Uncooking the books from toxic paper sub-prime mortgages CDS and CSOs material misstatements of the financial services industry: crisis challenges and counterparty surveillance of collateralised debt obligations

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Abstract: This paper studies the sub-prime mortgages, credit default swaps (CDS) and collateralised synthetic obligations (CSOs) cooking the books of the financial services industries at a global level. The paper uses the case of the Bank of Barclays to develop a methodology of uncooking the books from material misstatements of the financial industry. This research is about the current sub-prime markets crisis and shows how sub-prime mortgages, CDS and CSOs overstated the revenues of the financial services industries leading to the stock markets meltdown of October 2008. The paper attempts to develop regression models and software that detect fraud involved in the mortgages crisis and a method for fraud 'finger print' definition. This paper provides the readers with fundamental information about firms and auditors' misconduct. While this study researches primarily in the area of international economics and accounting, it also deals with computer information systems automation and specifically forensic accounting, expert witness testimony and computer litigation support.

Keywords: uncooking the books; toxic paper; credit default swaps; CDS; collateralised synthetic obligations; CSOs; counterparty surveillance; material misstatements; sub-prime mortgages; collateralised debt obligations; financial fraud detection; forensic accounting.

Reference to this paper should be made as follows: Rushinek, A. and Rushinek, S. (xxxx) 'Uncooking the books from toxic paper sub-prime mortgages CDS and CSOs material misstatements of the financial services industry: crisis challenges and counterparty surveillance of collateralised debt obligations', *Int. J. Economics and Accounting*, Vol. X, No. Y, pp.000–000.

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1 Introduction

It is evident that past stock market meltdowns could not rely on financial reports. The 'blame game' once again appeared after the fact. Reminiscent of the fall of Enron, lax auditing and management misconduct allegations were reported. Again, it seemed the problem was the failure of financial reports to report a crucial fact: a company's actual financial condition.

The mortgage credit crisis evolved into a worldwide financial panic in 2007. Feeding the panic was a lack of information about which lenders were at most risk, how many 'toxic' loans exist and where the next surprise would emerge.

Michael Missal, a US Bankruptcy Court examiner accused KPMG of lax auditing and some former New Century executives could be legally liable for millions of dollars in damages because of their conduct. Missal (2008) states in his report that "…Driven by a 'brazen obsession' with generating sub-prime mortgages, Irvine's New Century Financial Corp. engaged in improper accounting that overstated its profit and allowed top executives to reap millions of dollars in inflated or undeserved bonuses".

Michael J. Missal's report said senior managers 'turned a blind eye' to the 'ticking time bomb' created by the high-risk lending in 2005 and 2006. At the same time, Missal (2008) reports that "New Century's auditor, KPMG, contributed to the problems by failing to exercise due care in reviewing its books, leading to material misstatements in New Century's financial reports".

This was a sweeping accusation against one of the largest accounting firms that improper and imprudent practices by a once high-flying mortgage company were condoned and enabled by its auditors. KPMG denied the accusations in the report, which was commissioned by the US Trustee overseeing the New Century bankruptcy (Bajaj, 2008).

2 Credit default swaps (CDS)

At the time of the financial crisis Monks (2008) wrote that mortgage bailouts could trigger massive credit default swap settlements. The government takeover of Fannie Mae and Freddie Mac could trigger the largest credit default swap settlement ever. Actual payments could be limited, however, as a result of the relatively high value of the mortgage underwriters' bonds. Investors may be forced to settle contracts covering the mortgage giants' $1.6 trillion in outstanding debt because the government seizure constitutes a credit event that triggers the payment or delivery of their bonds. The International Swaps and Derivatives Association announced that it would establish a protocol to facilitate the settlement of CDS trades involving Fannie Mae and Freddie Mac.

Monks (2008) reported that J.P. Morgan analyst Eric Beinstein said that "this will likely be the largest CDS credit event in terms of the amount of CDS contracts outstanding. The settlement process will likely take 30 days, with investors cashing their CDS contracts at a price established through an auction process. Payouts could be limited, though, because most analysts believe CDS covering the mortgage companies' senior debt will be settled". In a cash CDS settlement, buyers are paid the difference between the par value and market value of the debt obligation.

2.1 Fannie, Freddie CDS may be settled

Biggadike and Harrington (2008) write that – "investors may be forced to settle contracts protecting more than $1.4 trillion of Fannie Mae and Freddie Mac bonds against default after the U.S. seized control of the companies in a bid to bolster the housing market. (Thirteen 'major' dealers of credit-default swaps agreed 'unanimously' that the rescue constitutes a credit event triggering payment or delivery of the companies' bonds, the International Swaps and Derivatives Association said in a memo obtained by Bloomberg News. Market makers for the privately traded contracts will discuss how to settle them in a conference call. The market is not experienced at settling a credit event for a name of this size, so it is a bit of an unknown. A settlement likely would be the largest in the market's decade-long history. Credit-default swaps on Fannie and Freddie have been among the most actively traded the past few months, according to reports from broker GFI Group Inc. Both companies also are among 125 companies in the benchmark Markit CDX North America Investment Grade Index, the most actively traded contract in credit markets, which investors use to speculate on corporate creditworthiness or to hedge against losses".

2.2 Conservatorship is a credit event Barclays PLC analysts note to clients

Harrington and Unmack (2008) report that "we believe conservatorship is a credit event", Barclays PLC analysts Vince Breitenbach and Jeff Meli said in a note to clients. Barclays is a member of the ISDA. US default protection costs as measured by the Markit CDX North America Investment Grade Index will also decline. Harrington and Unmack (2008) to write that "no one knows exactly who has what at stake because there's no central exchange or system for reporting trades. Sellers are required to post collateral, or pledge assets, to the buyer of protection, known as the counterparty, on the other side of the trade if the value of their positions declines".

