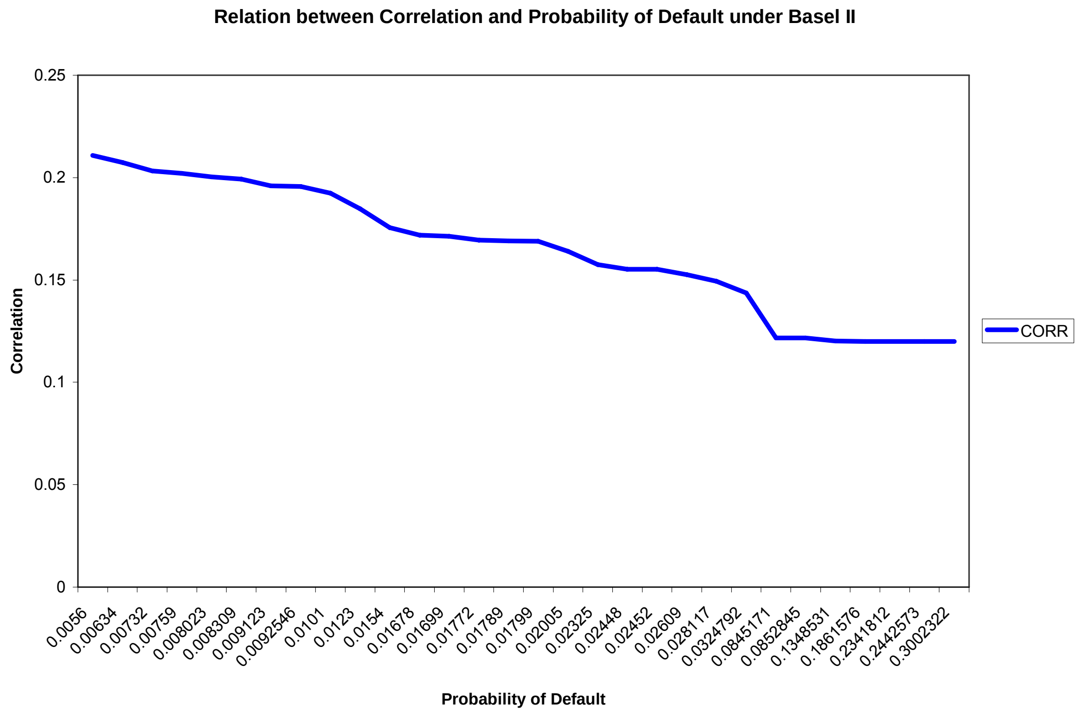
[45] Vasicek, O 1991, Limiting loan loss probability distribution working paper, KMV Corporation.

As seen above the capital requirement formula is a function of the loss given default, the probability of default and asset return correlation. The formula has been calibrated on a Single Systematic Factor at 99.9% confidence level. One can also see that the asset correlation is solely based on PD. As seen below it also shows the inverse relationship between PD and Correlation, using simulated default probabilities and the above formula.

Figure I-3-A Relation PD/Correlation under BASEL II



Correlation is very important in portfolio models because without correlation risk concentration cannot be measured. Basel II acknowledges the correlation factor and its approach is that a single systematic factor drives correlation. Specifically, all borrowers have the same sensitivity to that factor. The correlation was set initially at 0.2 but is now function of the PD.

$$\rho=0.12*[1-\exp(-50PD)]/[1-\exp(-50)] + 0.24*[1 - ((1-\exp(-50PD))/(1-\exp(-50)))$$

Implicitly this means that as PD increases, the level of idiosyncratic risk increases, thus decreasing correlation (less systematic risk). The single factor assumption means that all borrowers share a common sensitivity to a systematic risk, and correlation between borrowers is a simple function of each borrower' sensitivity to that single factor that can be thought of, as the GDP, the Unemployment or even the S$P500.

The idea is similar to Sharpe's Capital Asset Pricing Model[46], who was among the first to propose the vision of systematic risk versus idiosyncratic risk to model stock returns. A disadvantage of the one-factor model is that a single factor governs default environment in all future time periods. The second disadvantage is that it is not a dynamic model in the sense that spreads and correlation are not time varying. Again one can make the similarity to the development of multifactor APT (Arbitrage Pricing Theory by Stephen Ross[47]) stemming from the single factor CAPM.

Nevertheless, macroeconomic considerations on credit risk measurements have little role. Several credit risk models include a number of assumptions about the correlation of default probabilities across borrowers,

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[46] Sharpe, William F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance*, 19 (3), 425-442.

[47] Ross, Stephen, The arbitrage theory of capital pricing, Journal of Economic Theory, v13, 1976

about loss given default and about the correlation between Probability of Default and Loss Given Default (1-recovery rate, LGD). Most credit risk models treat Recovery as independent of Probability of Default and not dependent on the state of the economy. Basel II approach is similar.

In the foundation IRB approach for example, the LGD is set at 50% for unstructured loans, and between 40 and 50% for real estate, either way not function of the macroeconomy. Within the Advanced IRB approach framework, banks are able to use their own estimates of LGD. And the current debate focuses on how the banks should estimate Downturn LGD (Loss Given Default).

Indeed, according to a July 2005 note of the Bank for Internal Settlement, particularly the Paragraph 468 of the Framework Document[48] requires that LGD parameters used in Pillar I must reflect economic downturn condition to capture the relevant risks. The purpose of this requirement is to ensure that LGD will embed forward-looking forecasts of recovery rates on exposures that default during conditions where credit losses are expected to be substantially higher than average.

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[48] Guidance on the Paragraph 468 of the Framework Document, July 2005, see www.bis.org/publ/bcbs115.pdf.

Banks must have a rigorous and well documented process for assessing the effects, if any, of economic downturn conditions on recovery rates and for producing LGD estimates consistent with downturn conditions. They must identify downturn conditions for each supervisory asset class within each jurisdiction (example, periods of negative GDP growth, high unemployment rates…). They must also address any adverse dependencies, if any between default rates and recovery rates (example, a comparison of recovery during different phases of the economic cycle, a statistical analysis of the relationship between observed default rates and observed recovery rates over a complete business cycle). The result should produce LGD parameters for the bank's exposures consistent with identified downturn conditions.

The International Convergence of Capital Measurements and Capital Standards of the Basel Committee on Banking Supervision put it in the following terms in the published revised framework of June 2004[49]:

"A bank must estimate an LGD for each facility that aims to reflect economic downturn conditions where necessary to capture the relevant risks. This LGD cannot be less than the average long-run default weighted average loss rate given default calculated based on the average economic loss of all observed default within the data source for that type of facility .Certain facilities may not

[49] page 96, section vii "Requirements specific to own LGD estimates'.

exhibit cyclical variability and thus LGD may not differ from long run default weighted average. However for other exposures, this cyclical variability in loss severities may be important and banks will need to incorporate it into their LGD estimates".

CHAPTER II: CREDIT DERIVATIVES PRICING, LIQUIDITY & EQUITY MARKET

In general credit derivatives can be either single-name or multi-name contracts The pay-off of a single-name product (such as Credit Default Swap or Asset Swap) will depend on the credit event of the underlying entity, whereas the pay-off of multi-name instruments will depend on credit events of a portfolio of entities (such as nth to default baskets and CDOs).

Collateralized Debt Obligations (CDOs) are default-correlation-dependent credit derivatives. A CDO is an asset-backed security whose underlying collateral is typically a portfolio of bonds (corporate, sovereign) or bank loans. CDOs are complex financial instruments because the collateral pool underlying the CDO can be large and heterogeneous There are broadly 2 types of CDOs, Cash CDO and Synthetic CDO.

Cash CDO (the static cash flow CDO and the actively managed market value CDO) have their pay-offs coming from the actual cash flows of the assets in the pool.

Unlike a cash CDO, a synthetic CDO is linked to its reference entities by credit derivatives rather than backed by assets. Their important growth is largely due to the growth of CDS.

The business of CDO has been expanding for several reasons such as spread arbitrage opportunity, regulatory capital relief, funding or Economic risk transfer. A common structure of CDOs involves tranching the credit risk of the reference pool into different risk levels, generally called senior, mezzanine and equity tranches. Losses in the collateral pool are first absorbed by the lowest tranche and then, depending on the severity of losses, the mezzanine tranche will absorb those losses up to its detachment point[50].

Standard Synthetic CDO tranches refer to benchmark CDS Indices. The most liquid are the Dow Jones CDX in the US and the DJ iTraxx in Europe.

II-1 Implied Correlation Smile

The current market standard for price quotation of credit product dependent upon default correlation is the Gaussian Copula. Given each borrower's term structure of credit spreads and its debt recovery given default, the market standard version of this copula model uses only a single parameter to summarize all correlation among the various borrowers default time. For example in DJ CDX IG, there are 125 names in the collateral so instead of having 7750 pairwise correlations (n*(n-1)/2) we only have one. This makes it

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[50] See footnote 34 for excellent references on CDOs

easier but not very realistic. Market implied correlation shows different level of correlation for the equity, mezzanine and senior tranches.

Indeed there is a reported correlation smile in the CDO Market similar to the well known Black & Scholes implied volatility smile. Several models have been proposed to overcome this inconsistency. The main explanation of the correlation smile is a lack of tail dependence of the Gaussian Copula. In the literature, attention has been mainly on the choice of Copula. Several copula have been proposed to adequately take into account of the skewness, kurtosis and the heavy tail characteristic of the default distribution, example are Student, Frank or Gumbel copula.

Another possibility that has been hardly investigated is the analogy with the term structure of the interest rates[51]. Indeed, the Expectation, the Liquidity Premium and the Preferred Habitat Theories provide different assumptions to the term structure of the interest rates that can be applied to CDO tranche correlation.

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[51] The reason is that the credit derivatives market is mainly an OTC market (over the counter) and CDx indices have been quite recent (2004) so data is not widely abundant.

II-1-1 Literature

The most widely used model in the industry is the Gaussian copula approach initiated by David Li (2000) but this approach does not exhibit tail dependence and is the possible the reason of the correlation smile. Several approaches have been proposed. Gregory and Laurent (2004) present an extension of the one factor copula that allows a clustered correlation structure by specifying inter and intra sector correlation and they introduce dependence between default rates and recovery rates which leads to improved modeling of the smile. Hull and White (2004) discuss the effect of uncertain recoveries on the specifics of the smile. Andersen and Sidenius (2004) extended the gaussian factor copula model to random recoveries and random factor loadings. Tavares et al (2004) propose a composite basket model that combines the copula model with independent Poisson processes. Burtschell, Gregory and Laurent[52] (2005) performed a comparative analysis of CDO pricing models. with stochastic correlation extension to Gaussian copula Student t copula, double t factor copula, Clayton copula and Marshall-Olkin copula. The results of the double t factor model and stochastic correlation

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[52] For an excellent detailed comparative analysis see Burtschell, X, Jon Gregory and Jean Paul Laurent (2005),"A comparative analysis of CDO pricing models", *www.defaultrisk.com*, April 2005.

model were closer to market quotes. Kalemanova et al (2005) applied a Normal Inverse Gaussian Copula with four parameters that fit market quotes (using a top down approach).

The market practice has proposed more convenient ways to assess the level of correlation on different tranches. Since the spring of 2004, Base Correlation[53] has been proposed by JP Morgan which provide implied correlation from each tranche that correspond to the interval 0% to the upper bound of that tranche.

For example the base correlation given for the 0-10% interval is a correlation which equates the price of the first loss tranche of the combined observed market value of the 0-3%, 3-7% and 7-10% tranches. Similar to the correlation smile, we observe a correlation skew (examples of market quotes and correlation skew are given in II-1-3).

II-1-2 Data Methodology

There are two main broad indices for standard CDO tranche, the US DJ CDX and its European counterpart DJ iTraxx. The Morgan Stanley DJ CDX Investment Grade Index 5 years maturity was provided by Bloomberg with 54

[53] Base Correlations were introduced by JP Morgan in April of 2004 and an introduction can be found at http://www.math.nyu.edu/~cousot/Teaching/IRCM/Lecture10/IntroducingBaseCorrelations.pdf

daily observations on the spreads, bid-ask spread and correlation for each of the following tranche (0-3%, 3-7%, 7-10%, 10-15% and 15-30%). Daily data from 09/23/2005 to 01/26/2006 but there were missing daily observations, and totaling only 54 for that period (for 5 tranches so a total of 270 bid-ask observations). Morgan Stanley, via Bloomberg, quotes for each tranche, the Bid, Ask, and the Correlation (exactly base correlation, which is the correlation input required for a series of first loss tranches that give the tranche a value consistent with quoted spreads). The index has 125 reference names and is available for maturities of 5, 7 and 10 years, The 5 year maturity index was used (most traded). The lowest tranche (0-3%) is the equity tranche and it absorbs the first 3% on the index due to defaults. The second tranche (3-7%) absorbs the 3 to 7% losses (after the equity)…and so on. As a compensation for taking the risk of losses, investors receive quarterly payments from the buyers of protections. Those payments are premiums calculated as percentage (spread) of the notional amount in the collateral.

II-1-3 Relationship between Correlation and Liquidity

I first present (below) historical spreads for different tranches on the DJ CDX index since 09/26/05. Spreads on the equity tranche (0-3%) are more volatile than upper tranches, and indeed the equity tranche is the riskiest because it is exposed the first losses.

Figure II-1-3-A Historical spread for each tranche on the DJ CDX NA Historical Spreads

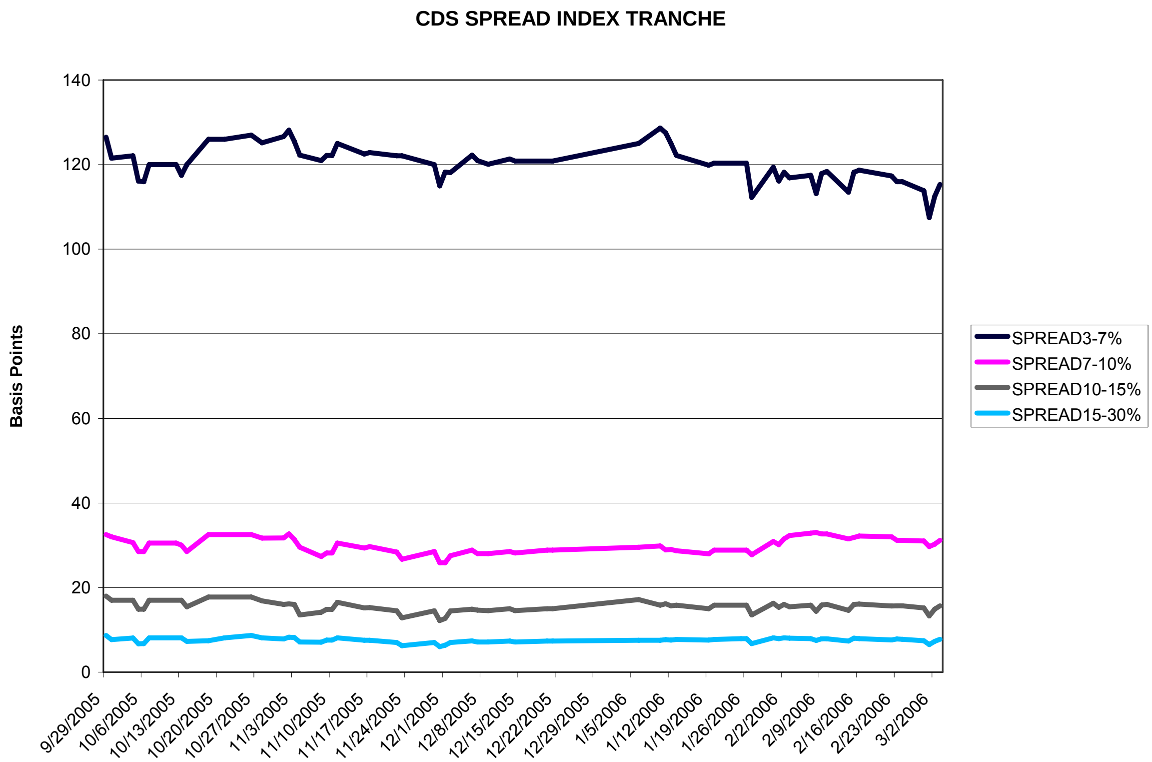
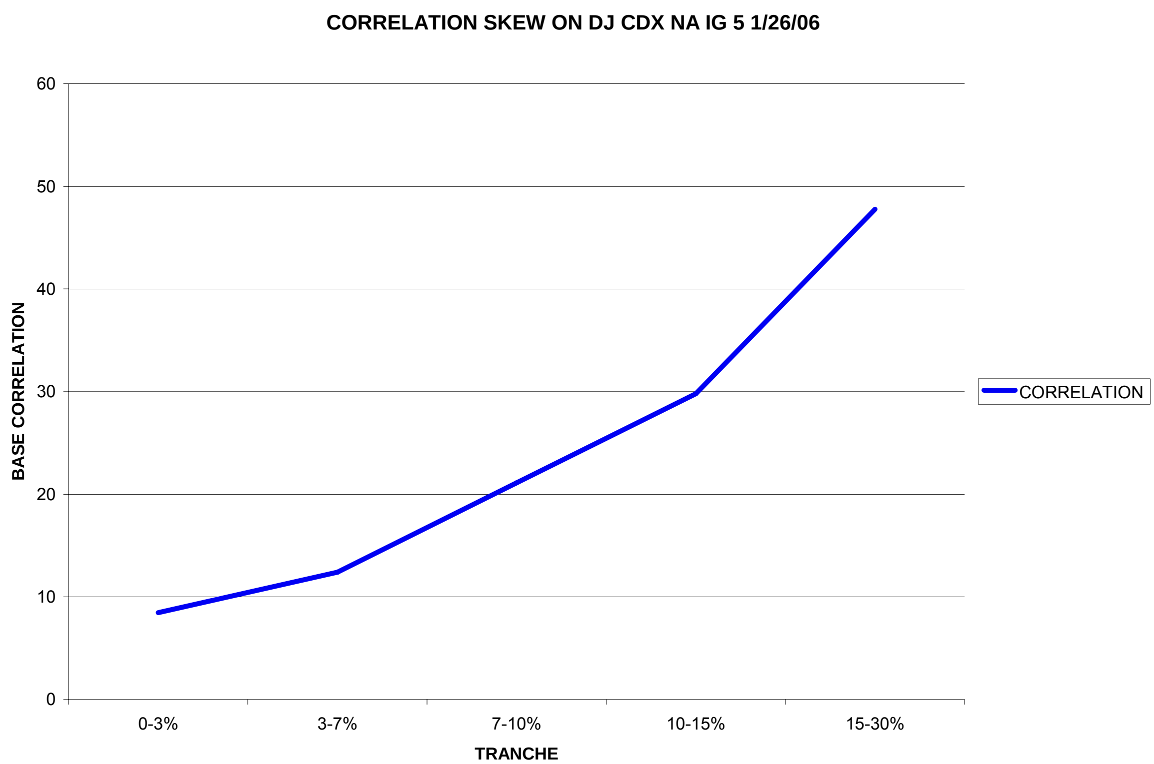


Figure II-1-3-A represents historical spread for each tranche of the CDS Spread Index from 09/29/2005 to 3/2/2006. One can notice that the tranche absorbing the first 3-7% loss on the notional amount has greater volatility than the upper tranches.

Table II-1-3-A Market quotes for DJ CDX NA on 09/29/05

TRANCHE	SPREAD in bps	CORRELATION
0-3%(add 500bps upfront)	40.5	8.447
3-7%	126.5	12.4
7-10%	32.5	21.101
10-15%	18	29.806
15-30%	8.625	47.768

Figure II-1-3-B Correlation Skew on the DJ CDX NA IG 5 on 1/26/06



It can be clearly seen on the figure above that correlation is not constant across tranches, although according to the standard One Factor Gaussian Copula Model the correlation should be constant. In this section, I use the approach of the term structure of the interest rates which distinguish several approaches to explain interest rates, such the Expectation theory, the Liquidity Premium theory and the Preferred Habitat theory.