Hedge funds, insurance companies and banks typically buy and sell credit protection, which is used either to insure a bond against default or as a bet against the company's ability to pay its debt. Some funds may be forced to dump assets to meet the payment demands if they have not hedged, But fund managers or hedge funds, once they have used their cash, have only one option: to sell assets.

According to Harrington and Unmack (2008) the failures of Lehman, once the fourth largest securities firm, and Seattle-based Washington Mutual Inc. as well as the government takeovers of Fannie Mae, Freddie Mac and Iceland's biggest banks have provided the ten-year-old CDS market with its biggest test to date.

In the same article by Harrington and Unmack (2008) cited James Pickel, the head of the International Swaps and Derivatives Association as stating that CDS contracts did not cause any firm to fail, the underlying cause of problems that has affected firms is the risk that they chose to take on. CDS are financial instruments that can be based on bonds and loans. They pay the buyer face value in exchange for the underlying securities or the cash equivalent should a borrower fail to adhere to its debt agreements.

As reported by Herman and Shields (2008) the bankruptcy court approved the sale of Lehman broker dealer to Barclays. They proceed to report: "questions raised about Lehman's transfer of assets among its businesses in the days before its bankruptcy filing did not interfere with swift action by the bankruptcy court to approve the sale of substantially all of the assets of Lehman Brothers, Inc., to Barclays Capital. The court's decision followed a marathon eleven-hour hearing in a packed Manhattan courtroom where attorneys from the SEC and other government agencies successfully supported Lehman's argument that swift approval of the deal was in the national interest. The national interest apparently is the prompt transfer of the broker-dealer's customer accounts instead of a lengthy brokerage liquidation process. The transfer of most retail accounts, which hold over one hundred billion dollars in assets, is expected to be completed within days. In one of the last liquidations of a major securities firm, when Drexel collapsed in 1990, it was weeks before customer accounts were transferred to a new firm. The expeditious transfer of Lehman's assets also avoids disruption of capital markets because securities transactions will continue to be completed and Lehman's counterparties can confidently continue to do business with the firm".

2.3 Barclays' auditors report that the financial statements are free from material misstatements

At the time of the mortgage crisis, the auditors were still stating that the financial statements are free from material misstatements. According to Barclays PLC annual report of 2007, quoting from the Report of Independent Registered Public Accounting Firm to the Board of Directors and Shareholders of Barclays Bank PLC, the accountants stated:

> "In our opinion, financial statements are free of $$ material misstatement. PricewaterhouseCoopers LLP, Chartered Accountants and Registered Auditors, London, United Kingdom, 10th March 2008, proceed in the 'Internal control' section of Barclays report they repeat the assertion that they provide 'reasonable assurance against $$ material misstatement or loss'."

On page 148 of Barclays, Annual Report 2007, the auditors use the same boilerplate stating that: "internal control systems obtain reasonable assurance about whether the financial statements are free of material $$ misstatement" (Barclays, 2007).

2.4 Implying that CDOs are safe assets and understating the toxic inherent risk

In the 'corporate bonds' section Barclays Annual Report of 2007 it states that "corporate bonds are generally valued using observable quoted prices or recently executed transactions. Where observable price quotations are not available, the fair value is determined based on cash flow models where significant inputs may include yield curves, bond or single name credit default swap spreads". They never mention any of the reports on the internet concerning the toxic paper and the debate in the press.

In the 'Derivatives' section of Barclays 2007 annual report, further explanations are that... "derivative contracts can be exchange traded or over the counter (OTC). OTC derivative contracts include forward, swap and option contracts related to interest rates, bonds, foreign currencies, credit standing of reference entities, equity prices, fund levels, commodity prices or indices on these assets. For many pricing models, there is no material subjectivity because the methodologies employed do not necessitate significant judgment and the pricing inputs are observed from actively quoted markets, as is the case for generic interest rate swaps and option markets. In the case of more established derivative products, the pricing models used are widely accepted and used by the other market participants", implying that they are safe assets and understating the toxic inherent risk.

2.5 Misrepresent reality by applying 'Monte Carlo simulation is used rather than analytic approximation' where totally unrealistic assumptions can overstate the performance and understate the toxic paper true risk exposure

In Barclays (2007) Annual Report in the 'Structured credit derivatives' section of the report states that: "collateralised synthetic obligations (CSOs) are structured credit derivatives which reference the loss profile of a portfolio of loans, debts or synthetic underlyings. The reference asset can be a corporate credit or an asset backed credit. For CSOs that reference corporate credits an analytical model is used. For CSOs on asset backed underlyings, due to the path dependent nature of a CSO on an amortising portfolio a Monte Carlo simulation is used rather than analytic approximation. The expected loss probability for each reference credit in the portfolio is derived from the single name credit default swap spread curve and in addition, for ABS references, a prepayment rate assumption.

A simulation is then used to compute survival time which allows us to calculate the marginal loss over each payment period by reference to estimated recovery rates. Significant inputs include prepayment rates, cumulative default rates, and recovery rates". Again, they misrepresent reality by applying 'Monte Carlo simulation is used rather than analytic approximation' where totally unrealistic assumptions can overstate the performance and understate the toxic paper true risk exposure In the 'derivatives' section the report continues to confuse the issues and understate the risk by saying that "derivative contracts can be exchange traded or over the counter (OTC). OTC derivative contracts include forward, swap and option contracts related to interest rates, bonds, foreign currencies, credit standing of reference entities, equity prices, fund levels, commodity prices or indices on these assets” (Barclays, 2007).