The equivalent of the liquidity theory is checked to see if there is an explanatory power of the liquidity on the correlation skew. The approach is to proxy the liquidity level by the Bid and Ask spread[54] for each tranche and specifically to compute a relative liquidity measure that takes into account the level of spread in each tranche.

A ratio of relative liquidity was computed in the following way:

BidAsk37= (BIDASK SPREAD)/MID PRICE for the tranche 3 to 7%

The same ratio was computed using subsequent tranches except for the equity tranche because equity tranches are not rated by rating agencies.

[54] As suggested in Houweling, Patrick, Albert Mentink and Ton Vorst (2005), "Comparing possible proxies of corporate bond liquidity", *Journal of Banking & Finance* 29 (2005) pp1331-1358

Then univariate regressions were computed for each tranche to test the effect of relative liquidity on correlation, using the following model:

Equation 1 $COR_{ij} = \alpha + \beta(BIDASK_{ij})c + e$

i: attachment point

j: detachment point

The results are presented below:

Table II-1-3-B Correlation/BidAsk Spread Regression results for all tranches

TRANCHE	α	β	R^2
3-7%	28.17394 (8.647169*)	-158.659 (-2.69163*)	0.114553
7-10%	30.78736 (15.46841*)	-30.2589 (-1.91635***)	0.05592
10-15%	40.44233 (16.64884*)	-18.1563 (-1.4641)	0.033418

15-30%	63.04062 (28.86351*)	-18.6354 (-2.52185**)	0.093033

Note: * means significant at 1%, ** significant at 5% and *** significant at 10%

As can be seen from the results in the above table, there is a liquidity effect for all tranches except the 10-15% tranche. All β coefficients are significantly different from zero except for the 3rd tranche, they also have all expected sign (negative).

Indeed this negative relationship can be explained by the fact that as the Bid-Ask increases, liquidity decreases, thus one would expect higher relative spread and thus lower correlation. An important point here in relation with the correlation smile and that seems to confirm Jeffrey D'Amato (March 2005), it is that the degree of default clustering appears to be higher for the lower and senior tranches. This can be seen by the fact that the coefficients on the 3-7% and the 15-30% tranches are significant at 5% whereas the remaining two tranches (7-10% and 10-15%) are respectively significant at 10% and not significant. This result suggests that as the credit derivatives market develops and as liquidity and pricing efficiency increase, the correlation smile should flatten.

II-2 Relationship between the Credit Derivatives Market and Equity Market

Most of the credit risk pricing models rely on Merton's Model. The reason is that data on default is rather scarce. Usually modeling default relies on three types of data sources:

- Historical Default Data.
- Credit Spread Data.
- Equity Data.

Since historical data is scarce, the credit spread quotes still in its development (the CDx market is mainly an OTC market) and the equity market fully mature with plenty of data, the use of equity return as a proxy for asset return in a Merton like framework is abundantly possible and highly valuable (also important for hedging purposes). As the CDx market develops, its data will probably be the main source for all credit risk models.

Thus remain the question of the relationship between the credit default swap market and the equity market. In this section I provide evidence of a relationship between the credit default swap market and the equity market.

II-2-1 Literature

This section actually relies on the methodology used by Hans Bystrom[55] (2005) who studied the same link but using the european counterpart, the DJ iTraxx. Previous studies were essentially on the relationship between bond yields and stock prices such as Kwan (1996) or between single-name CDS spread changes and stock returns (Longstaff, Mithal and Neis, 2003), Norden and Weber (2004), Blanco, Brennan and Marsh(2004), Yu(2004). Other authors who discussed the link between equity volatility and bond spreads are Collin-Dufresne,, Goldstein and Martin (2001), Campbell and Taskler (2002), and Blanco, Brennan and Marsh(2004)).

II-2-2 Data and Methodology

Historical daily data was computed from Bloomberg on the Morgan Stanley DJ CDX IG High Volatility from June 7th of 2004 to March 13th of 2006. Data on SP500 was computed from Yahoo Finance.

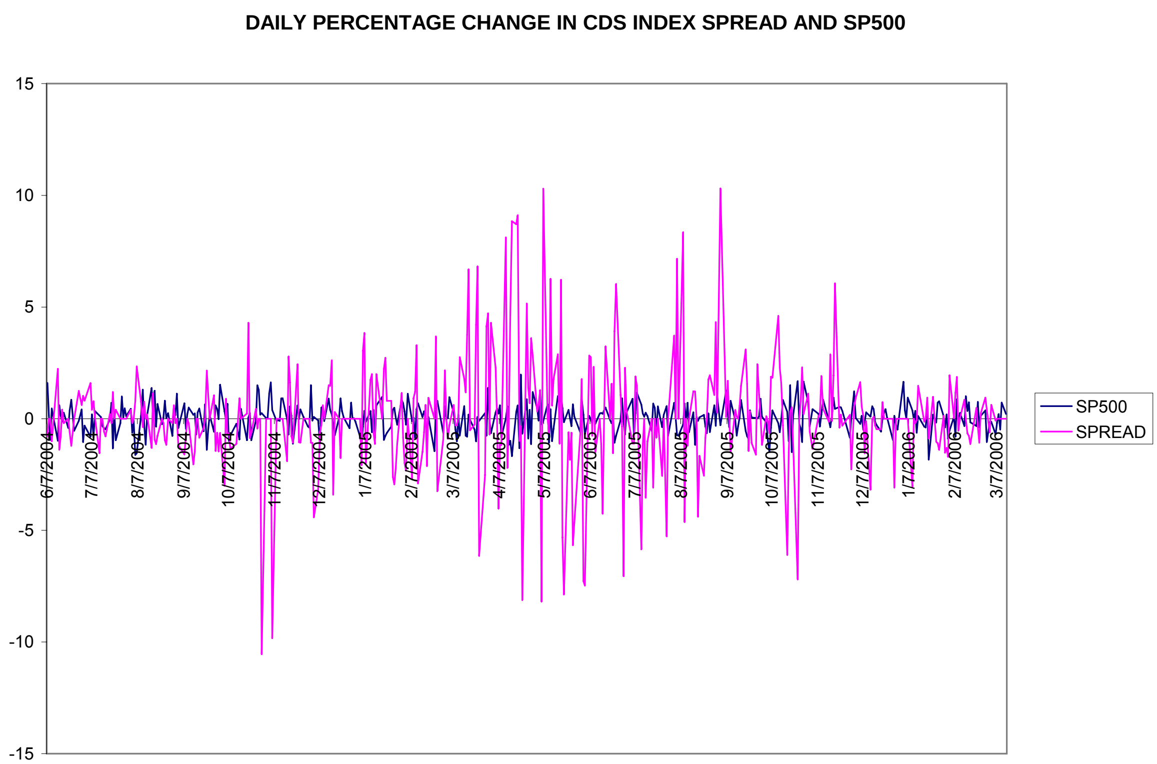
The methodology is similar to the one in the previous section except that more data was available for the spread (450 observations). The

[55] Bystrom, Hans (2005), “Credit Default Swaps and Equity Prices: The iTraxx CDS Index Market”, *Lund University, Department of Economics*, May 2005

relationship between the percentage change in the spread and the percentage change in the SP500 is modeled via a vector autoregressive Model estimation (VAR), in addition to a unit root test (Augmented Dickey Fuller Test for unit root) and Granger Causality test are also performed.

II-2-3 Credit Default Swap Spread and the Stock Market

Figure II-2-3 Daily Percentage Change in CDS Spread Index and SP500



II-2-3-1 Unit Root Tests

A series is said to be (weakly or covariance) stationary if the mean and autocovariances of the series do not depend on time. Any series that is not stationary is said to be nonstationary.

A common example of a nonstationary series is the random walk:

Equation 2 $Y_t = Y_{t-1} + e_t$

Where e_t is a stationary random disturbance term. The series Y_t has a constant forecast value, conditional on t, and the variance is increasing over time. The random walk is a difference stationary series since the first difference of y is stationary:

Equation 3 $Y_t - Y_{t-1} = e_t$

A difference stationary series is said to be integrated and is denoted as I(d) where d is the order of integration. The order of integration is the number of unit roots contained in the series, or the number of differencing operations it takes to make the series stationary.

Standard inference procedures do not apply to regressions which contain an integrated dependent variable or integrated regressors. Therefore, it is important to check whether a series is stationary or not before using it in a regression. The formal method to test the stationarity of a series is the unit root test.

The unit root test on the CDS Index Spread daily percentage change and the SP500 daily percentage change showed that both are stationary in level.

See Results below:

Table II-2-3-1A Unit Root Test CDS SPREAD

Null Hypothesis: SPREAD has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic based on SIC, MAXLAG=17)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.61836	0.0000
Test critical values:	1% level	-3.445445	
	5% level	-2.868089	
	10% level	-2.570323	

The sp500 was also stationary.

Table II-2-3-1B Unit Root Test SP500

Null Hypothesis: SP500 has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic based on SIC, MAXLAG=17)

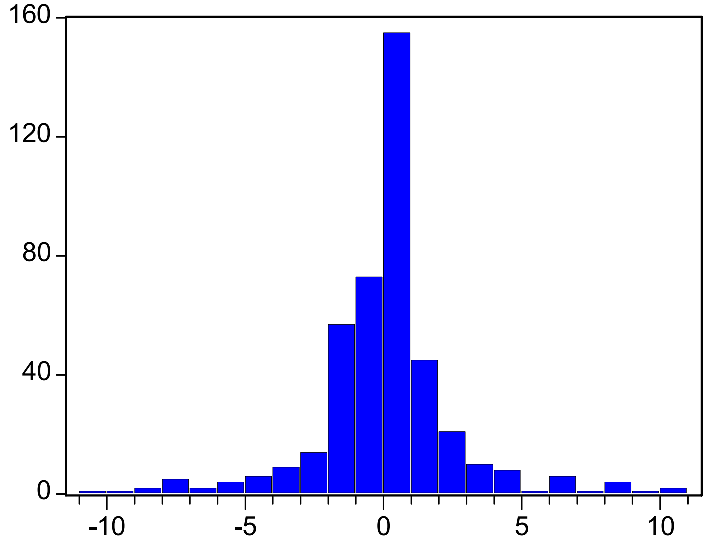
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-22.51179	0.0000
Test critical values:	1% level	-3.445445	
	5% level	-2.868089	
	10% level	-2.570323	

*MacKinnon (1996) one-sided p-values.

Also it is noteworthy to show that a Jarque-Berra test of normality was rejected for Spread but not for SP500, which comforts the argument on the heavy tail distribution of default and consequently on the inappropriateness in the use of a Gaussian distribution in Li's model.(a usual argument on the critic of the Gaussian assumption, see below).

Figure II-2-3-1A   Histogram and Jarque-Bera test of CDS Spread

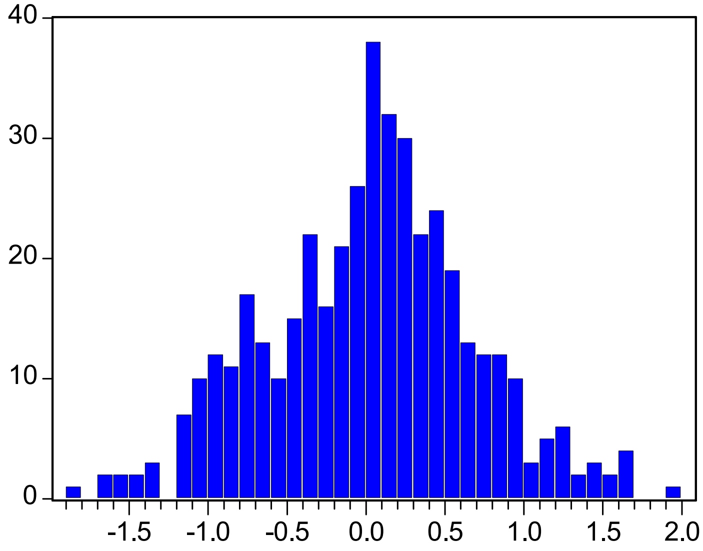
HISTOGRAM OF PERCENTAGE CHANGE IN CDS SPREAD



Series: SPREAD	
Sample 6/07/2004 3/13/2006	
Observations 428	
Mean	0.060635
Median	0.000000
Maximum	10.30225
Minimum	-10.54945
Std. Dev.	2.502187
Skewness	0.161518
Kurtosis	7.499168
Jarque-Bera	362.8524
Probability	0.000000

Figure II-2-3-1B Histogram and Jarque-Bera test of SP500

HISTOGRAM OF PERCENTAGE CHANGE IN SP500



Series: SP500	
Sample 6/07/2004 3/13/2006	
Observations 428	
Mean	0.027136
Median	0.055882
Maximum	1.973626
Minimum	-1.832628
Std. Dev.	0.654099
Skewness	-0.019707
Kurtosis	3.002542
Jarque-Bera	0.027818
Probability	0.986187

II-2-3-2 Vector Autoregressive Model (VAR) estimation

The vector autoregression (VAR) is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables. The VAR approach sidesteps the need for structural modeling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system.

VAR Model:

Equation 4

SPREAD = C(1,1)*SPREAD(-1) + C(1,2)*SPREAD(-2) + C(1,3)*SP500(-1) + C(1,4)*SP500(-2) + C(1,5)

Equation 5

SP500 = C(2,1)*SPREAD(-1) + C(2,2)*SPREAD(-2) + C(2,3)*SP500(-1) + C(2,4)*SP500(-2) + C(2,5)

Since only lagged values of the endogenous variables appear on the right-hand side of the equations, simultaneity is not an issue and OLS yields consistent estimates. Moreover, even though the innovations may be contemporaneously correlated, OLS is efficient and equivalent to GLS since all equations have identical regressors.

SPREAD = 0.05621308398*SPREAD(-1) + 0.0660425725*SPREAD(-2) - 1.19798862*SP500(-1) - 0.08554167498*SP500(-2) + 0.08495892326

SP500 = 0.01403523091*SPREAD(-1) - 0.007129776556*SPREAD(-2) - 0.07616031669*SP500(-1) + 5.73502951e-005*SP500(-2) + 0.02445861015

The VAR estimation with 2 lags showed a significant effect of SP500 (t-1) on the Spread.

Table II-2-3-2A Vector Autoregression Estimates Spread/SP500

Vector Autoregression Estimates

Date: 03/17/06 Time: 23:23

Sample (adjusted): 6/09/2004 3/13/2006

Included observations: 426 after adjustments

Standard errors in ( ) & t-statistics in [ ]

	SPREAD	SP500
SPREAD(-1)	0.056213	0.014035
	(0.04905)	(0.01341)
	[1.14597]	[1.04689]
SPREAD(-2)	0.066043	-0.007130
	(0.04652)	(0.01272)
	[1.41958]	[-0.56074]
SP500(-1)	-1.197989	-0.076160
	(0.18000)	(0.04920)
	[-6.65535]	[-1.54808]
SP500(-2)	-0.085542	5.74E-05
	(0.18736)	(0.05121)
	[-0.45656]	[0.00112]
C	0.084959	0.024459
	(0.11570)	(0.03162)
	[0.73431]	[0.77348]
R-squared	0.106631	0.010262

This result is in line with the findings of Bystrom (2005), that stocks market return has a significant relationship with the CDS Index Spread. The coefficient of determination found here of about 10.6% is also close to his findings (11%). The difference is that Bystrom used the European DJ iTraxx whereas I used its US counterpart, the DJ CDX.

II-2-3-3 Granger Causality Tests

Correlation does not necessarily imply causation in any meaningful sense of that word. The Granger (1969) approach to the question of whether X causes Y is to see how much of the current Y can be explained by past values of X and then to see whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X if X helps in the prediction of Y, or equivalently if the coefficients on the lagged X's are statistically significant.

The granger causality confirmed the expectation that SP500 granger causes the spread.

Table II-2-3-3 Granger Causality Test Spread/SP500

Pairwise Granger Causality Tests

Date: 03/17/06 Time: 23:31

Sample: 6/07/2004 3/13/2006

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Probability
SP500 does not Granger Cause SPREAD	426	22.1972	6.8E-10
SPREAD does not Granger Cause SP500		0.66185	0.51643

Indeed, the test of if SP500 does not granger cause the Spread was rejected at 1%, (P-Value of 6.8E-10) ,whereas the reverse was not accepted (P-Value of 0.51). Thus it can be stated that not only there is a significant relationship between the CDS spread and the SP500 but also that the SP500 granger causes the CDS Spread. This result is in line with Merton approach relating default to asset return.

CHAPTER III: PROBABILITY OF DEFAULT AND RECOVERY: PROCYCLICALITY AND DEPENDENCE

III-1 INTRODUCTION

This section analyzes the procyclicality and dependence of default rates and recovery rates of bank loans using 15 years of financial data provided by Call Reports[56] for all US commercial banks with over $300 million of assets. This study uses a similar approach to that of a paper published George French of the FDIC[57] in using Net Charge-Off rate as a proxy for Expected Loss except that we use the ratio of Charge-Off/Loan Amount as a proxy for Default Rate, and in addition we compute the ratio Recovery/Charge-Off as a proxy for Recovery Rate. To analyze procyclicality and dependence of Charge-Off and Recovery for Bank Loans The results show that effectively Bank Loan Charge-Offs and Recovery Rates are Procyclical and dependent, thus convergent with many recent papers on the same subject but using Corporate Bond Defaults and Recoveries (Altman et al, 2003). These findings should add to the current debate over Banks' own estimation of Probability of Default and Loss Given Default within the Advanced Internal Rating Approach for Capital Requirement

[56] Call Reports are "Consolidated Reports of Condition and Income", the FFIEC provides balance-sheet and income statement for about 9000 US banks. The FFIEC sets the standards for federal examination of financial institutions by the Board of Governors of the Federal Reserve, the FDIC, the NCUA (National Credit Union Administration), the OCC and the OTS (Office of Thrift Supervision).

[57] 2003, see footnote 4.

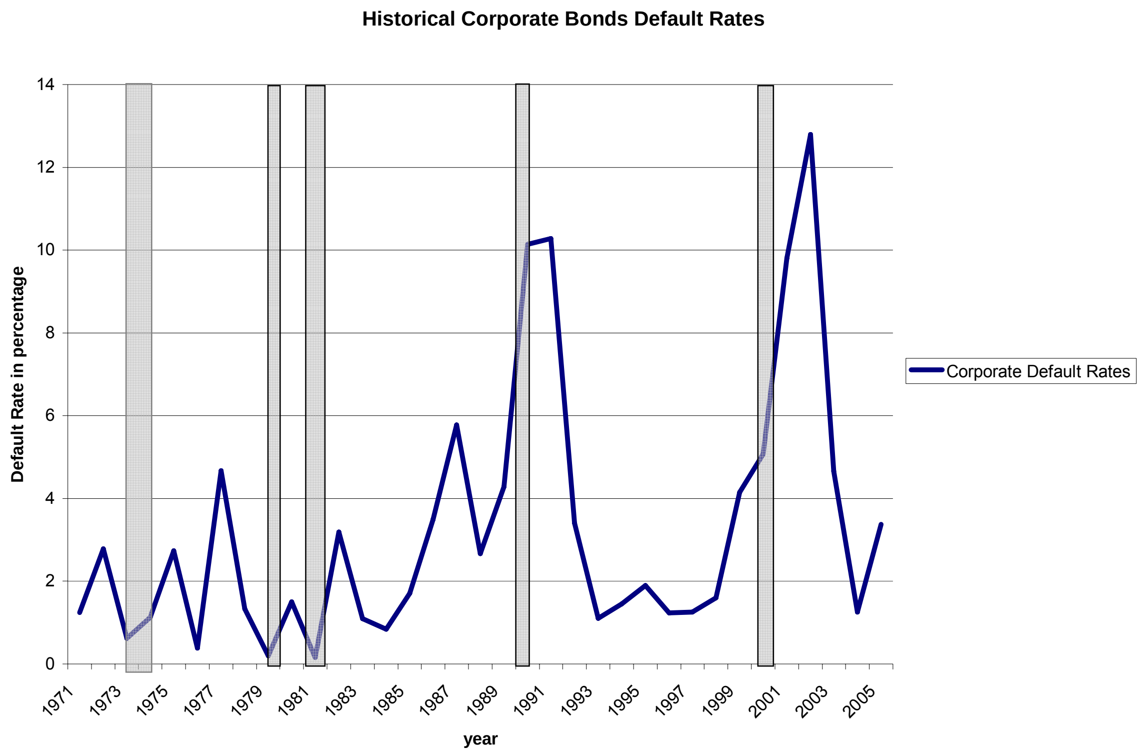
computation as proposed by the Banking Committee on Banking Supervision new proposed rules known as Basel II.

III-2 Literature

On the cyclicality of Probability of default, Fama (1986) and Wilson (1997) find cyclical probability of default, especially during economic downturns when PDs increase significantly. Ferri, Liu and Majnoni (2000), Monfort and Mulder (2000) and Reisen (2000) shows that rating agencies behave cyclically. Bangia, Diebold and Schuerman (2000) and Nickell, Perraudin and Varotto (2000) find evidence of macroeconomic and industry effects on rating transitions. Carey (1998) classifies evidence of difference in default rates for “good” years compared to “bad” years.

Altman and Brady (2001) show the apparent relationship between PD and macroeconomics conditions.

Figure III-1-1 Historical Default Rates for Corporate Bonds and US Recession



The chart above was computed using data available from Altman at a recent conference[58] organized by PRMIA which I attended. It is noteworthy to see the cyclicality in default rates for corporate bonds. The shaded bars

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[58] Altman, Edward (2006), "Current Conditions in the Distressed and High Yield Bond and Bank Loan Markets and Outlook 2005/2006", *Presentation at PRMIA, Credit Year in Review*, February 2006.

represent US recessions as given by the National Bureau of Economic Research[59]

One can notice that after all recessions the default rate peaks. It shows also that the default rate peaked around 1978 and 1987 which can be explained consecutively by the oil crisis and the stock market crash of 1987.

Fridson, Garman and Wu (1997) find a relation between macroeconomic conditions and PD, especially as real interest rates increase, asset values decrease thus increasing PD in a structural model (Merton). Barnhill and Maxwell (1999) find that systematic risk exposure increases as credit quality falls, thus there is an increased sensitivity to macroeconomic conditions in downturns. Gersbach and Lipponer (2000) find that macroeconomic shocks (as interest rate shocks) increase positive default correlations and thus decreasing portfolio diversification benefits. Zhou (2001), using a first passage time model (time until default) finds stronger macroeconomic effects for low credit quality firms than for high credit quality firms. He finds that default correlations increases as time to maturity increases and as credit quality decreases. Crouhy, Galai and Mark (2000, 2001) find the existence of an asymmetric procyclical impact on PDs such that default

[59] http://www.nber.org/cycles/cyclesmain.html

probabilities increase significantly during economic downturns but do not decrease significantly during economic upturns.

On the cyclicality of Recovery rates or Loss Given Default (one minus recovery), there has been little literature, especially for bank loans. The reason is that loans are relatively less tradable than corporate bonds which have a more mature secondary market.

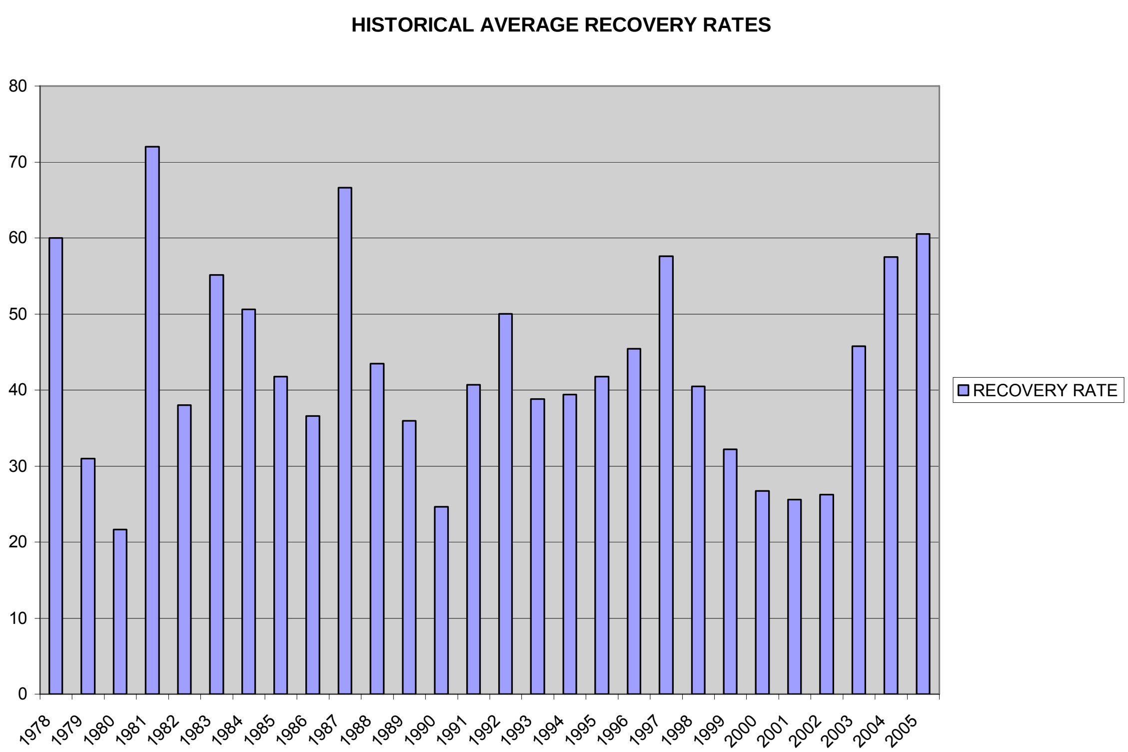
Altman et al (2001), Gupton and Stein (2002), Altman et al (2004), Franks et al (2004) show that recovery rate increases during good macroeconomic environments. Acharya et al (2004) find that the impact depends on the factor that represents the macroeconomic condition. Frye (2003) analyzes 960 securities that defaulted between 1983 and 2001 and finds that the LGD is usually higher in high default years, which indicates a presence of systematic effect.

Acharya et al (2003) study the empirical determinants of the variability of recovery rates. They identify the conditions of the industry sector of the defaulted firm as an important driver of recovery. Gupton, Gates, and Carty (2000) and Crouhy, Galai and Mark (2000) find LGD variability around a mean value that is consistent with cyclical effects.

Machlachlan (1999) finds that credit spreads are highest and therefore bond prices lowest during low points in the business cycle, which suggests a negative correlation between LGD and macroeconomic conditions.

The figure below shows historical recovery rates as presented by Altman at a recent conference. One can notice the three lows in recovery corresponding to recessions in 80-81, 90-91 and 2001.

Figure III-1-2 Historical Recovery Rates



Data used from Altman's presentation at PRMIA's conference

On the relationship between PD and Recovery Rates, Altman, Resti and Sironi (2002) exhaustively look at the correlation between both ex post and simulated default rates and recovery rates. They find strong evidence of an inverse relationship between recovery and PD. Their explanation of the results used supply and demand consideration.

In essence, if default rate increases, there is an increase in the supply of distressed debt available for sale in the distressed debt market, and the demand being stable, the price decline, so recovery being a ratio of the defaulted price over par value, it will decline.

Frye (2000) uses the conditional approach suggested by Finger (1999) and Gordy (2000) where defaults are driven by a single systematic factor, the state of the economy. In Frye's model the correlation between PD and Recovery stems from their mutual dependence on the systematic factor. The idea, here is that during recession, collateral values drop, thus recoveries decrease during recession (when default rates are higher).

Both Altman et Al and Frye find a negative relationship between PD and Recovery but they differ on the impact of macroeconomy on the recovery. For Altman et Al, the performance of the economy is less predictive than what Frye's model would suggest.

Regarding the treatment of PD, Recovery Rates and their dependence in credit risk models, within Merton's structural model, PD and RR are function of the characteristics of the firms and therefore inversely related. In the later structural models developed by Hull & White, Longstaff and Schwartz (among others), the recovery rate is exogenous and independent of the firm value, independent of PD. In Reduced forms models developed by Jarrow and Turnbull, Duffie and Singleton (among others) Recovery Rates are assumed exogenous, constant or stochastic and independent of PD.

III-3 Data and Methodology

Recovery Rates can be estimated as either the trading price of a distressed security shortly after default or at the end of the default process as ultimate recovery. The problem is that trading price recoveries are not available for all defaulted bonds and loans, as it depends on the availability of a distressed debt market and the supply-demand condition.

The vast majority of papers use data sets comprised of a sample of defaulted bonds or loans.

I use banks financial data provided in their Call Reports from 1991, first quarter to 2005 fourth quarter. Having a sample of over a thousand banks with more than $300 Million in asset. allowed me to compute a large aggregate portfolio of bank debt by type of loan. This has the effect of increasing the diversification, thus reducing borrower specific risks and thus increased the sensitivity of the portfolio to systematic risk. It is about a thousand because since 1991 there has a consolidation in the banking system and also banks that are just below or just above $300 million might get in and out of sample several times.

I distinguish default rate (realized proportion of companies that defaulted over a period of time) and default probability (assumed constant and estimated as the average default rate across all period).

The fact that we have a large set of data comprising all commercial banks allows me to assume a highly diversified portfolio, reducing idiosyncratic risk and therefore be subject only to systematic risk.

There are 6 categories of loan:

- Commercial and Industrial Loans.
- Loans to Individuals.
- Acquisition-Development and Construction loans.
- Home Equity Line of Credit.
- 1-4 Family residential loans.
- Non Farm Non Residential Loans (commercial real estate loans).

For each type of loan and for each individual bank I select the Charge-Off [60]amount, the Loan amount and the Recovery amount quarterly.

I computed mainly two ratios as proxies for analyzing the procyclicality, in a similar way to that of Georges French of the FDIC, in a 2003 paper for the charge-off, by using Charge-OFF Amount/Loan Amount. George French (2003) used that ratio as a proxy for default rates to estimate the effect of Basel II on the level of capital requirements.

In addition, I also compute the ratio of Recovery Amount/Charge-Off Amount as a proxy for recovery rate. One needs to mention again that these are proxies for the sole purpose of procyclicality and dependence study.

I also use another set of data provided by the federal reserve[61] on Net Charge-Off Rate (which are: Charge-Off minus Recovery divided by Loan amount) on a quarterly basis from 1985 to 2005 on equivalent type of loans for all commercial banks.

Unlike previous studies, I do not have individual loan specifics in terms of amount, maturity, facility and workout process. Rather for each category, we

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[60] Charge-Offs are the value of loans and leases removed from the books and charged against loss reserves.

[61] Quarterly net charge-off rates are available from http://www.federalreserve.gov/releases/chargeoff/

have total loan amounts, charge-off and recovery at the individual aggregate bank portfolio level.

The methodology consists of looking at trends and relationships using historical data and quantifying those relationships, if any, using univariate and multivariate regression analysis as done in several papers such as in Altman (2003).

For regression analysis I have checked among about 18 explanatory variables representing either macroeconomic variables or more market specific indicators, with and without lags.

Using charge-off/loan as a proxy for PD, I believe it is important the mention the differences between this study and most of the studies (except French's and others) and to point the advantage to have an aggregate portfolio of loans.

- Workout of some loans can extend over lengthy period of time resulting in a reduced data set until the workout can be deemed resolved and all cash flows reasonably recovered.
- Cash flows recoveries can take place over widely varying parts of the cycle including upturns as well as downturns.

- It is often difficult to separate out recoveries on multiple facilities, some with and some without collateral to the same borrower.

- If default is defined as non-payment of bank debt, it is possible that a borrower defaults on public debt but not on bank debt.

- Banks provide flexibility to borrowers to satisfy their financing needs but in exchange banks gain certain advantage (can restructure when credit to deteriorate, workout process more favorable, trigger covenants…).

- As a loan converges to default, the borrower can be pressured to sell off higher quality asset to reduce bank's exposure, or if unsecured, collateral can then be obtained.

But again these are large aggregate portfolios of loans and the idiosyncratic risk is highly reduced. Thus the data remains more exposed to systematic risk.

III-4 Procyclicality

III-4-1 Descriptive Statistics on Bank Loan Structure

In the annex A, I present first in figure III-4-1A the current (as of December 2005) composition of total loans for all US Commercial Banks with assets of at least $300 millions. This is similar to what the US Federal Reserve provides in its website although the Fed provides for all commercial banks regardless of the asset size. I also present in Figure III-4-1B the evolution of that composition since 1991. We can notice the increasing share in Home Equity Line of Credit.

The Annex B shows in table III-4-1A and III-4-1B the evolution of the ratio charge-off/loan and recovery/charge-off since 1991. It is evident that defaults during recessions are higher than defaults during expansion. This is true for all types of loans except for Home Equity Line of Credit. For example default rates for Commercial & Industrial Loans have an average of 2.39% during recession whereas the default averages 1.09% during economic expansion. Similarly, looking at the table III-4-1B, recoveries are significantly higher during expansion than during recessions for all types of loans except for loans to individuals where the difference is not as significant as for the other types of loans. Commercial and Industrial Loans have an average recovery ratio of 31.84% with 12% during recession and 34.8% during economic expansions.

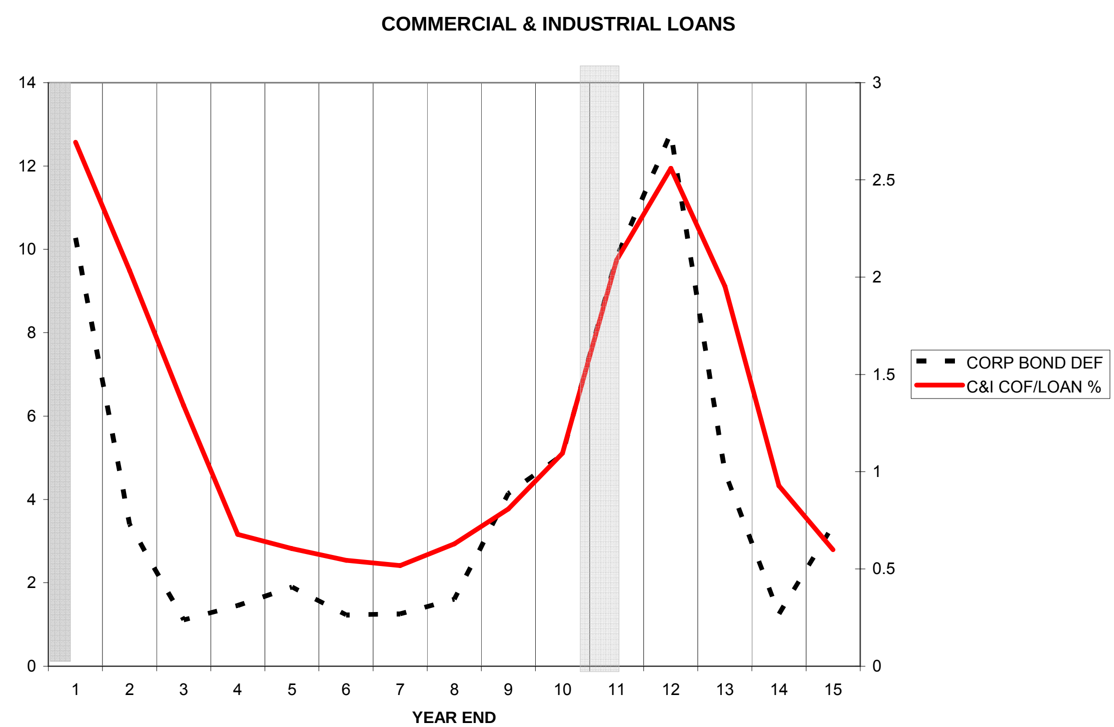
ADC loans (Acquisition-Development and Construction) and non farm non residential loans (which are commercial real estate loans) exhibit the highest level of variability when looking at their relative standard deviation to their average for both default and recovery.

III-4-2 Procyclicality of Charge-Off and Recovery

In this section I present first a graphical evidence of procyclicality of charge-off and recovery amount for several loan categories. We also show the historical corporate bond default as provided by Altman to underlie the similitude between bank loan default and corporate bond default in some loan categories. The data starts from 1991 to 2005. For each type of loan I show graphically the historical change in the default rate (as proxied by charge-off/loan amount) and recovery rates (as proxied by recovery/charge-off)

I illustrate below figure III-3-2-A1 for Commercial & Industrial Loans (all figures remaining are in annex A):

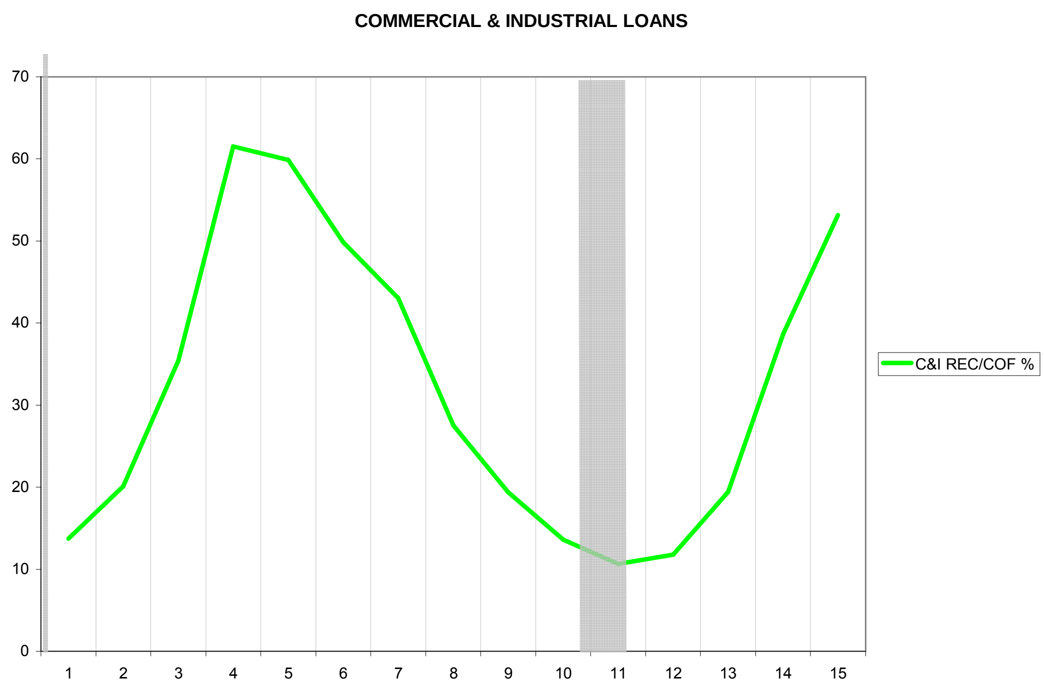
Figure III-3-2-A1 Commercial & Industrial Charge-Off/Loan



For all figures, data go from 1991 to 2005 (with year1=1991), the vertical axes are scaled for the corporate default rates (left) and for commercial & industrial loan default (cof/loan, right).