So one can see, history does seem to repeat itself. Financial reporting could not always portray the financial health of the markets. Sub-prime mortgages, CDS and CSOs overstated the revenues of the financial services industries leading to the stock markets meltdown of October 2008.

2.6 Net Sales/total assets estimating 10% inflated net sales and receivable, to increase gross profit and stock market values: a simulated banking fraud software case study

2.6.1 Overview

This study finds the ratios net sales/total assets, SG and A/sales and net sales/employees as the best predictor percent differenced financial ratios (BP%DFR) and most effective in constructing a fraud cost model. These BP%DFR variables are estimating 10% inflated net sales and receivables, to increase gross profit and stock market values fraud value. We use these variables to build a regression model. This is a case study of fBarclays Bank PLC (f = fictitiously simulated fraud, contrary to r = real) and the commercial banks. We decompose fraud values into fixed fraud (FF), variable fraud (VF) and their sum mixed fraud (MF), building a regression model for each component. Thus, we develop a cost function (CF) for each component, fixed fraud cost function (FFCF), variable fraud cost fraud (VFCF) and mixed fraud cost function (MFCF).

Our goal is to simulate a fraud (SF) on the net sales item which is the first account in the income statement. We balance this 1st account against the receivables account, the 2nd account. The FF remains fixed starting from the 1st period, 12/31/85, to the last period, 12/31/94, at $1,318,800. We have calculated the FF as greater than 10% of the 1st primary SF account or 1% of net sales. Add the FF to the VF and you get the MF for the last year $2,637,600. Add this MF to the initial balance of the 1st account, the real account balance. This rNET SALES balances $13,188,000, for the last period of this study. This way, you get the phony (f = fraudulent) balance of 1st account, fNET SALES, $15,825,600. Likewise, for the 2nd balancing account, start with the real balance, (r prefixed account), $115,356,000, combine the SF, $2,637,600 and you get the phony value (f prefixed) of the fRECEIVABLES balancing the SF at $117,993,600.

We difference (deduct) the fNET SALES (fraudulent, post SF) from the, rNET SALES (real, pre SF), calculating the SF dollar values. Likewise, we difference all the financial ratios (%DFR), to identify the fraud drivers. We regress the SF dollar values on the %DFR, to discover the best [highest R-square (RS)] predictor percent differenced financial ratios (BP%DFR). In this case, these (BP%DFR) include: net sales/total assets, SG and A/sales and net sales/employees.

2.6.2 Introduction of %DFR

According to new securities legislation, auditors will need to report more quickly than at present any suspicion of fraud. A tougher approach is also coming from the auditing standards board of the American Institute of Certified Public Accountants (AICPA, 1988). The new standard will require external auditors to be more aggressive in not only reporting but unearthing fraud and faulty financial statements. Failure to comply with the institute's measure will include civil penalties and possible loss of a CPA's license. These proposed standards will have auditors spotting higher risk of fraud to develop specific plans to eliminate that risk. The board has been considering stiffening auditing standards for several years as research showed that current standards were not tough enough on discovering major frauds (Berton, 1996). Congress has also considering a bill would create a Financial Services Oversight Council made up of the Treasury secretary, the Federal Reserve chairman and heads of regulatory agencies to monitor the financial markets for potential threats to the US system. It would identify firms and activities that should be subject to heightened standards, including requirements that they place more money in reserve. Companies would have to plan for their own demise, detailing how they would be dismantled if they failed (Kuhnhenn, 2009).

This study defines the %DFR as a predictor variable for estimating the value of fraud. We are developing several theories and applying other theories to design this study. The reversed accounting theory (RAT) contends that to discover fraud, we have to go from the final financial statements, in reverse, to the original fraudulent transaction. To pick the proper methodology, we are applying activity based costing (ABC) to RAT and fraud, developing a derivation of ABC, activity based fraud (ABF). ABF contends that like any other cost, fraud originates from some activities. Since we do not know what these activities are, we could use highly correlated surrogates to these activities to act as fraud drivers. These %DFR are such drivers.

We intend to supplement existing expert systems (ES) software that can discriminate between fraudulent and fraud free companies, but cannot pinpoint the amounts and the accounts. Integrating such a model into these ES, will extend their abilities beyond current technology. Such extension will enable the ES to quantify the fraud and flag its sources (accounts). The supplementary nature of model we develop explains its limitations. This model is not for discovering fraudulent companies, since it will be redundant to the existing ES. Thus, we optimise it for a relevant range, that outside the vicinity of the origin, where both the %DFR and the fraud approach a value of zero. Therefore, we hypothesise that the intercept will be statistically insignificant about the origin, which it turns out to be. In contrast to the insignificance of the intercept, we hypothesise that the entire model will be significant, as well as at least one PERCENT. Indeed, the analysis of variance (ANOVA) confirms our expectations, rejecting the null hypothesis that the model is insignificant and that the regression coefficients are equal to zero.

Since we intend to use it ultimately on a fraud suspect (a company that ES has identified), we refer to that company as the focus company. In contrast, the industry or competitors' ratio averages constitute a fraud free peer review group (PRG). We calculate the percentage as the ratios of the focus less the peers divided by the peers. These assumptions that fraud is the single difference between the focus and the peers highlight the limitations of this approach. These limitations exclude heterogeneous industries where companies are not very similar, as well as countries where fraud (e.g., bribes) is part of doing business and generally accepted accounting principles and auditing standards (GAAP/S) are rare.