One can see in the figure above that for Commercial & Industrial Loans, there is procyclicality in default rates, the ratio of charge-off/loan (COF) peaks at the 2001 recession and since the data starts in 1991(fourth quarter) it is obvious also that COF was at a peak during the 1991 recession. On this graph, one can also see the similitude with corporate bond default rates (dotted line). Both series peak during recession and are at their lowest during economic expansion.

Figure III-3-2-A2 Commercial & Industrial Recovery/Charge-Off



Similar to have been observed for COF, recoveries tend to be highest during economic expansion and lowest during recession.

For the remaining types of loans, as can be seen in the annex, they all show a drop in recovery during recessions and they all show peaks in default rates except for ADC and Non Farm Non Residential Loans. The graphical evidence of this section shows that most types of loans are cyclical and the behavior of default rates is inversely related to recovery.

III-4-3 Univariate and Multivariate Regression Analysis

III-4-3-1-Using net Charge-Off Rates

This section is aimed to analyze the macroeconomic determinants of Net Charge-Off Rate ((charge-off minus recovery)/loan amount)) provided by the Federal Reserve website on a quarterly basis since 1985 at the aggregate level and by type of loan.

The loan types are similar to the other set of data from Banks Call Report provided by the New York State Banking Department and the FFIEC. We first estimate the effect of macroeconomic variables on the net charge-off rates on Commercial & Industrial Loans using the following equation. The COF rate was regressed against LoanGrowth/YieldSpreadt-4/UEt-1/FedFund/ and percentage change in ALCBCIL (which is the US commercial Bank Asset Loan & Lease to Commercial and Industrial Loans). Loan Growth measure the change in the growth of loan written by banks, the yield spread at t-4 is the difference between the 10 year Treasury bond rate and the one year treasury bill 4 quarters earlier (although the federal funds rate and the 3-month Treasury can be used). UEt-1 is the unemployment rate one quarter earlier.

All coefficients are significant at 1% except FedFund, significant at 5%. The R-square was 70% (see table III-4-3-1)

Table III-4-3-1 Commercial & Industrial Loan Regression Results using Net Charge-Off rates

NCOFCI = LoanGrowth/YieldSpreadt-4/UEt-1/FedFund/ %chge ALCBCIL

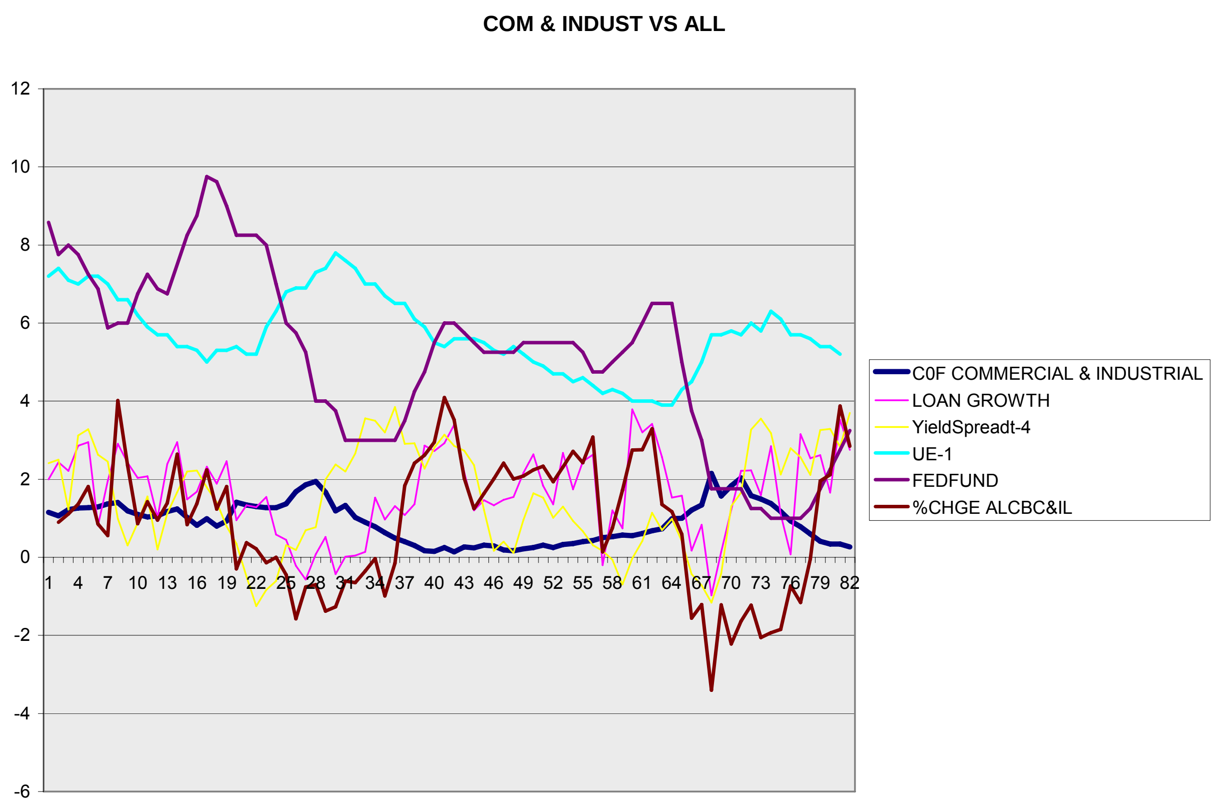
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-0.34104891	0.252929458	-1.34839540	0.1815
Loan Growth	0.161305208	0.045305549	3.560385266	0.0006
YieldSpread t-4	-0.14306567	0.036249415	-3.94670301	0.0001
Unemployment-1	0.207042246	0.04465256	4.636738584	1.46E-05
FedFund	0.047864805	0.018809315	2.544739385	0.0129
%chg ALCBCIL	-0.27578834	0.02987692	-9.23081587	5.42E-14

NCOFCI stands for net charge-off rate for commercial & industrial loans.

The signs of the coefficients are as expected and they are all significant at 5% level of significance. An increase in unemployment increases the “default rate”. The federal funds rates increases the default rates, because most rates are based on prime rate, itself based on the federal funds rates.

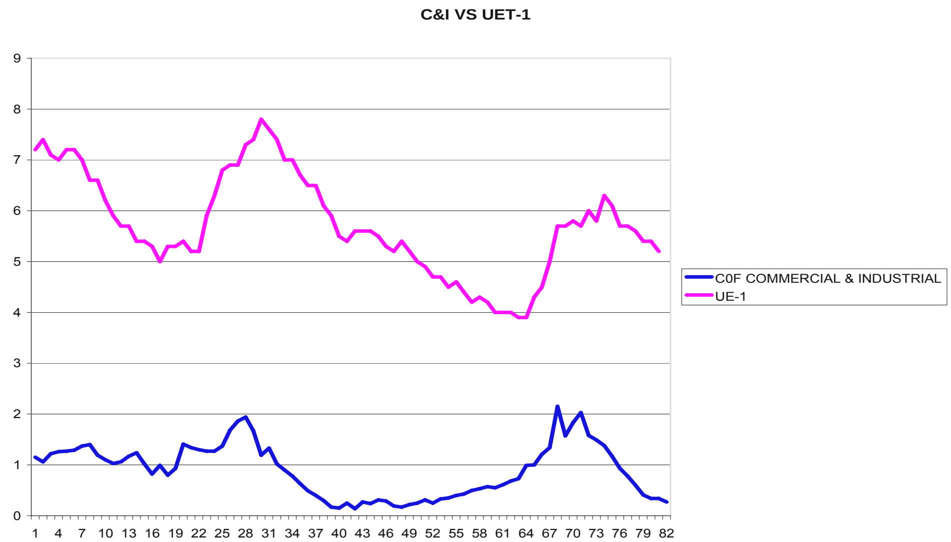
The yield spread has a negative relation with the charge-off rate. A larger spread indicates an stepper slope in the yield curve, meaning economic growth and thus less defaults.

Figure III-4-3-1A Commercial & Industrial Loan Historical Net Charge-Off rate



It is also interesting to look only at the relationship between Commercial & Industrial Loans Net Charge-Off rates and the level of unemployment a period before. By isolating graphically that relationship, one can measure the extent of the significance of the one-factor assumption mentioned earlier in this study (see graph below).

Figure III-4-3-1B Commercial & Industrial Loan net Charge-Off versus unemployment rate



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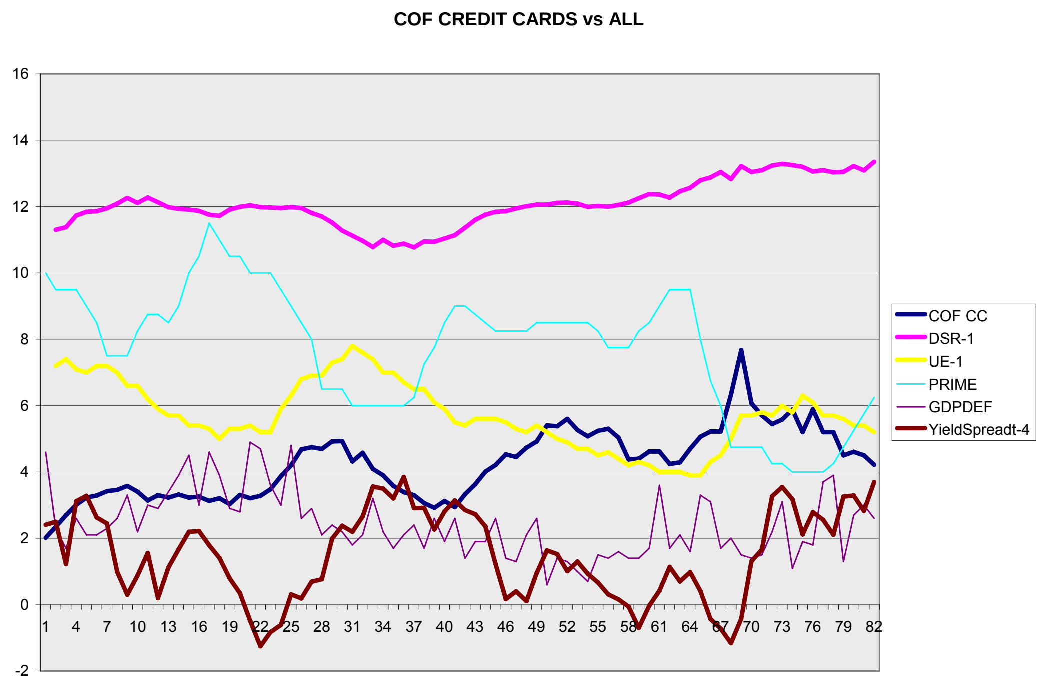
CREDIT CARDS LOANS

The COF Credit Cards was regressed against the Debt Service Ratio at t-1, Unemployment at t-1, the Prime rate, The GDP Deflator and the Yield Spread at t-4. All coefficients were significant at 5% and the Coefficient of variation was about 73%, meaning that about 73% of the variation of the COF were explained by the model.

Table III-4-3-2 Credit Cards loans net charge-off rate regression results

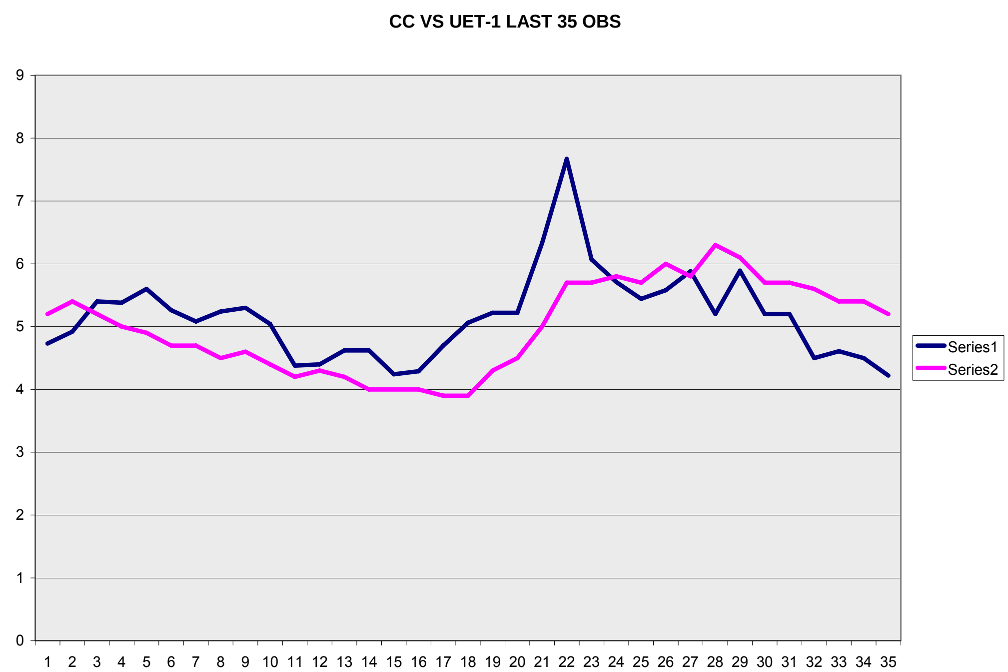
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	5.14362050	2.18509022	2.35396253	0.021194952
DSR t-1	0.30877254	0.133913364	2.305763511	0.023889576
Unemployment-1	-0.19394247	0.087727709	-2.210732217	0.030103003
Prime	-0.32965311	0.048221862	-6.836175419	1.88003E-09
GDP deflator	-0.25033163	0.069569258	-3.598308126	0.000571722
YieldSpreadt-4	-0.23575998	0.055006946	-4.286003801	5.33881E-05

Figure III-4-3-2A Credit Cards Net charge-off rate versus all macroeconomic variables



A separate figure shows similar trend of the COF with the last 35 observations of Unemployment or last 9 years.

Figure III-4-3-2B Credit Cards Net charge-off rate versus unemployment



COMMERCIAL REAL ESTATE

This type of loan corresponds to Acquisition- Development-Construction Loans and Non Farm Non Residential Loans.

A set of 18 explanatory variables was used to determine a subset of variables that displays the most significant relationship to the COF rate. The prime rate, loan growth, unemployment and the CPI appeared to be the best combination, showing a coefficient of determination of 85%.

The prime rate, loan growth and unemployment partial coefficients were all significant a 1%, CPI at 5%.(the CPI is the consumer price index.

Table III-4-3-3A Commercial Real Estate Net Charge-Off rate regression results on all selected variable

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-3.91517757	0.402696839	-9.72239459	2.23082E-13
Prime Rate	0.123451706	0.028705641	4.300607901	7.3454E-05
Loan Growth	-0.11048150	0.038432133	-2.87471693	0.005809403
Unemployment	0.601385779	0.052567915	11.44016811	6.19083E-16
CPI	0.142081815	0.060692664	2.341004773	0.02302607

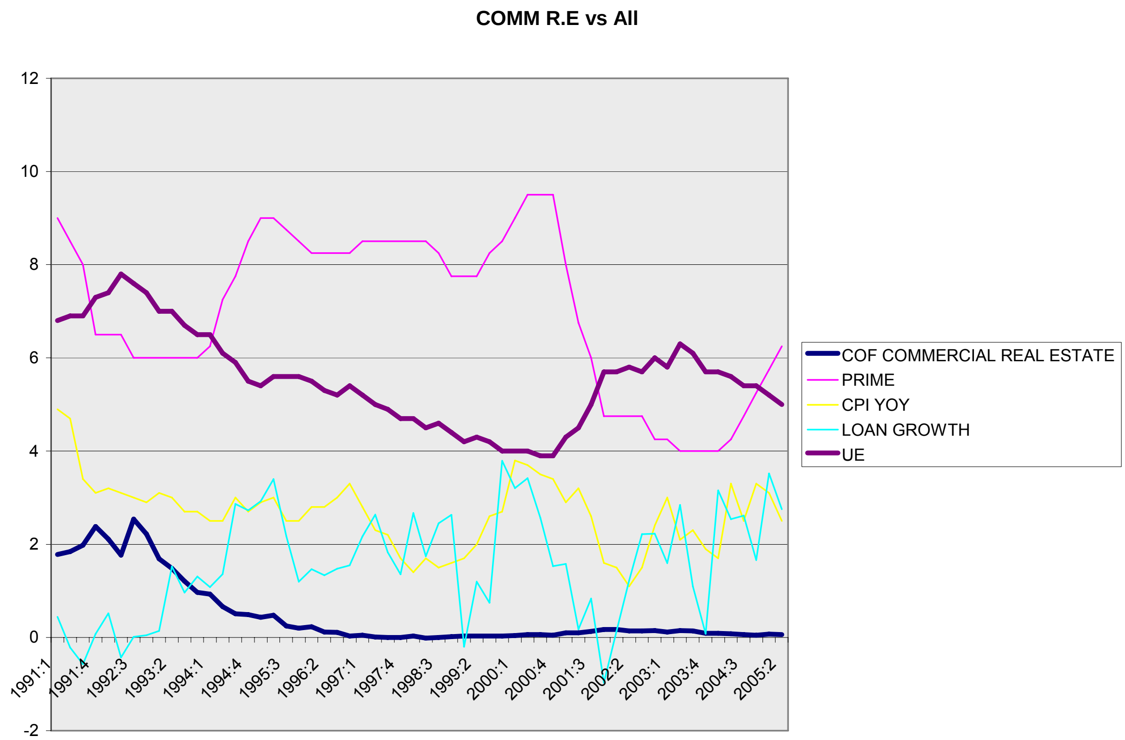
Below is the result of a simple linear regression of COF on Unemployment rate alone. Notice the high coefficient of determination (70%).

Table III-4-3-3B Commercial Real Estate Net Charge-Off rate regression results on unemployment

	Coefficients	*Standard Error*	*t Stat*	*P-value*

Intercept	-2.826	0.294152	-9.60668	2E-13
X Variable 1	0.598	0.052061	11.48724	2E-16

Figure III-4-3-3A Commercial Real Estate Net Charge-Off rate versus selected macroeconomic variables



RESIDENTIAL REAL ESTATE

This category corresponds to 1-4 Family and Home Equity Line of Credit.

COF Residential=Primet-1/GDP/CPIt-1/NHSLNFS

NHSLNFS=New Homes Sales

The Coefficient of Determination was 52%

Table III-4-3-4 Residential Real Estate Net Charge-Off rate regression results on all selected variables

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.510909602	0.071368327	7.158772283	2.76244E-09
Primet-1	-0.02410718	0.004315732	-5.58588533	8.60773E-07
GDP	-0.00916581	0.003442727	-2.66236977	0.010301167
CPIt-1	0.036300303	0.009098684	3.989621111	0.000208114
NHSLNFS	-0.00080694	0.000163222	-4.94383869	8.37995E-06

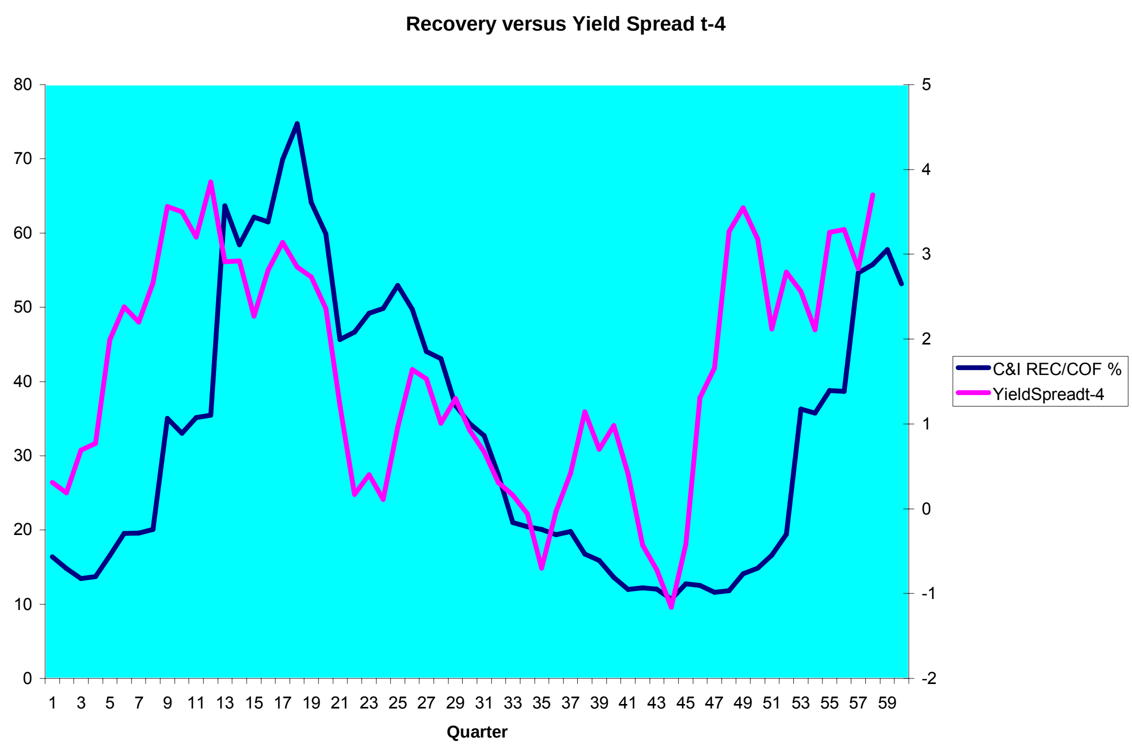
III-4-3-2- Using Recovery

Regression Analysis of the Macroeconomic Determinant of Recovery

As mentioned in the introduction, within Basel II proposals and especially the rules set for paragraph 468, Banks using the Advanced IRB approach are to estimate their own Loss Given Default considering economic downturn. Thus remains the question that if indeed recovery rates are procyclical, what should the banks use as an input for estimating downturn LGD.

If LGD are procyclical on the business cycle, they are therefore expected to be lower during recessions, thus if one can predict recession, one can use it for Downturn LGD estimation. I think that, given that literature has well established the predictive power of the yield curve, especially the spread between the 10 year treasury and the one year treasury note[62].(or equivalently the federal funds rates or 3 month T-bill).I propose to look at the relationship between recovery and the spread of the yield curve.

Figure III-4-3-2 Commercial & Industrial Loan Recovery versus Yield Spread



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[62] Estrella Arturo (2005),"The Yield Curve as a leading indicator: Frequently Asked Question". *Federal Reserve Bank of New York*, October 2005

Data start in 1985:1 (first quarter) and ends in 2005:2 (59th quarter). In the chart above, one can see clearly that both variable follow similar trend.

A simple regression of ln (Recovery) on Yield Spread (t-4) gave a coefficient of determination of about 35%.

Table III-4-3-2A Commercial & Industrial Loan regression results of recovery on yield spread (with 4 quarter lag)

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	2.917119	0.10015	29.12739	1.6E-35
Yield Spreadt-4	0.265091	0.047699	5.55758	7.8E-07

A multivariate regression of LN of Recovery on Yield Spread, Unemployment and Industrial Production resulted in a coefficient of determination of about 48%.

Table III-4-3-2B Commercial & Industrial Loan regression results of recovery on selected macroeconomic variables

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	3.637601	0.333499	10.9074	4.76E-15
YieldSpread	0.289039	0.047597	6.072602	1.48E-07
Unemployment	-0.15803	0.0632	-2.50049	0.015593
Industrial Production	0.419691	0.132014	3.179144	0.002489

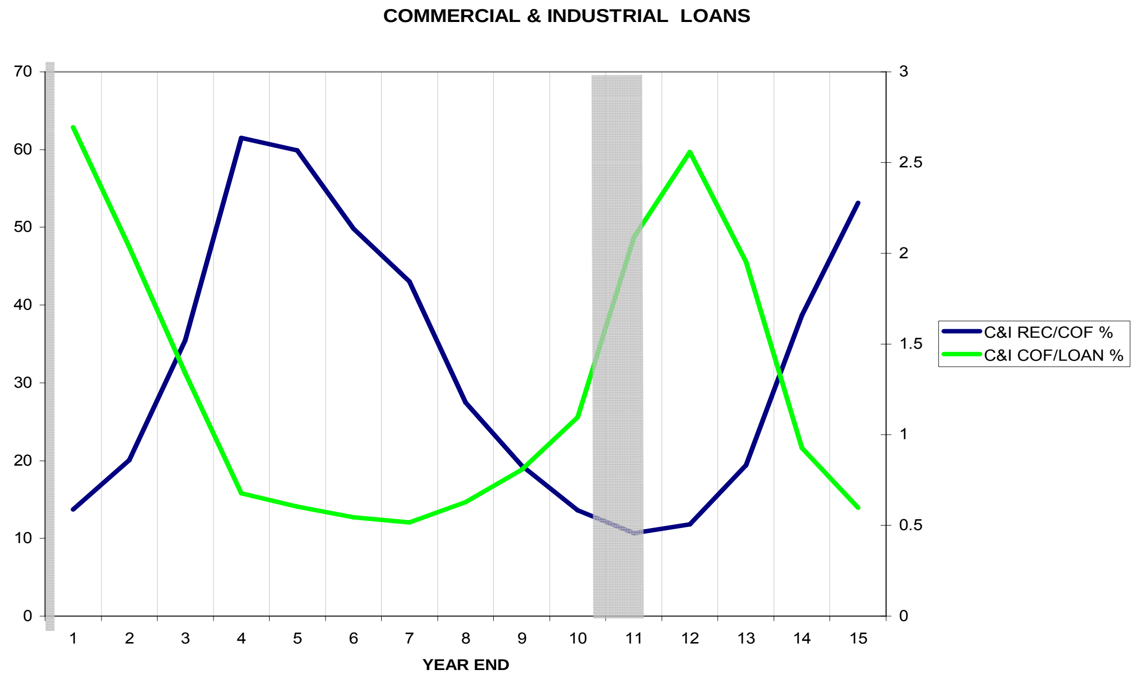
This is an important result because this relationship between recovery and the yield spread (t-4) can be used to model and predict recovery.

Indeed Arturo Estrella has established strong evidence of the predictive power of the yield curve and since there might be a relationship between recovery and the yield curve, risk managers and banks subject to Basel II can use the spread on the yield curve (between 10 years and 1 year, or 3month t-bill) for estimating downturn LGD(1-RR).

III-5 Dependence between Default Rates and Recovery

III-5-1 Graphic Evidence

Figure III-5-1-1 Commercial & Industrial Loan Recovery versus Charge-Offs



In the figure displayed above, I show the historical relationship between PD and RR using charge-off/loan as a proxy for PD (similar to what Georges French did at the FDIC in 2003) for commercial and industrial loans. One can see that, when the default rate is at its highest, the recovery rate is at its lowest. This is true for all types of loans except for Acquisition-Development-Construction and Non Farm Non Residential loans (see Annex A).

III-5-2 Univariate regression

Statistical analysis of the relationship

I have used 2 types of proxies for default rates and recovery rates. I used Charge-Off/Loan(t-1) which is COF/loan(t-1) and Recovery/COF(t-1) for which I regressed RR on PD and then I used RR over Ln(PD) in a second set of model called Model II and finally I used Logs in both and called it Model III .

I then compute the same models but using Charge-Off/Loan(t) and Recovery/Loan(t). The reason is that loans have different maturities; so that it might more appropriate to compute the ratios using one lag for both the charge-off and the loan amount.

Table III-5-2-1A Regression results for all type of loan using linear and non linear models and one year lag

Using COF/LOANt-1 & REC/COFt-1

LOAN TYPE	Model I			Model II			Model III		
	α	β	R^2	α	β	R^2	α	β	R^2
Commercial & Industrial	53.22 (10.0)*	-19.6 (-4.92*)	0.66	31.35 (15.66*)	-25.9 (-6.2*)	0.76	3.33 (64.75*)	-0.92 (-8.6*)	0.86

Loans to Individuals	31.47 7.49*	-3.41 (-2.64**)	0.36	33.32 7.24*	-11.1 (-2.8**)	0.39	3.59 (16.4*)	-0.51 (-2.7**)	0.38
1-4 Family	25.54 (6.5)	-28.51 (-1.6)	0.17	9.47 (1.5)	-6.14 (-1.6)	0.18	2.44 (6.9)	-0.29 (-1.4)	0.15
Home Equity Line of Credit	25.10 (4.3*)	-14.64 (-0.6)	0.03	17.23 (2.29**)	-2.98 (-0.5)	0.026	2.88 (7.8*)	-0.10 -0.43	0.01
Acquisition Development Construction	38.58 (8.27*)	-10.87 (-3.05*)	0.43	19.13 (3.6*)	-9.02 (-3.1*)	0.45	2.59 (12.9*)	-0.45 (-4.2*)	0.59
Non Farm Non Residential	48.31 (6.8*)	-23.9 (-2.5**)	0.34	19.38 (2.1***)	-13.6 (-2.4**)	0.33	2.73 (12.1*)	-0.51 (-3.6*)	0.52

Table III-5-2-1B Regression results for all type of loan using linear and non linear models without lag

Using COF/LOANt & REC/COF

LOAN TYPE	Model IA			Model IIA			Model IIIA		
	α	β	R^2	α	β	R^2	α	β	R^2
Commercial &	54.04	-17.45	0.56	33.42	-23.5	0.61	3.34	-0.83 (-5.03*)	0.66

Industrial	(8.5*)	(-4.09*)		(10.9*)	(-4.5*)		(34.4*)		
Loans to Individuals	33.4 (17.3*)	-4.82 (-7.6*)	0.81	33.39 (17.9*)	-13.3 (-7.9*)	0.82	3.65 (36.9*)	-0.66 (-7.4*)	0.81
1-4 Family	32.15 (17.4)	-73.35 (-8.0)	0.83	-6.36 (-2.4)	-14.1 (-9.6)	0.87	1.42 (8.8)	-0.81 (-9.1)	0.86
Home Equity Line of Credit	21.12 (3.67*)	-12.12 -0.45	0.015	16.26 (1.97***)	-1.44 (-0.28)	0.006	2.75 (6.22*)	-0.07 (-0.28)	0.006
Acquisition Development Construction	51.06 (5.2*)	-10.63 (-2.07***	0.248	28.73 (2.75**)	-9.3 (-7***)	0.195	2.74 (10*)	-0.42 (-3.07*)	0.42
Non Farm Non Residential	57.33 (5.9*)	-29.89 (-2.4**)	0.31	22.68 (1.94***)	-15.1 (-2.1***)	0.26	2.62 (9.1*)	-0.6 (-3.4*)	0.47

* significant at 1%, ** at 5% and *** at 10 t-stat in parenthesis.

The first observation of importance in these results is that all slopes are negative (which is expected). Regardless of the lag, for commercial and industrial loans, the relationship between COF and Recovery is significantly different from zero at 1% level of significance. For Loans to individuals, the short recovery seems more appropriate and the relationship is significant at 1% with a coefficient of determination of about 80%. The same result is shown on the types of loans, except for HELOC (not significant).

Despite the specific behavior of one or 2 types of loans, this chapter has put some evidence on the procyclicality of Probability of Default and Recovery. It also shows an inverse relationship between both, which is relevant given the fact that most credit derivative pricing models and Basel II assume independence between PD and RR.

IV-CONCLUSION

For the last few years, a lot of attention has been given to credit risk modeling for two main reasons, first the exponential growth in credit derivatives market(8.4 $ trillion in notional amount) and simultaneously the perspective of a new regulation on banks capital requirement more risk sensitive and more complex, namely Basel II.

Most likely, this will continue because on one side, the credit derivatives market is still projected to grow, the market did not find yet “The” pricing model due to the inconsistencies cited in this dissertation. On the other side Basel II implementation for the US is still in debate.

This dissertation has tried to tackle these inconsistencies and made some suggestions. The more available, although still limited data (credit derivatives market being mainly an OTC market) on Credit Default Swap Index , in this dissertation, has permitted to provide an explanation to the observed implied correlation skew (suggesting also that as the market develops and efficiency increases, we should observe a flattening of the correlation smile) and confirmed Merton’s argument on the relationship between firms assets and liabilities in linking the credit default swap spread and the equity market.

The analysis on the procyclicality and dependence of PD and RR in bank loans by using charge-offs as a proxy for default rates has shown that default rates and recovery rates are not only procyclical but they are also negatively related.

The implication is valuable for both credit derivatives pricing and Basel II. I suggest, based on my findings and based on the recent literature, that indeed credit risk models and Basel II Advanced IRB formula (for computing the level of bank capital requirement) should take into account the cyclicality of PD and RR and their dependence as input, especially when maturity increases, and I suggest that LGD(loss given default) be a function of the yield curve spread(10 year minus 3 month Tbill) to more appropriately compute downturn LGD.

APPENDICES

ANNEX A

LIST OF FIGURES

Figure III-4-1-A Composition of Total Loans for all US Commercial Banks

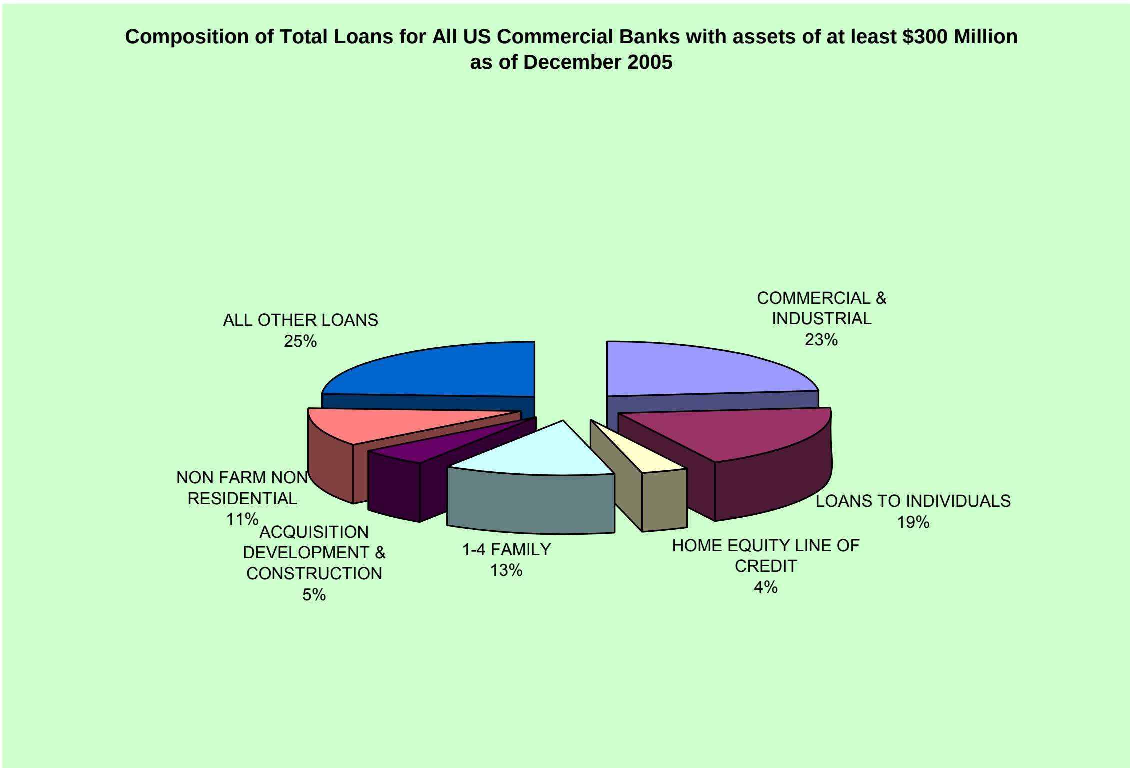


Figure III-4-1-B Historical Composition of Total Loans for all US Commercial Banks