We search for the ratios that will maximise the correlation between the %DFR, the predictor variable(s) and the SF, the predicted variable. We find that these ratios can help in auditing, detecting and deterring fraud, as well as help develop rules for the ES software for analytical review (ARES). We apply it to one company and one industry, but design it to be more generic, so we can expand it to other companies and industries

(Rushinek and Rushinek, 2000, 2003). This study simulates fraud (SF) in the financial statements. This SF combines VF and FF into an MF. We regress, correlate and decompose such an MF into its VF and FF components. We compare accounts, ratios, periods and companies. We regress a focus company with SFs on its PRG average (assumed to be without the same MF). We apply RAT to ES software and then test the hypothesis that RAT can decompose MF and help in flagging the MF's riskiest financial ratios. Eventually, the riskiest ratios will be part of the riskiest accounts.

Applying RAT, we decompose the MF into its VF and FF components. To decompose the MF, we regress it on sales. We define the FF as regression's intercept and the VF as the regression's slope. Using the least square regression, we construct the MF function. We forecast sales as a function of serial date, testing this date as a surrogate for sales, whenever it is a good predictor of sales. We construct a statistically significant fraud model. This study calculates risk for analytical review diagnostics controls for automated personal computer (PC) expert systems (ARES) based RAT. We integrate RAT and the decomposition of this MF into the design of ARES, demonstrating some rules, screen and reports that will result from applying these ideas. By scanning financial statements and their ratios and regressing them against the peers, averages the ARES could fire some rules. These rules will quantify the risk of the likelihood of over or under stating balances of accounts, helping auditors plan their audit. We could use such risk measures to allocate audit time to accounts.

Likewise, such fraud coefficients help the ARES prioritise its output and rate its opinions (related to problems in different accounts: phony sales ore receivable) from the most to the least risky accounts. Thus, the ARES could minimise over loading the user with reports that they cannot process. This way the users can limit the ARES to report only on the top most risky accounts and/or ratios, or pages of reports. This will relieve the users from evaluating hundreds of accounts and ratios. This is especially true when the users are not knowledgeable, do not have the resources to conduct such an evaluation, and cannot set apriority the materiality level. This could facilitate the deployment of ARES for inexperienced managers and auditors. Next, we would like to define the SF and some of its assumptions.

2.6.3 ABC and cost and management accounting theory (CMAT)

Applying ABC theories to fraud, we develop the ABF theory. ABF treats fraud as a cost that we want to trace back to the activities that generate it, much like any cost. Except that for fraud, that unlike traditional costs, which we simply want to minimise, we want to completely eradicate and eliminate, approximating a zero level fraud. To calculate the cost effectiveness of fraud controls, we have to estimate it (since criminals never report frauds voluntarily – unlike other costs), decompose it, leading to the activity sources. For that purpose, we deploy the RAT to trace the fraud back to its sources as a step to eliminate such fraud. Our unique contribution is going in 'reverse' to traditional auditing. Instead of going from the individual transactions to the financial statements, we go in reverse, from the financial statements trying to reconstruct fraudulent entries. Hence, we develop the concept of RAT. Much like reversed engineering, RAT goes in reverse to the common sequence of accounting work. We test the hypothesis that RAT can construct a statistically significant fraud function.

We deploy the CMAT and define VF, FF and MF, as well as develop software integrity controls. CMAT suggests that the slope of mixed cost (MC) regressed on the sales denotes variable cost rate (VCR). Likewise, the intercept of MC regressed on sales estimates the fixed cost (FC). Similarly, our dollar SF regressed on the sales has a slope and an intercept. This slope shows the variable fraud rate (VFR), which is analogous to the VCR. Likewise, the intercept (of the SF on sales) shows the FF, analogous to the FC. RAT contends that whenever we are dealing with unknown fraud. Decomposing this fraud (into its fixed and variable components) will be helpful in classifying its behaviour and eventually pinpointing its sources.

3 Fraud simulation (FS) definition

3.1 fBarclays Bank PLC net sales – FS definition

3.1.1 VF, FF and MF definition

The 10% SF of the net sales primary (1st) account is balanced against the SF of the secondary (2nd) balancing receivables account. The FF remains fixed starting from the 1st period, 12/31/85, to the last period, 12/31/94, at $1,318,800 amount. We have calculated dollar fraud amount as 10% higher of the 1st primary SF account or 1% of net sales. Add the FF to the VF and you get the MF for the last year $2,637,600. Add this MF to the initial balance of the 1st account, real, rNET SALES balance $3,188,000, for the last period. You get the phony, fraudulent, balance of 1st account, fNET SALES, $15,825,600. Likewise, for the 2nd balancing account, start with the real balance, rRECEIVABLES, $115,356,000. Then, combine the SF, $2,637,600, and you get the phony balance of the fRECEIVABLES balancing that SF at $117,993,600. Our question is which ratio is this fraud's top predictor?[1]

3.2 fNET SALES fraud, why would criminals create it and what predicts it?

The objective and the result of such a fraud may be the inflated net sales and receivables, to inflate gross profit and stock market values. However, this may not explain why a criminal would do it in a certain way. We could understand the possible purpose of such a fraud by looking at the financial results. An fBarclays Bank PLC Executive working in the commercial banks industry (COB) may want to raise net income (reduce loss), credit ratings, commissions, or promote his or her reputation. For example, a fraud that overstates the sales balance, will in turn overstate the net income. Overstating net income will make the company appear to be more profitable. Such an overstatement of the sales and profitability of the company may benefit employees who own stock options, and/or commission employees. An overstatement of sales may easily translate to a pay raise, for certain employees. Misclassifying long term (LT) assets as current assets, can improve the credit rating of a company. However, such a fraud may not affect the income statement at all. We expect to find a ratio that can forecast such fraud.

3.3 10% fNET SALES fraud: account and amount

A fraud perpetrator may prefer to misstate an account with a balance greater than zero. It is possible, that overstating an account with a positive balance may appear a bit easier to conceal, compared to an account with a zero balance. In the case of fBarclays Bank PLC, and the COB, the rNET SALES (r = real) account, is more likely to have a positive balance, compared to other companies and industries. An account such as cost of goods will have a positive (debit) balance. Unlike some other accounts, such as investment gains/losses, this is equally likely to have either balance, positive (debit), negative (credit). Likewise, it is most likely to have a zero balance in a non-banking or finance environment. Once we have picked up an account, the next question is concerning the amount. The criminal (the perpetrator of the fraud) may not know in advance what the normal balance of the account should be at all times. Therefore, a fraud that is a percentage of the real balance may appear safer (easier to conceal, automate and harder to detect) choice. Likewise, small percentages such as 10%, as used in the present case, may appear to be safer than larger percentages. If the 'criminals' got away with the fraud for one period, their greed may lead them to try it repeatedly. Therefore, a multi-period fraud is likely.

3.4 The real peer company rNET SALES (source account) and its phony (f) partner[2]

The common criminal would make a fraudulent entry, where the debit and the credit do balance. Accounting software may prevent unbalanced entries. Such entries may also be too obvious and too easy to detect. Therefore, to supplement the present fraudulent entry, the criminal should make a balancing entry in other accounts that normally balance the source account. Such an account could be the (focus company) fRECEIVABLES. Such an account normally couples the source account, in this environment. Furthermore, it is not as easily verifiable as the cash account, for example. Since it is much easier to verify the balance of the cash account and to detect phony balances, the criminal may prefer to use accounts other than cash, for the phony entries. Likewise, auditors are usually less likely to audit it as compared to the cash account. The peers (fraud free) less the focus company balance is the fraud.

RAT will help us pinpoint the source of the fraud and estimate its damages. This should help us detect it, if we can possibly classify it correctly (variable versus fixed). For example, if the fraud positively correlates with sales, or varies proportionately with the sales account, that gives us a clue as to which account actually contains this VF. Such a fraud most likely originates from sales itself, or one of its derivatives, such as sales commissions. In contrast, we can more easily eliminate fraud sources that typically do not vary with sales, such as fixed assets and depreciation frauds of all kinds.

3.5 Activity base cost/fraud (ABC/F), short and long runs and regression analysis

The developments in ABC since the late 1980s have improved accounting information systems. However, no one has ever applied ABC to fraud, which is the focus of the current study. Applying ABC to fraud produces ABF. The literature covers other extensions of ABC to management, or activity based management (ABM), but not to ABF. Hartnett and Lowry (1994) predict total cost for change in product mix. We are also trying to predict costs, except that we predict the cost of fraud damages as a function of fraud mix (VF, FF and MF). Holmen (1995) suggests that ABC has primarily a long-run horizon. Therefore, we apply it to long-run fraud estimation problems, frauds that continue for one year and usually much longer. Macintosh (1994) suggests that in the 'scientific ABC' method, the designer uses multivariate regression analysis.

Hartnett et al. (1994) confirm that ABC supplies better approximations of long-run variable costs. This is one of the reasons that we are focusing strictly on long-term frauds. Likewise, we suspect that ABF may also lead to similar results; it may supply better results in the long run, rather than short run analysis. Even if we detect no material fraud, just by estimating the fraud, we may reduce its damages by acting as a deterrent. There are, however, obstacles to using ABF, much like ABC in reporting. Such obstacles include applying standards rather than actual values, subjectivity and verifiability in the choice of cost-drivers and ABC or ABF integration into the nominal ledger. We use the pre-fraud as surrogates of fraud free standards, normally based on competitors' financial statements. The problem is that selecting proper competitors is subjective and may vary greatly depending on the industry, economy and other variables.

Pattison and Arendt (1994) implemented a modified ABC system. We have modified ABC so much that we have to rename it ABF. It is too different from ABC, to retain the same name. Sheu and Wacker (1994) integrate time series forecasting and ABC analysis. Similarly, we are doing the same thing. We also integrate time series into ABF. Datar and Gupta (1994) suggest that an ABC generates more accurate product costs than other systems. For a similar reason, we hope that ABF will generate more accurate fraud cost estimates than other systems. Groth and Kinney (1994) suggest ABC and cost driver analysis may reduce business risk, promoting value creation in a firm. Similarly, we contend that ABF and its cost drivers may help reduce fraud risk. In a counter sense, fraud cost management not implemented properly result in an intensified eradication of value. These reasons attest to the importance of studying fraud costs in value creation. This may ultimately lead to a cost benefit analysis of fraud eradication investment.

3.6 ABF as a control for LT fraud and as a function of sales

Mak and Roush (1994) argue that ABC controls costs. Likewise, we feel that ABF controls. Under one proposal, they formulate flexible budgets for each activity using the cost driver for that activity. We are using sales or some of the financial ratios as the surrogate cost drivers of the fraud in order to develop an estimation method. In the future, we may try other cost drivers. Smith (1995) extends ABC to a management context and calls it: ABM. Similarly, we extend ABC to ABF. Our extension is a bit less radical in the sense that we can view fraud as a cost category, while management is a much broader concept than cost alone. We all agree that most of the emphasis in the literature, thus far, has been on costs (ABC) and quality (total quality management). We also consider other areas and factors. A time-based focus has a number of positive implications for the management accountant in designing improved management information systems. This ensures that decision-making is linked to an appropriate time horizon by matching short run and long run costs with decisions. For these reasons, we focus on the long run in the current model, reserving the short-run for future studies.