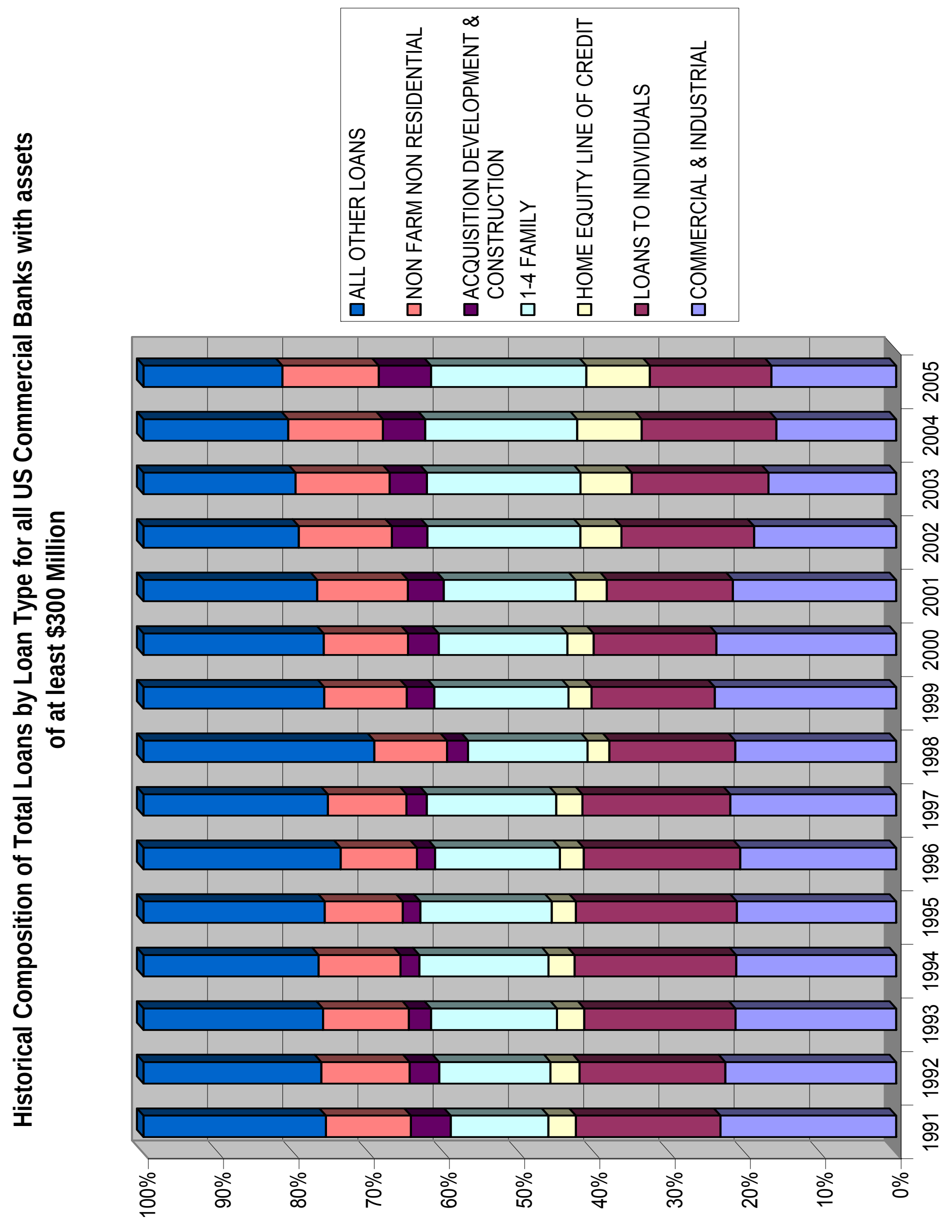


Figure III-3-2-A1 Commercial and Industrial Charge-Off/Loans

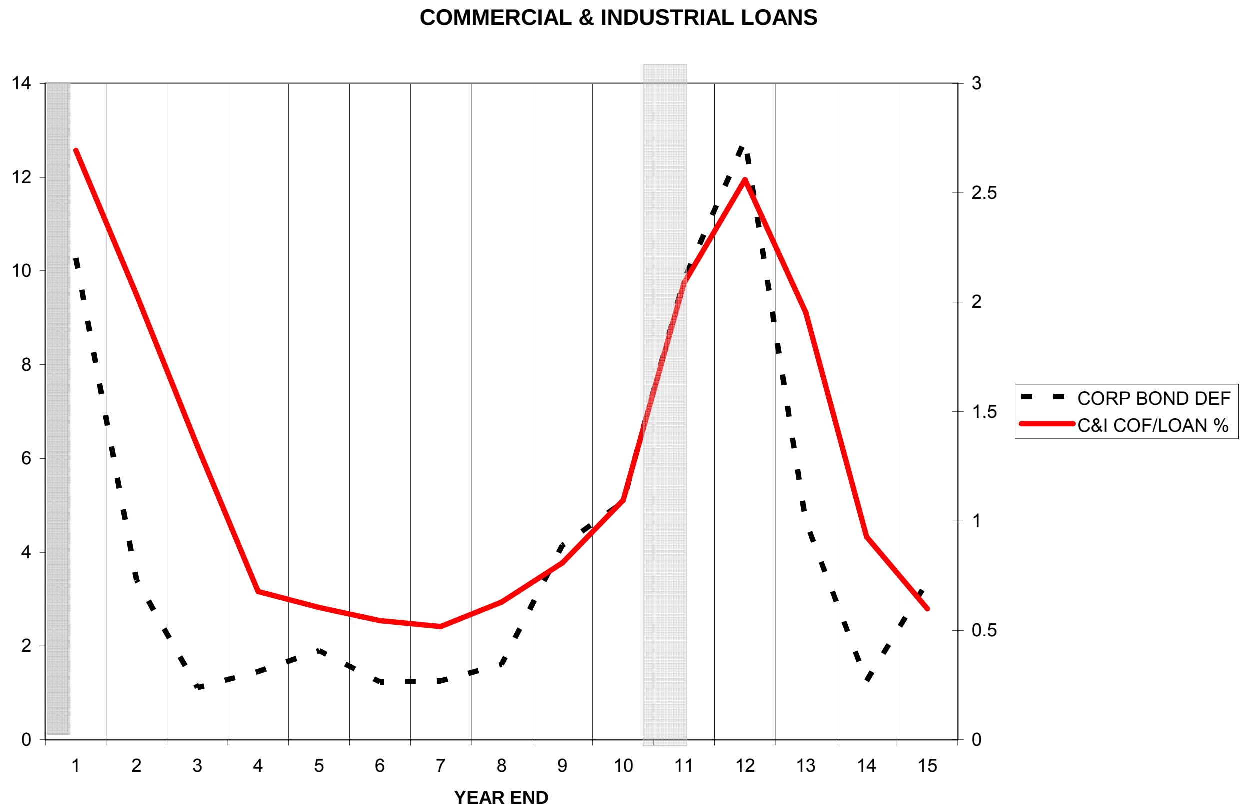


Figure III-3-2-A2 Commercial & Industrial Recovery/Charge-Off

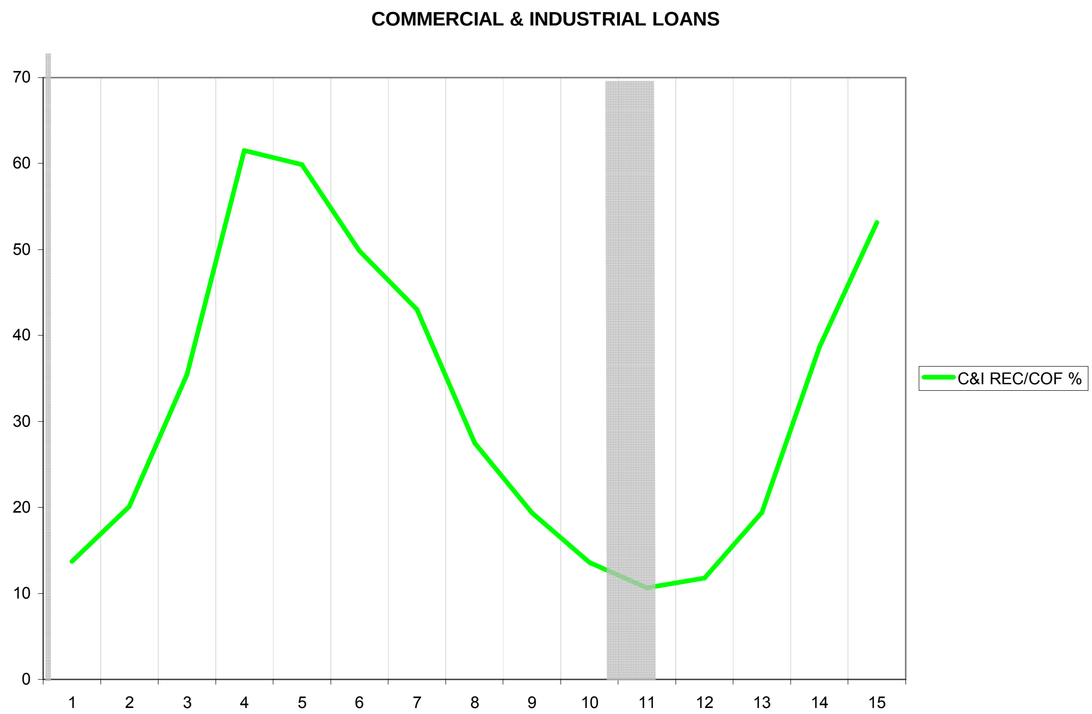


Figure III-4-2-B1 1-4 Family Loans Charge-Off/Loan

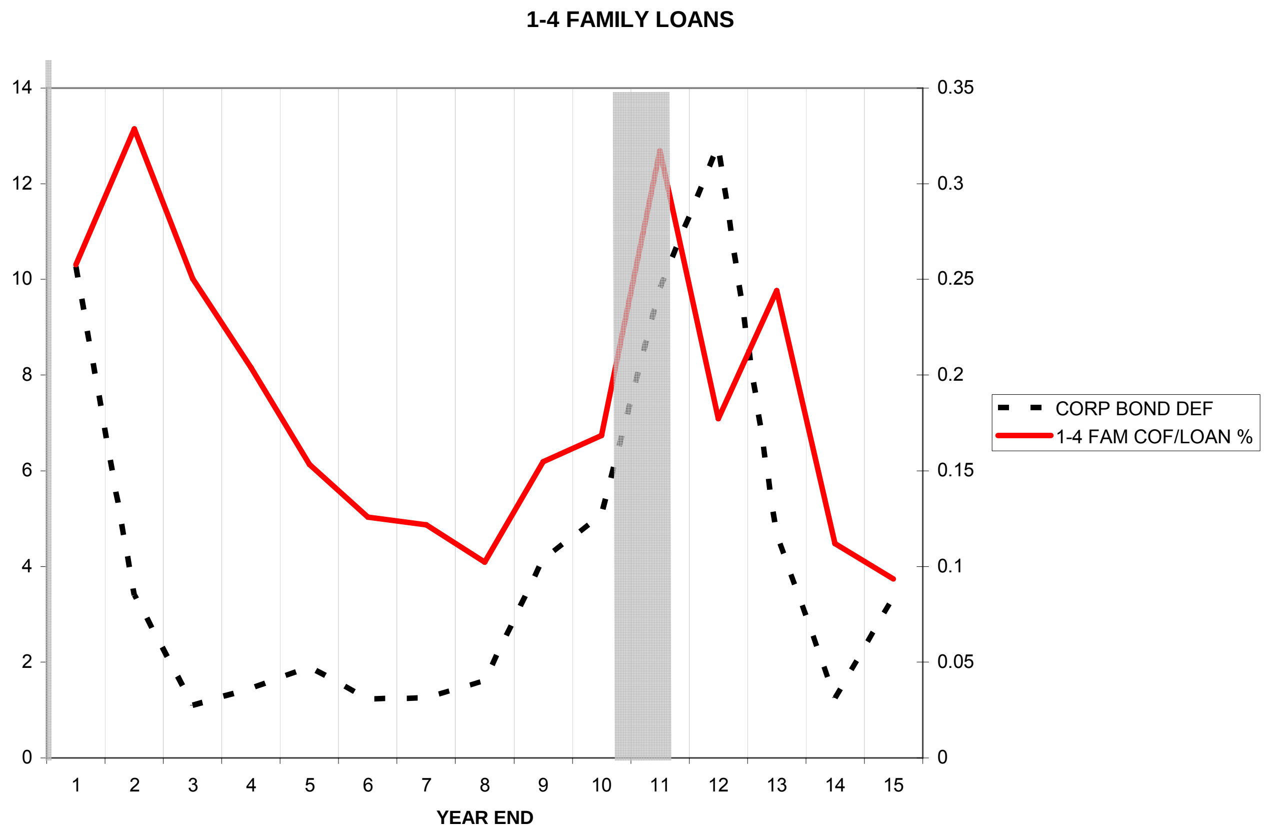


Figure III-4-2-B2 1-4 Family Loans Recovery/Charge-Off

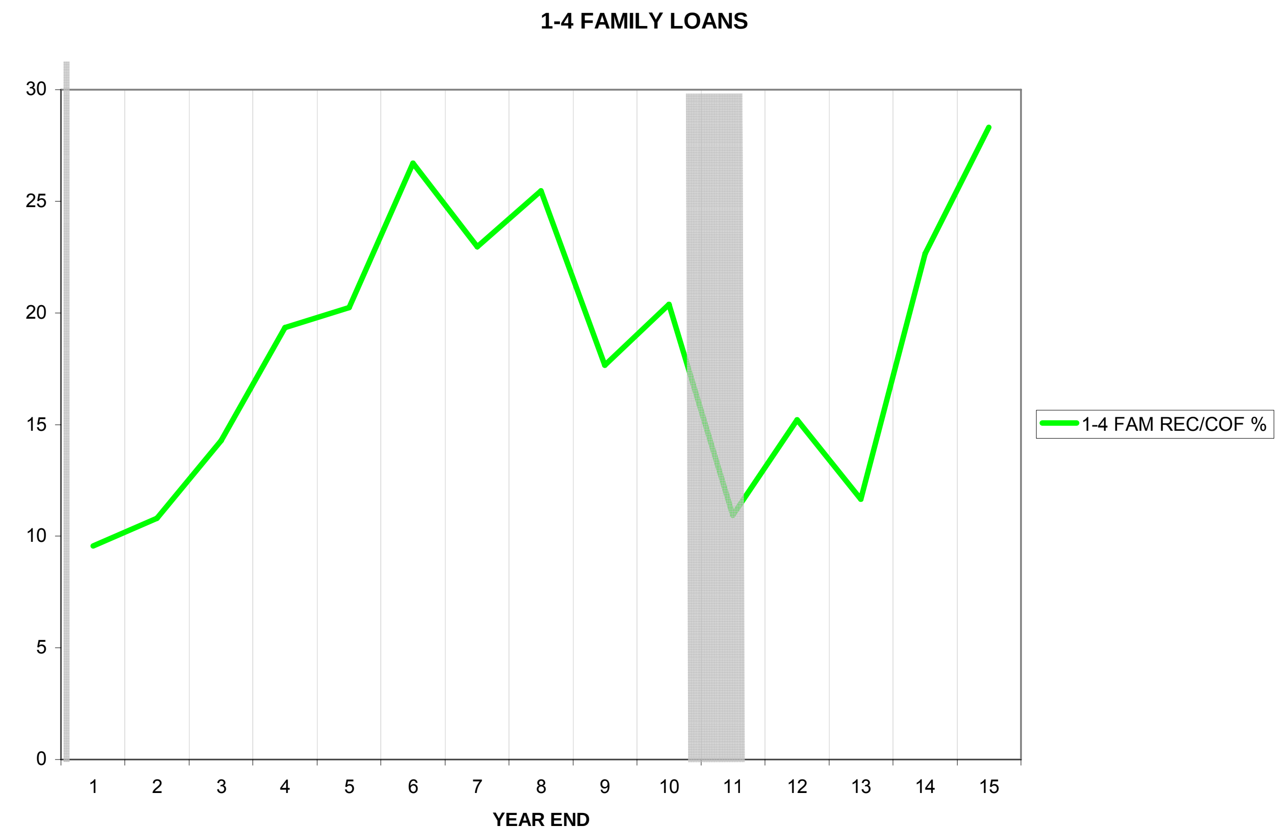


Figure III-3-4-C1 Loans to Individuals Charge-Off/Loan

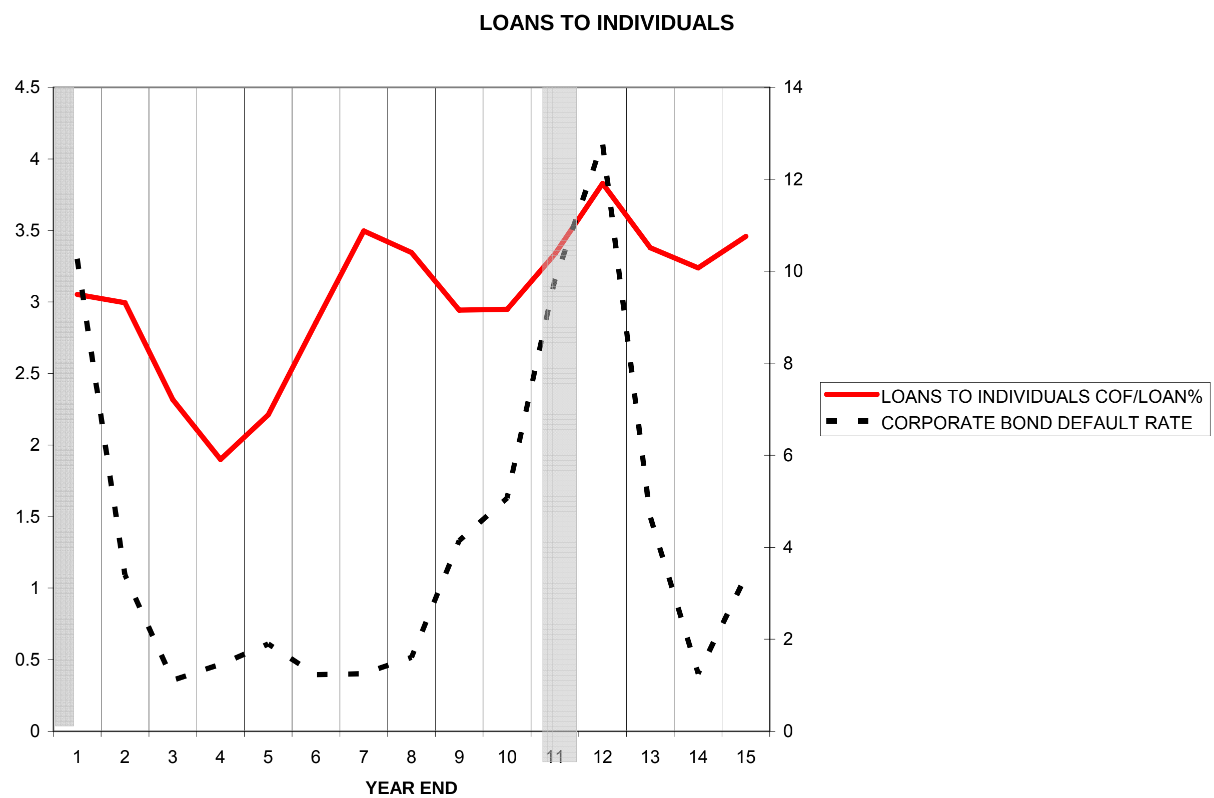


Figure III-4-2-C2 Loans to Individuals Recovery/Charge-Offs