3.7 Literature of fraud, damages, detection ES and disclosure

A major problem in fraud detection is the lack of education on the part of those who must detect it (Rushinek and Rushinek, 2000, 2003). Some early warning signs may be found by parsing financial statements (Rushinek and Rushinek, 1997). We combine an SF educational approach with parsing financial statements to find the best fraud predictor as warning signs in our ABF theory. Redirected cash flows, the wrong receivables or the wrong disbursement location is a common early warning sign of a cash fraud (Rushinek and Rushinek, 2007). Employees commit the overwhelming majority (90.8%). Although at a much lower rate, executive fraud is only 26% (Campbell and Lindsay, 1994). Therefore, SF deals with an employee fraud, such as a cash fraud. The Financial Fraud Detection and Disclosure Act, requires exception reporting when control systems fail, such as material financial frauds (Campbell and Lindsay, 1994). Neural networks can help to find patterns and relationships, even obscure and non-linear relationships (Rushinek and Rushinek, 2007). In our SF the relationships are fairly linear; therefore, we use linear regression. One way to combat management fraud involves analytical procedures (AP). Quantitative APs alone will not detect fraud; they simply signal the likelihood of a problem (Calderon and Green, 1994). This is where our model comes in. Our model actually estimates the dollar damage of the fraud, after the AP signalled a high likelihood of a problem (Rushinek and Rushinek, 1997, 2001).

4 Overview and definition of problems

The problem is that we do not know how to eradicate and prevent fraud. In addition, we do not know even how to estimate fraud and how to trace its sources, which may be a prerequisite to prevention. Estimating fraud and tracing it back to its initial transaction is the focus of this study. To find the initial fraudulent transaction we developed the RAT. RAT states that, unlike ordinary accounting, where we start from individual transactions and conclude with summarised financial reports, the reversal may be more effective for fraud estimation and definition. Thus, RAT starts from the summarised financial reports, which may be conceal fraudulent transactions, concluding with estimating the value of the fraud and defining the fraudulent transaction.

To define the culprit transaction, we use the %DFR, such as the dollar sales per employee or quick ratio, instead of the original accounts, such as cash or inventory. There are some advantages to using %DFR instead of using the original accounts. There are fewer %DFRs (dozens) compared to the original accounts (hundreds). The process of eliminating the irrelevant suspects is easier. The %DFR are much more standardised and uniform across times-series, companies and industries, than the original accounts themselves. The relative (percentage) unit of measurement is more comparable than the original unit of measurement (inter or intra company or industry or currency comparisons of $ sales per employee to the quick ratio)

Our accuracy of spotting and forecasting the existence of frauds is ‘extremely good’ (Fanning et al., 1995; Coates and Fant, 1991). Likewise, we know what the red flags that indicate perpetrated frauds are (see Pincus, 1987). This sounds sufficient to scare auditors about being held liable for not reporting the fraud (AICPA, 1988). Yet, such indications are much too vague to enable auditors, prosecutors, or managers to pinpoint the fraud. We still do not know how to estimate that fraud, what activity generates such frauds and which transaction initiates such fraud. We think that if we can figure out the activity that generates the fraud, we should be closer to tracking the fraudulent transaction and eventually the culprits themselves. For that we propose an ABF theory.

We view fraud as a cost item. Fraud is certainly not a revenue item, nor is it a liability, assets or an equity item. Therefore, it is most similar to cost items, even in the sense that we are undoubtedly trying to minimise fraud (at least in theory). In fact, fraud may be the oldest cost, from biblical times, yet we do not estimate and account for it like any other cost. Fraud is currently the leading cause and cost of auditing litigation (Palmrose, 1991; St Pierre and Anderson, 1994). Auditors have changed the way they operate due to the increase of litigation (O'Malley, 1993; Elgin, 1992; Fuerman, 1992). Auditors charge escalating fees to fund such litigation risk.

Based on ABC theories, every cost originates from some activity. Such activity is the cost driver, which are among the best cost predictors. Therefore, if we can treat fraud like any other cost, we may apply ABC to fraud. Like any other cost, certain activities produce fraud. Therefore, it only follows that like any other cost, every fraud may have its own drivers, which are its best predictors. We try to develop a method of identifying these drivers for specific types of fraud, using ABC methods.

Unlike any other costs that are legal, fraud is illegal. Therefore, we cannot simply use traditional transaction-to-financial reports accounting. Thus, we deploy the RAT approach and combine it with ABC. From this, we create the activity base fraud (ABF) theory. ABF states that if we can find the BP%DFR, we will be further along the way of estimating the fraud, its drivers and eventually it original culprits. Furthermore, by just deploying ABF, it may act as a deterrent to fraud. Just as we are using standards to cost the unknown overheads, we may eventually also use standards to cost the unknown frauds.

We have some red flags that fire up whenever the likelihood of multi-year fraud rises. Others have clearly defined such flags (discussed above), so that not only an auditor could use it, but also a computer base ES could use it, while it is emulating an auditor. Our current objective is one step further, to estimate the amount of the fraud and its original transaction or activity that created that transaction.

For this purpose, we have simulated multiple frauds (SF) on the financial statements of this company. The SFs include increasing net income over the last few years. Thus for example, we could have overstated sales and understated all the expenses by 10% of their values. At the same time we have also entered a balancing entry, so that the debit and the credit remain balanced and do not obviate the frauds.

We have then benchmarked the SF company against its own financial ratios prior to the SF. We use that to emulate how a real fraud ridden company may compare to its peers, which are not involved in the same type of frauds. This way we hope to identify a methodology of spotting red flags and patterns to detect and deter fraud.

4.1 Overview of banking industry

At the nation's 11,970 FDIC-insured institutions, total assets grew $84 billion from September 30 to December 31, compared to growth of $90 billion during the fourth quarter of 1994. Fourth-quarter asset growth was funded to a greater extent by deposits in 1995 than in 1994. Total deposits increased $96 billion during the fourth quarter of 1995, with most of this growth occurring in domestic deposits at commercial banks, which were up $91 billion. In 1994's fourth quarter, by comparison, total deposits increased $70 billion, including just $42 billion in domestic deposit growth (Helfer, 1995).

The reserve ratio of the Bank Insurance Fund (BIF) was 1.30% of insured deposits on December 31, down nominally from 1.31% on September 30 but still above the statutory minimum of 1.25%. The reserve ratio of the Savings Association Insurance Fund (SAIF) rose from 0.43% to 0.47% during the fourth quarter but remains far below the target level of 1.25%. As a result of the BIF's full capitalisation, the FDIC was able to reduce BIF assessment rates twice in the latter half of 1995. The average BIF assessment rate fell from 23.3 cents per $100 of assessable deposits to just 0.4 cents (effective January 1, 1996), improving the attractiveness of BIF-assessable deposits relative to other funding alternatives. Because SAIF assessment rates cannot be lowered significantly until the fund is fully capitalised, the average assessment rate for SAIF members remains at 23.7 cents per $100.

1 This premium disparity between the BIF and the SAIF may partially explain deposit growth patterns in 1995. Deposits assessable by the BIF grew $110 billion (4.6%) during 1995, with $83 billion of the increase coming in the fourth quarter. Deposits assessable by the SAIF grew $20 billion (2.8%) in 1995 but decreased, by less than $1 billion, in the fourth quarter.

2 Other factors, such as loan demand, also may affect deposit growth patterns (Helfer, 1995).

4.2 Barclays Bank company profile

Group profit before tax improved by 1,198 m as a result of a decline in provisions for bad and doubtful debts. Of this reduction, 856 m occurred in the UK, where new gross specific provisions were 791 m and 309 m in the USA, where new gross specific provisions were 97m. Although falling significantly, non-performing lending remained at a high level, particularly in regard to the UK property, construction, hotel and leisure sectors. As a consequence of work that is being undertaken to improve the assessment of credit and credit losses throughout the business, the general allowance to cover unidentified bad debts has been increased by 74 m to 850 m (Barclays, 1994b).

Profit before tax showed a significant improvement over the two previous years as budget debt provisions fell, helped by releases in the UK and the rest of Europe. The reduction in provisions was achieved despite one large corporate provision of 65 m in Europe and further provisions in Canada (Barclays, 1994b).

4.3 Future of Barclays Bank Company

The trust company profit for the year was adversely affected by an ongoing reorganisation process, the result of which will be to improve efficiency and customer service in the future. Most of the group's trading activities are customer oriented. In anticipation of future customer demand, the group maintains access to market liquidity by quoting bid and offer prices with other market makers and carries an inventory of capital market instruments including a variety of derivative and non-derivative (or 'cash') financial instruments. Positions are also taken in the interest rate, foreign exchange, debt, equity and commodity markets based on expectations of future market conditions. These activities constitute the proprietary trading business of the group. Given the relationships between instruments and markets, trading strategies depend on both market-making and proprietary positions and are managed in concern in order to maximise trading related revenue. Trading positions and any offsetting hedges are established as appropriate to accommodate customer or group requirements (Barclays, 1994a).

5 Methods and procedures, data analysis and interpretation

5.1 Data definition, input and output of regression analysis theories

5.1.1 Differenced financial ratios (DFR) measure fraud impact and identify fraud insensitive ratios

We download the company profile, annual report and financial ratios from the disclosure database and then upload them into our fraud simulator spreadsheet software programme (the programme). The programme recalculates all these financial ratios verifying their values and extending their decimal point. Then the programme applies the SF to the recalculated and verified annual report, producing a second set of phony fraudulent fAnnual reports. The programme inputs the fAnnual reports to the financial ratio calculation and produces a second set of phony fraudulent financial ratios. The difference between the 1st real financial ratios and the second fraudulent financial ratio produces the DFR. Such DFR measures the effects of a fraud on that particular ratio. If the DFR equals zero, then we can conclude that a particular fraud does not affect it. Likewise, if the DFR of another ratio also equals zero, then we can conclude that like the 1st ratio, the same fraud does not affect the second ratio. Thus, both ratios are insensitive to this fraud. The DFR is only comparable when it is zero. When it is different than zero, we cannot use it effectively for comparisons.

5.1.2 Fraud damage cost estimating software programme (FDCESP) and DFR/%DFR two stages

Due to the difficulty that computers have in calculating divisions by zero, it is sometimes necessary to initially use a measure like DFR. In developing an FDCESP we have to be considering such issues. Since we want to extended current ES technology with such an FDCESP system, we have to consider machine difficulties. Furthermore, since we typically want to minimise computer resources and maximise efficiency, we would use DFR as well as %DFR. We have to calculate DFR before we can calculate %DFR. Therefore, we will also use it in our FDCESP development as a two stage process. The programme will first calculate and use DFR, if it can choose the most sensitive ratio. If it can decide at this stage, it can then store its decisions in a case based reasoning knowledge base (CBEKB). The programme needs to go no further. It does not need to calculate %DFR. This may be a case where the DFR will be zero, anyway. Therefore, we do not need to calculate %DFR for a decision. Furthermore, the attempt to calculate it may result in a division by zero error, creating all kinds of problems.