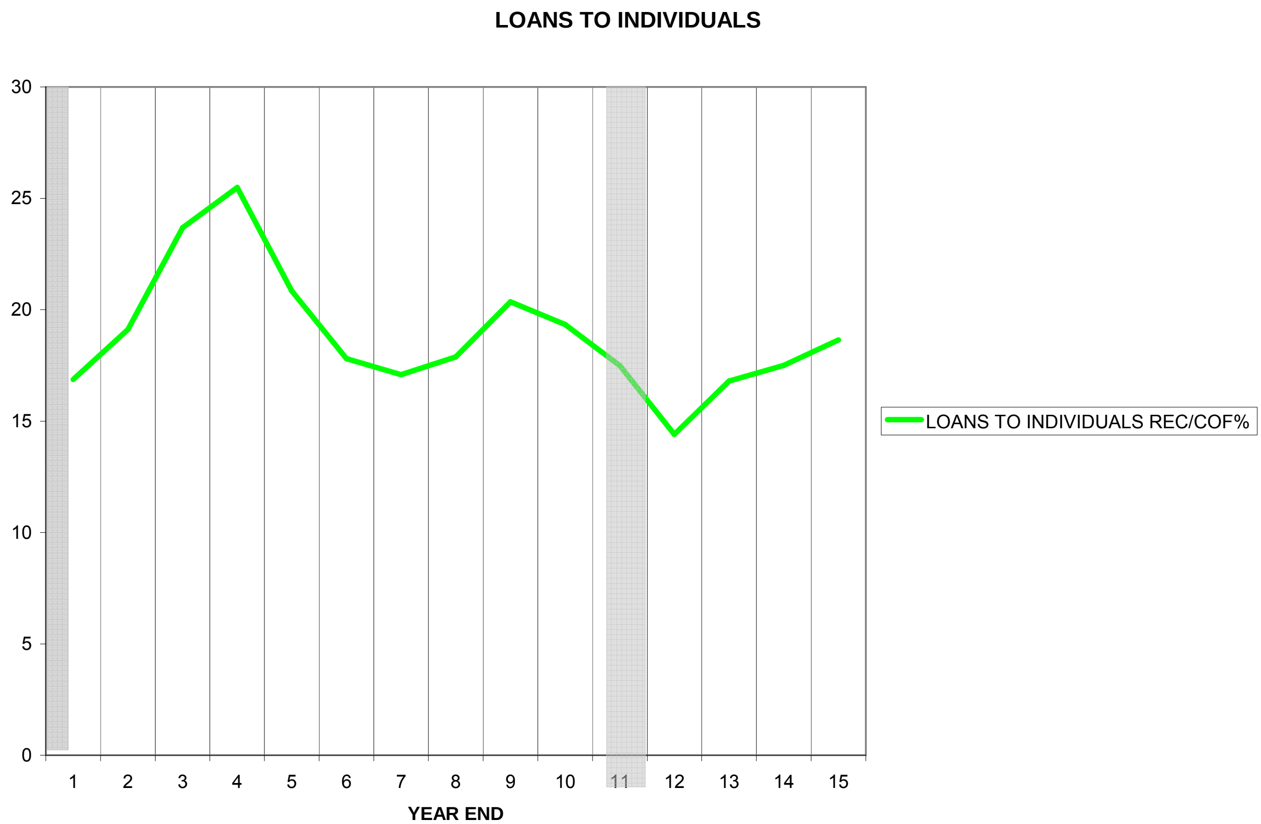


Figure III-4-2-D1 Home Equity Line of Credit Charge-Offs/Loan

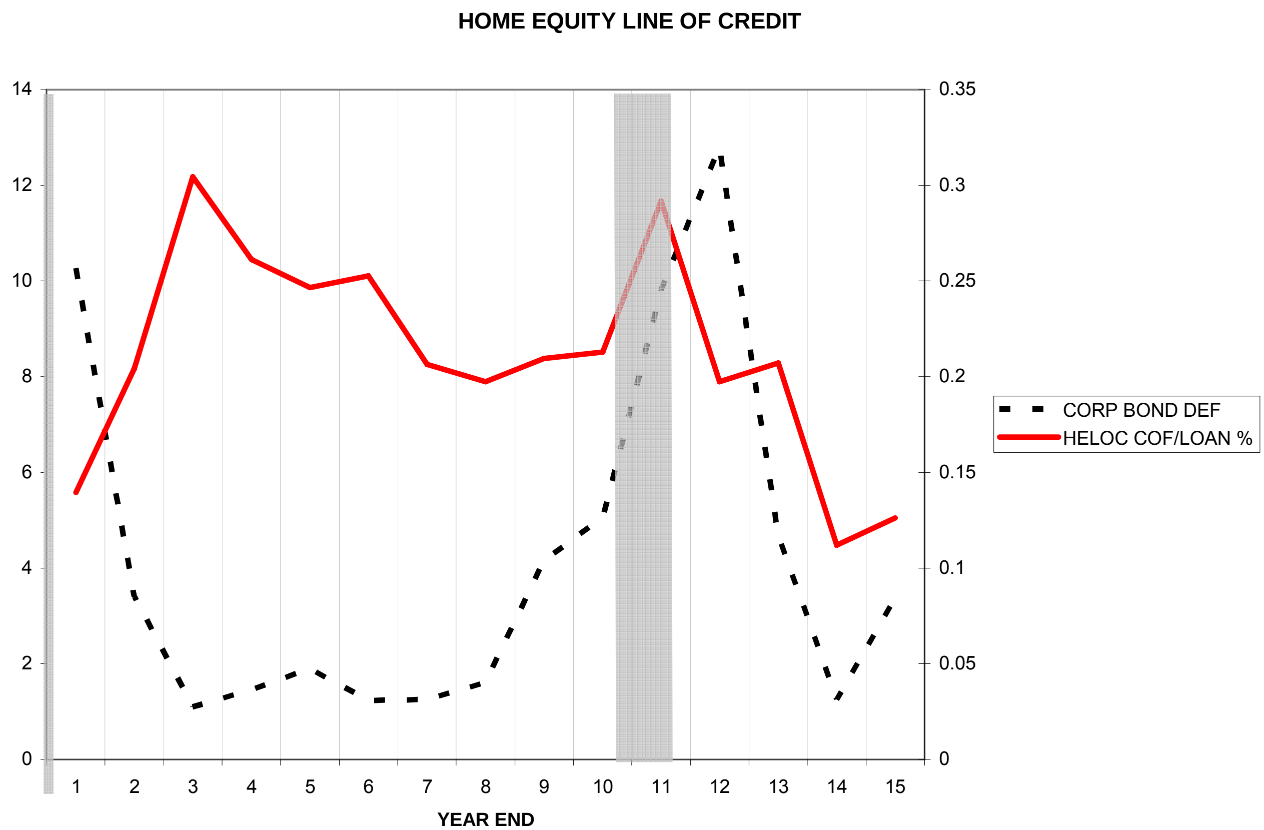


Figure III-4-2-D2 Home Equity Line of Credit Recovery/Charge-Offs

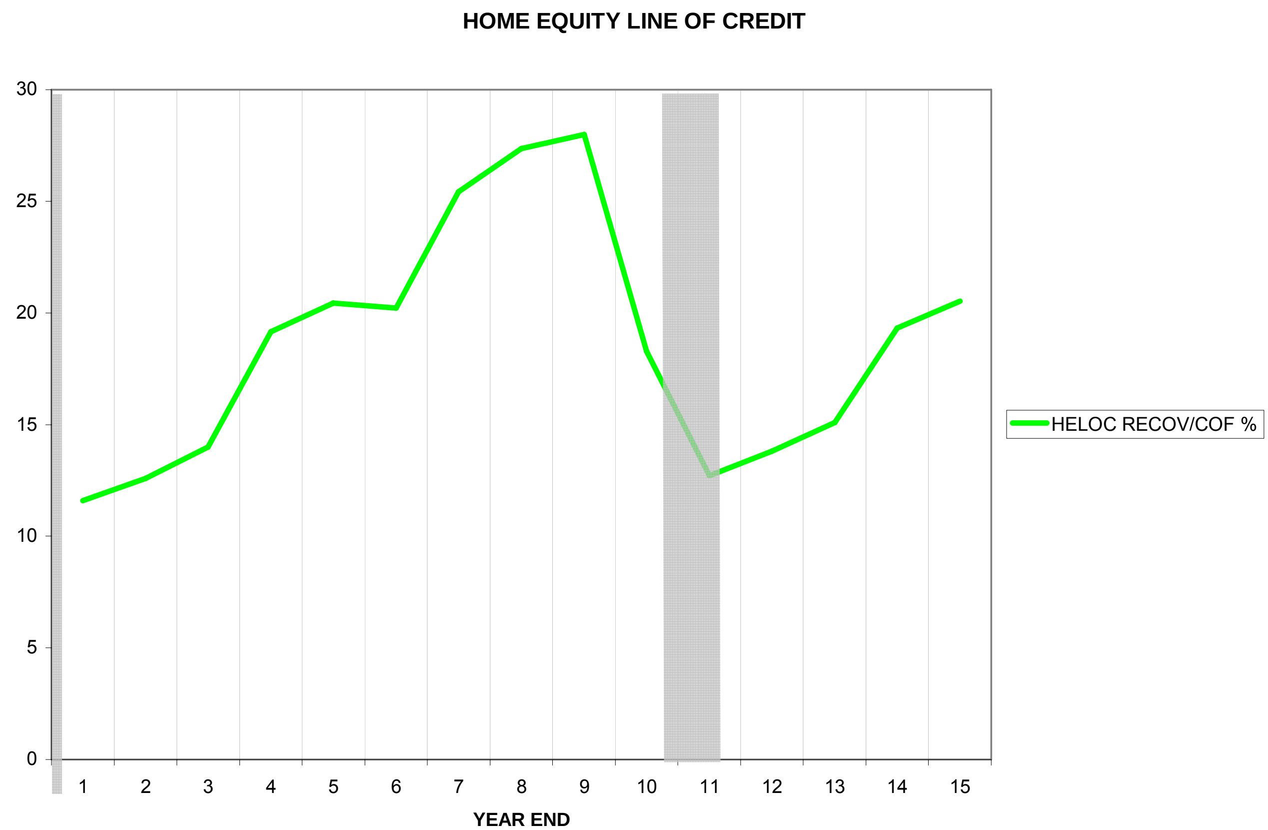


Figure III-4-2-E1 Acquisition Development Construction Charge-Off/Loan

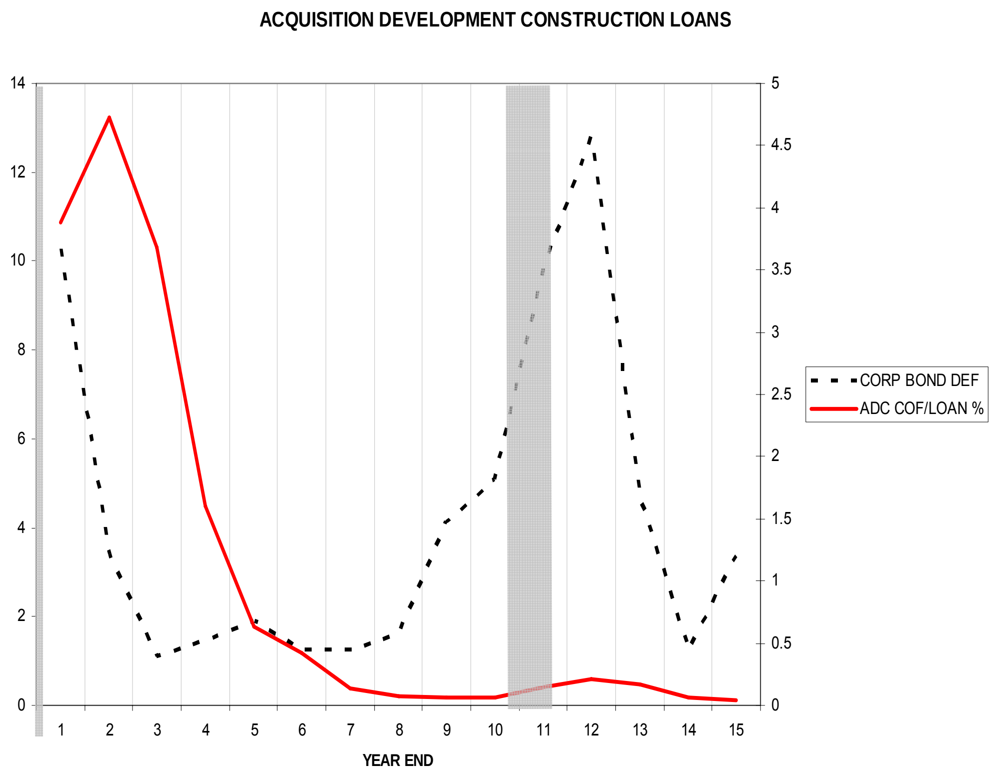


Figure III-4-3-E-2 Acquisition Development Construction Recovery/Charge-Offs

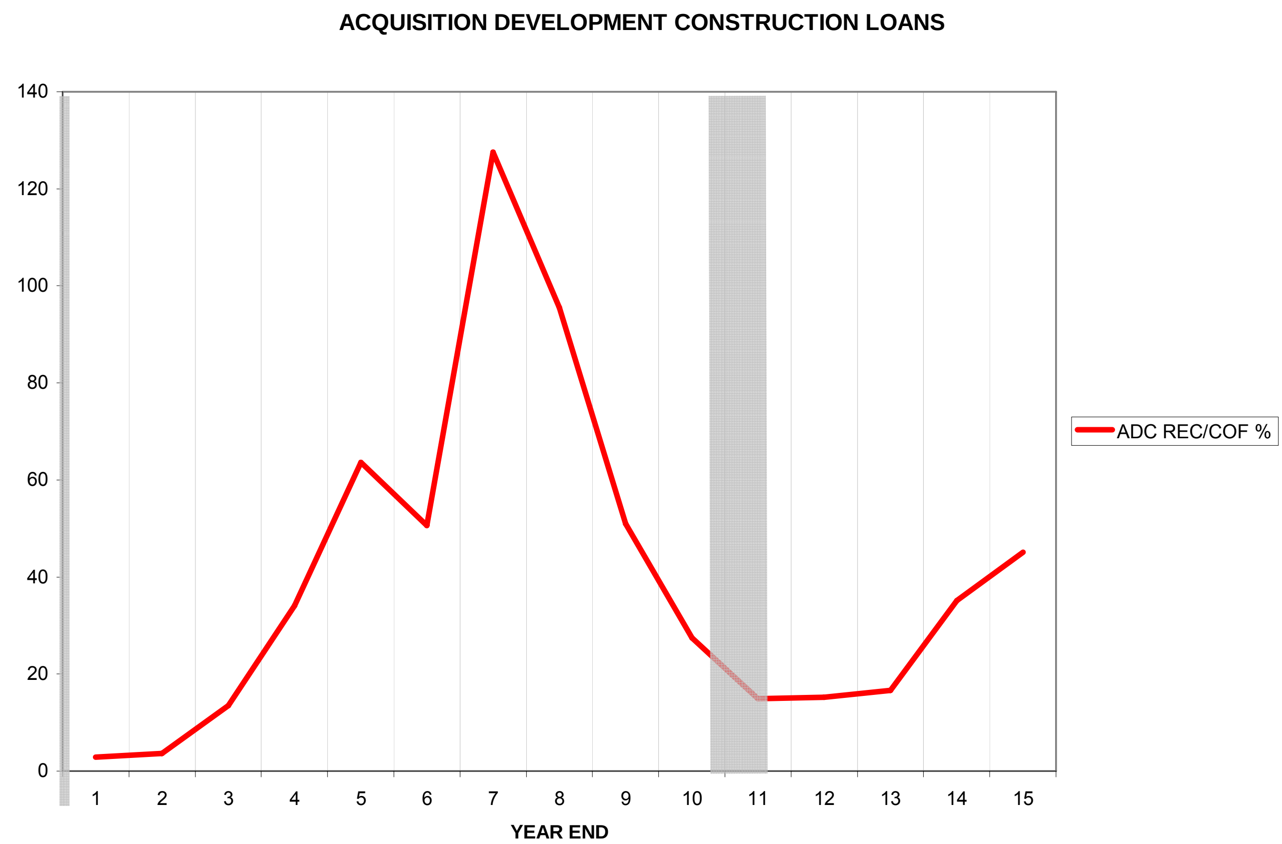


Figure III-4-2-F1 Non Farm Non Residential Charge-Offs/Loan

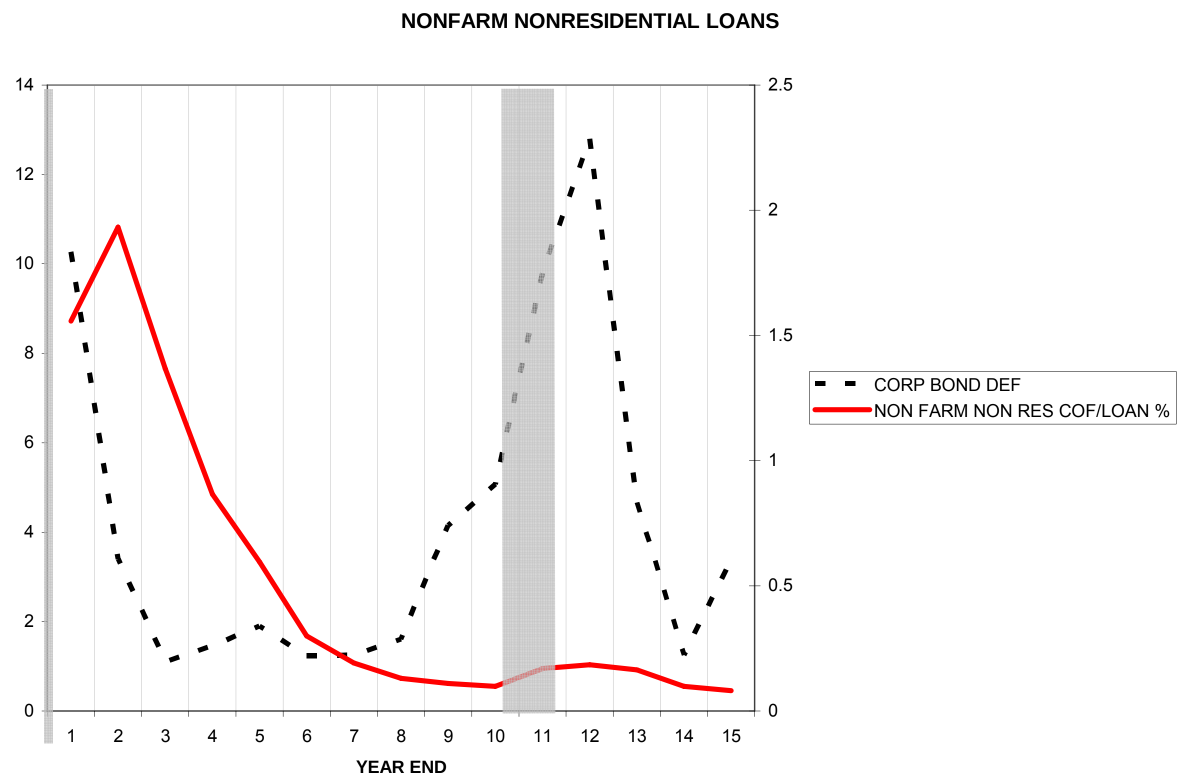
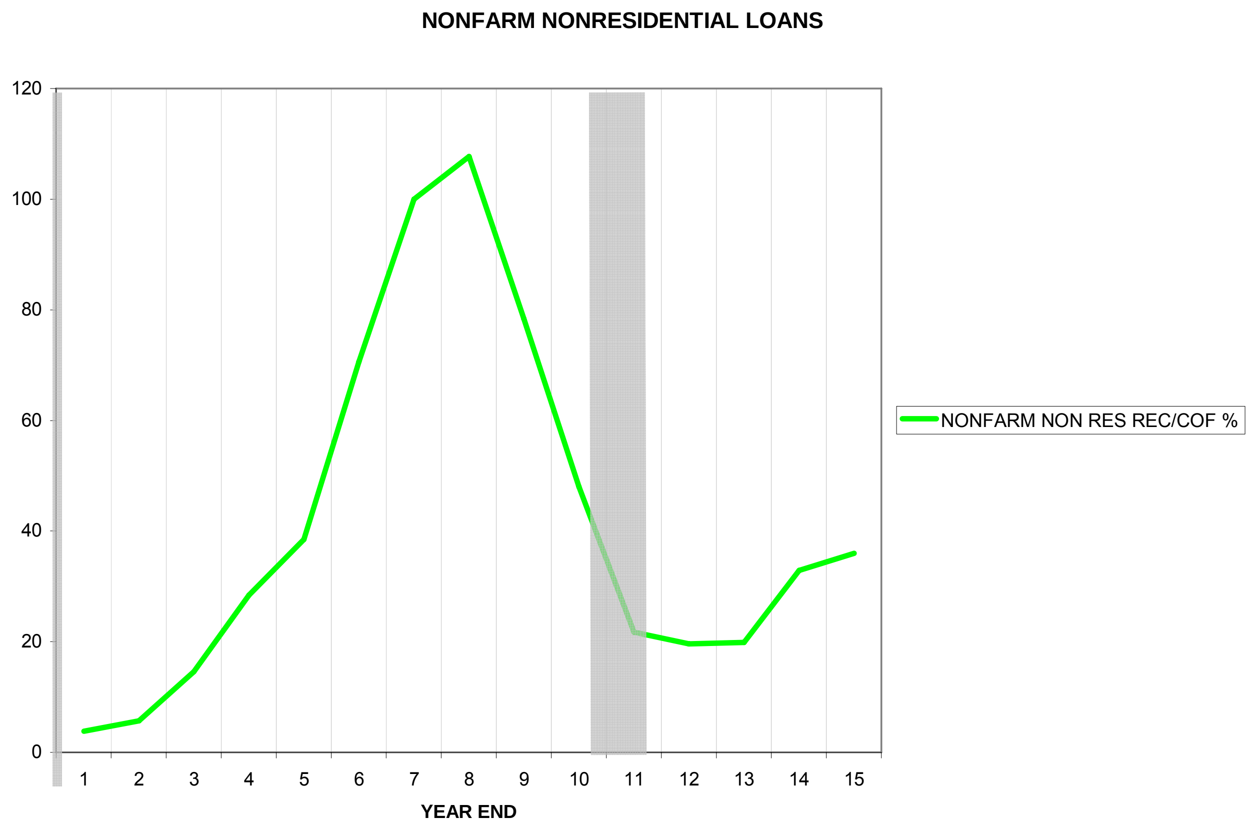


Figure III-4-2-F2 Non Farm Non Residential Recovery/Charge-Offs



GRAPHIC EVIDENCE RELATIONSHIP PD RECOVERY

Figure III-5-1-1 Commercial & Industrial Loan Recovery versus Charge-Offs

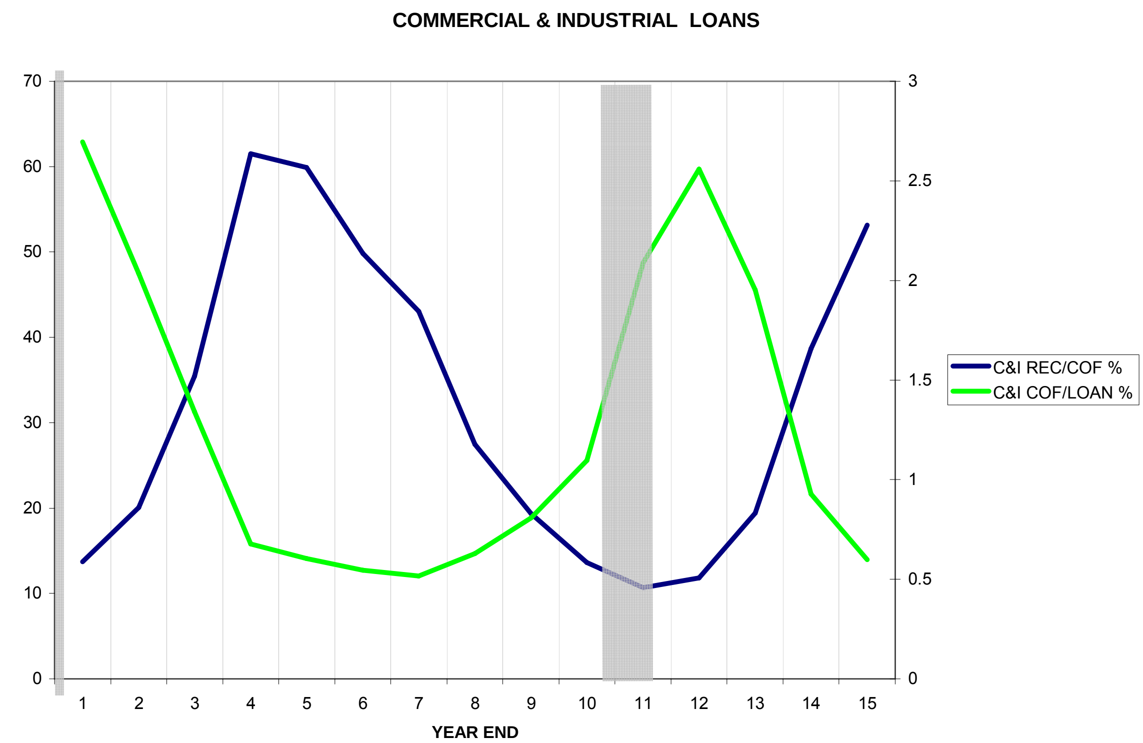


Figure III-4-2-D3 Home Equity Line of Credit Recovery versus Charge-Offs

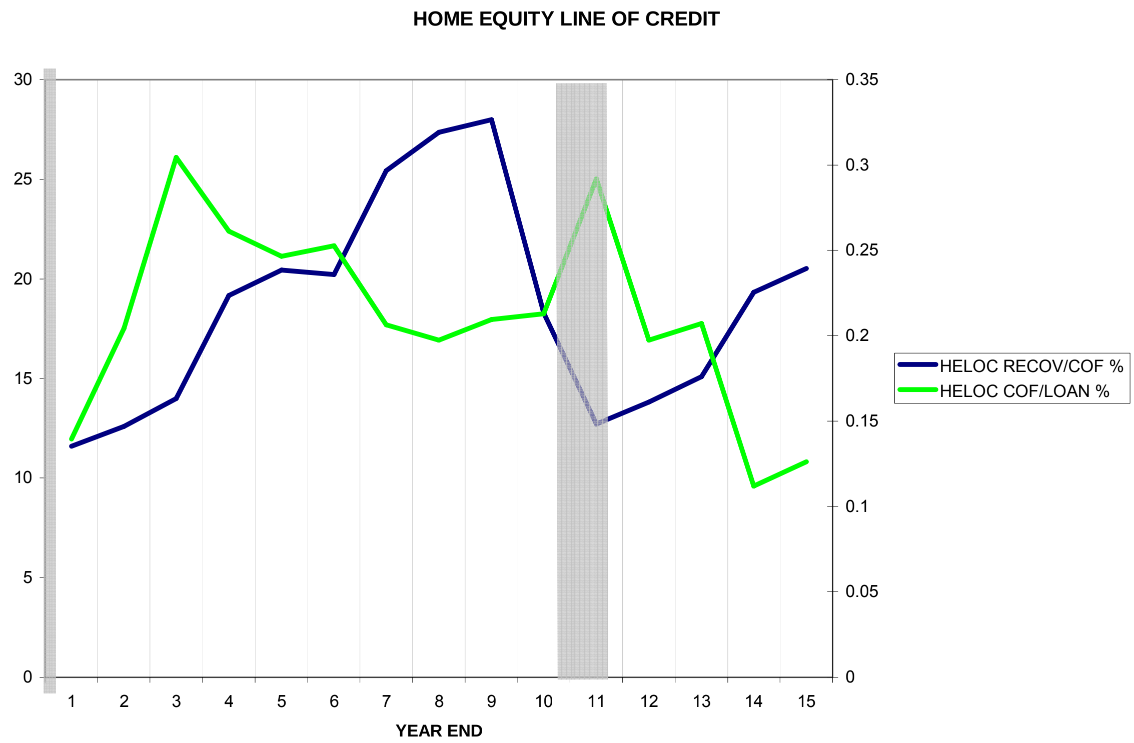


Figure III-4-2-B3 1-4 Family Loans Recovery versus Charge-Off

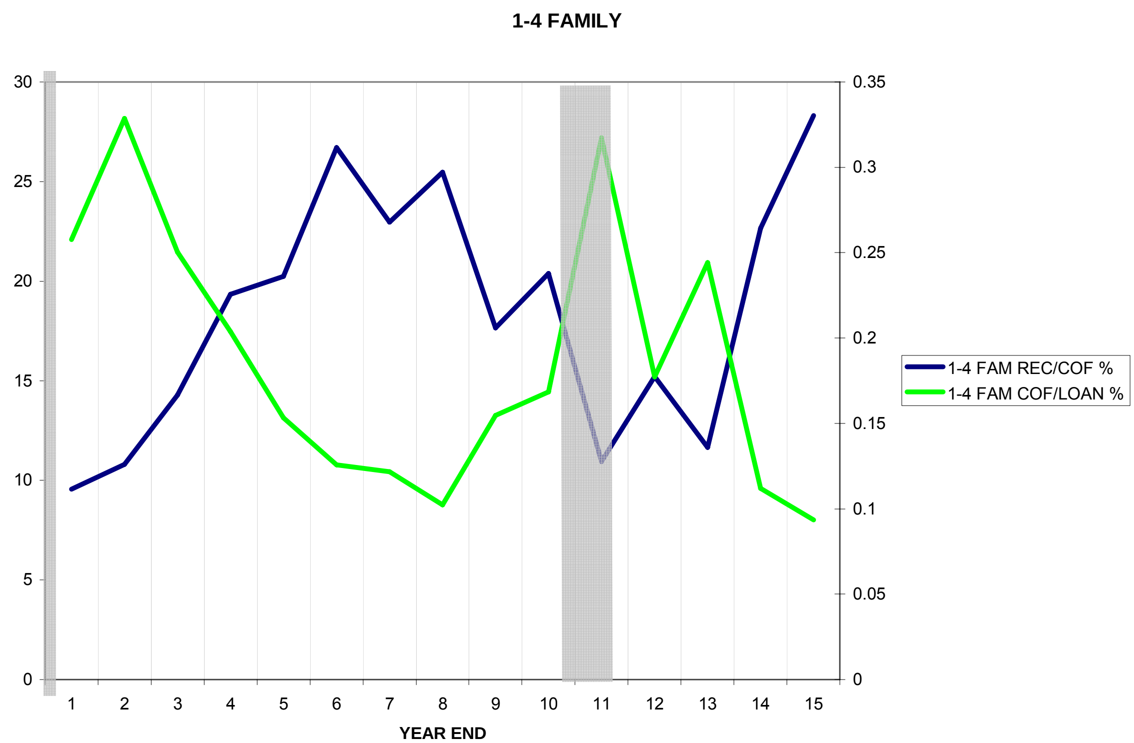


Figure III-4-2-E3 Acquisition Development Construction Recovery versus Charge-Offs

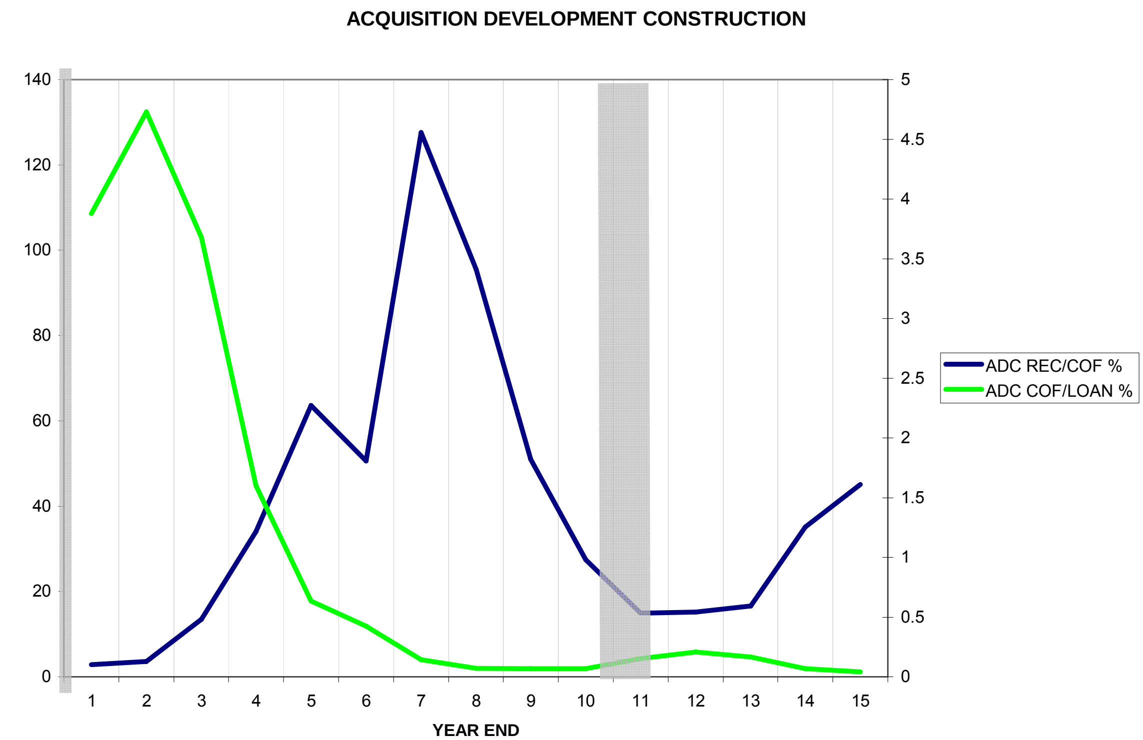


Figure III-4-2-C3 Loans to Individuals Recovery versus Charge-Offs

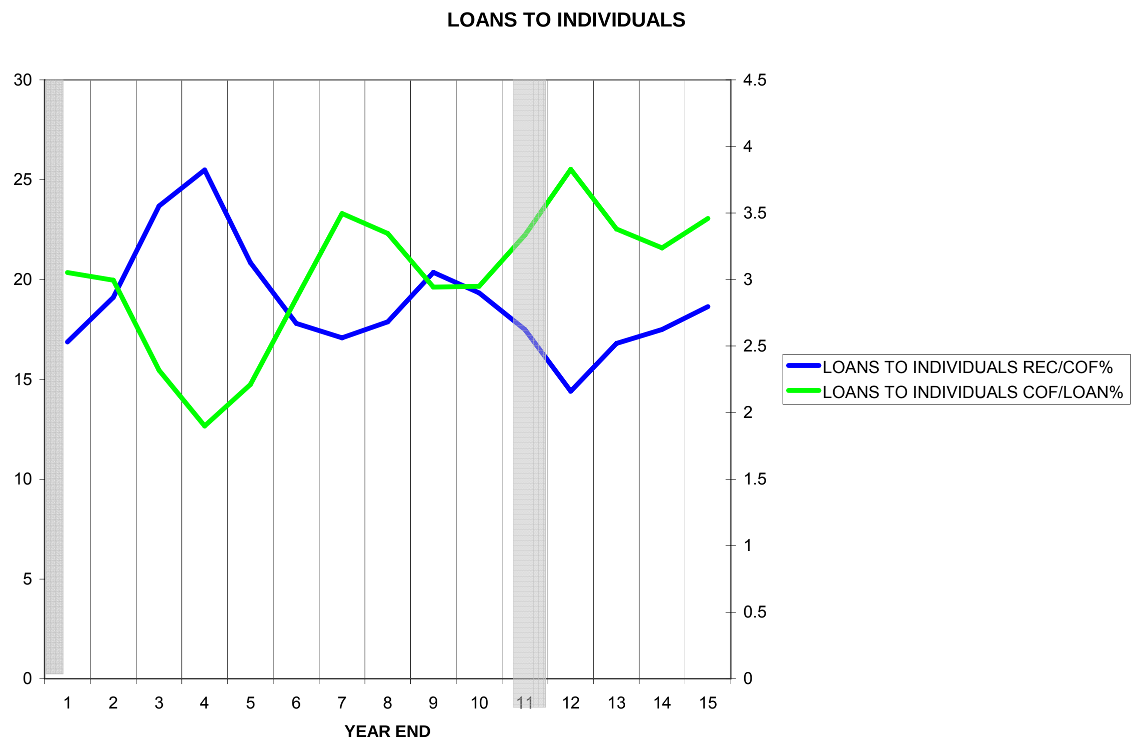
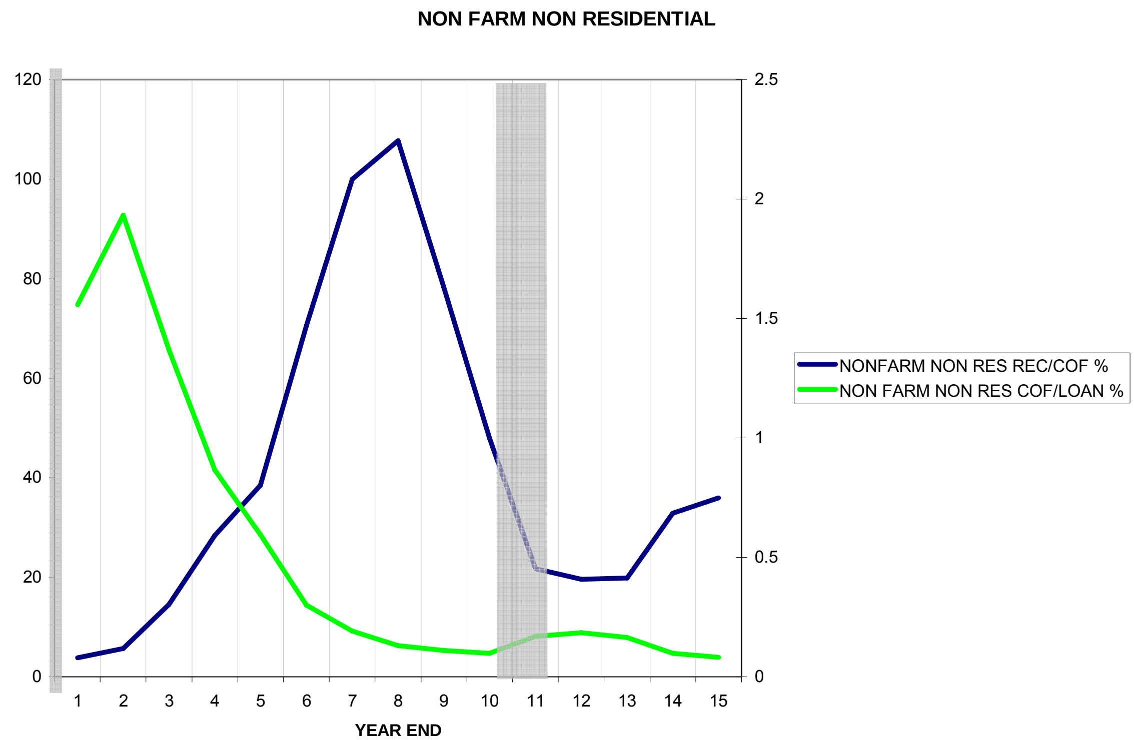


Figure III-4-2-F3 Non Farm Non Residential Recovery versus Charge-Offs



ANNEX B

LIST OF TABLES

Table III-4-1A Historical Ratio Charge-Off/Loan Amount by loan type

YEAR	C&I	1-4FAM	HELOC	LOANS TO INDIVIDUALS	ADC	NONFARM
1991	2.694052	0.257724	0.13951	3.051597138	3.878132	1.5578671
1992	2.033109	0.328649	0.204316	2.9948419	4.730474	1.9317536
1993	1.340267	0.250246	0.304433	2.316989859	3.679639	1.3674991
1994	0.677498	0.203821	0.261314	1.898845405	1.601514	0.865397
1995	0.604683	0.153192	0.246564	2.211320141	0.634602	0.5950734
1996	0.544357	0.125814	0.252814	2.857091868	0.423185	0.2992872
1997	0.517447	0.12184	0.206407	3.495860943	0.141426	0.1919336
1998	0.629042	0.102291	0.197342	3.346155521	0.071805	0.1296864
1999	0.808332	0.154623	0.209444	2.942156262	0.066539	0.1102735
2000	1.095321	0.168573	0.212956	2.949148819	0.067756	0.0986168
2001	2.087826	0.317196	0.291803	3.334742188	0.152619	0.1690696
2002	2.559535	0.177205	0.197422	3.828483404	0.20617	0.185494
2003	1.952625	0.244154	0.20705	3.378935474	0.165835	0.1640172
2004	0.928129	0.111901	0.112103	3.237208134	0.067966	0.0990181
2005	0.598616	0.093382	0.126219	3.45846337	0.039196	0.0805391
Average	1.271	0.187	0.211	3.020	1.062	0.523
Stand Deviation	0.754	0.074	0.054	0.510	1.577	0.594
Average Recession	2.391	0.287	0.216	3.193	2.015	0.863
Average Expansion	1.099	0.172	0.211	2.994	0.915	0.471

Table III-4-1B Historical Ratio Recovery/Charge-Off by loan type

YEAR	C&I	1-4FAM	HELOC	LOANS TO INDIVIDUALS	ADC	NONFARM
1991	13.728	9.564	11.593	16.87003319	2.844	3.863
1992	20.084	10.808	12.584	19.10788983	3.637	5.733
1993	35.469	14.284	13.987	23.683012	13.503	14.524
1994	61.496	19.351	19.162	25.48764232	34.114	28.371
1995	59.893	20.236	20.432	20.8422207	63.565	38.469
1996	49.853	26.702	20.227	17.79854574	50.551	70.581
1997	43.050	22.966	25.432	17.08284232	127.536	100.019
1998	27.493	25.456	27.358	17.88803219	95.530	107.676
1999	19.372	17.644	27.989	20.35957181	51.007	78.352
2000	13.599	20.388	18.278	19.32992881	27.385	47.994
2001	10.677	10.934	12.708	17.48612509	14.914	21.692
2002	11.806	15.223	13.813	14.40294986	15.164	19.599
2003	19.413	11.657	15.091	16.80143129	16.633	19.885
2004	38.657	22.665	19.316	17.50310256	35.156	32.837
2005	53.141	28.319	20.520	18.6405685	45.120	35.925
Average	31.849	18.413	18.566	18.886	39.777	41.701
Stand Deviation	17.525	5.938	5.155	2.717	33.639	31.728
Average Recession	12.202	10.249	12.151	17.178	8.879	12.778
Average Expansion	34.871	19.669	19.553	19.148	44.531	46.151

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