5.1.3 Case based reasoning knowledge base (CBEKB) and ES

In this context, a CBEKB is a data base of fraud cases and its related decisions. Such CBEKB can be a part of an ES that issues fraud detection, damage estimation, investigation and prevention opinions (Rushinek and Rushinek, 1993, 2007, 2008). Such opinions will rely on a cost benefit analysis comparing the benefits of fraud damage reduction to its costs. This is where FDCESP integration fits. For a system like this to work, identifying a few best predictors of fraud value could be very useful. These variables will be the BP%DFR.

5.1.4 BP%DFR flags fraud patterns

BP%DFR variables will estimate the dollar (or other currency) value of damages. Such analysis should be done when existing ES predict that the financial statements do contain fraud, and the main question is which kind of fraud is it? Is it a credit sales and fixed assets fraud? Is it a credit sales and accounts receivable fraud? This is where various BP%DFR can red flag the various types of frauds that may be present. As we can reasonably expect, different ratios will become BP%DFR for different types of fraud. For example, if the fraud pattern appears to have fixed values over time, then it may be a FF. It is more likely to originate in fixed assets accounts rather than in a sales commission account. In contrast to FF, a VF is more likely to originate in a sales commission account or may be in a direct labour cost type of account. Likewise, an MF may be split over both types of accounts, etc. Furthermore, this BP%DFR will estimate the total dollar amount of the fraud telling us how many resources will it justify and most importantly which accounts are the culprits.

5.1.5 Regressing fraud values on BP%DFR

Regressing fraud values on BP%DFR will help build a model to estimating fraud values. To set up the data for such a regression analysis, we split the data into two parts. The first part constitutes the pre-fraud condition. Naturally, for these observations, the independent predictor variables, the BP%DFR, as well as the dependent predicted variable, the fraud values, are both zeros. In an experimental simulation, that is certainly true. This is saying that if no fraud what so ever exists, then the pre-fraud and the post-fraud ratios will be the same. Thus, the BP%DFR, as well as all other differenced ratios, must equal zero. In contrast, in the real world, if no fraud what so ever exists, then the peer review company, or companies and industry averages (like pre-fraud, free fraud) and the focus company (like the post-fraud, fraud ridden) ratios will not necessarily be the same. However, they may approximate identity, if the peers are almost identical to the focus company. Although, identity between a focus company and its peers is very unrealistic condition, there are ways to approximate such condition, by statistical and mathematical means. Such methods are beyond the scope of the present study, however, we will discuss them briefly later and in future studies. The second part of these observations will typically be different than zero. These two parts will make up two parallel time series, first is time series without fraud and the second one with fraud. Using these two sets of time series in parallel, makes this analysis a cross sectional and time series regression analysis.

5.2 Data input for the regression analysis: its empirical aspects

5.2.1 Net sales/total assets top Barclays Bank PLC predictor ratio[3]

For the top predictor, X1 BP%DFR, X1 = net sales/total assets, we compute the second part of the positive fraud observations, as follows. Following are steps that calculate some of the predictor variables' values, such as X1, X2, etc. We start with the first variable, X1. The fraudulent, phony, fNET SALES/TOTAL ASSETS has a value of

0.13049. In contrast, the real, rNET SALES/TOTAL ASSETS, has a value of 0.10669. To difference, one needs to deduct the fraudulent from the real balance. The difference can be the gain in NET SALES/TOTAL ASSETS of 22.307620%. This percentage loss (–) or gain (+) in the ratio due to the fraud is the value of X1, the 1ST BP%DFR independent predictor variable. Applying the same process to SG&A/SALES, and NET SALES/EMPLOYEES, you calculate X2 = SG&A/SALES and X3 = NET SALES/EMPLOYEES, the additional BP%DFRs. Calculate the dependent predicted variable, Y = NET SALES, as the MF, sum of FF and VF and you are ready to regress it on the BP%DFRs.

The MFCF is calculated by regressing VF, FF and MF on net sales. Start with VF. We classify such a VFCF as a case of pure VC definition. Continue with FF. The FF regression has an intercept of $1,318,800.00 and a Slope of 0.00%. We classify such a FFCF as a pure FF definition. Proceed with MF. The MF regression has an RS of 1, an intercept of $1,318,800.00 and a slope of 10.00%. We classify this MFCF as a pure MF definition. Now, instead of regressing the sum, MF = VF + FF, try adding the intercepts and slopes of the separate VF and FF regression, producing a 2nd redundant, but independently calculated intercept and slope. Deduct the independently calculated intercepts and slope.

Theoretically, for a pure VF definition, the intercept should be a perfect zero, but that may change due to rounding errors. A gross VF definition may cause an error, if we define the VF as a percentage of a primary account (not perfectly correlated with net sales). Such an account may be LT assets. The FF should be the exact complement (mirror image) of the VF, a slope of zero and an intercept that is positive. At the same time, the VF should have the opposite values, zero intercept and a positive slope. Their sum, MF, should have both positive intercept and slope. Likewise, we made MFCF by combining the separately regressed VF and FF. These two functions (VF and FF) should have the same two regression parameters (intercept and slope). Much like, the single MFCS regression, it should also have an intercept and slope. These redundant calculation controls demonstrate how to promote software integrity. Classify and decomposing fraud into its parts will help detect, measure and ultimately minimise fraud damages.

The RS shows the statistical quality of this model, which we will discuss later. Such MFCF can estimate fraud prevention benefits. It traps error by comparing actual and expected results. Thus, the growth rate and variance of FF should be zero. If it indeed is zero, then we may have avoided this error. In this case, these error values are equal to 0.00%. Even if it is not zero, it may be due to an immaterial error such as a rounding error, or an error in the database. This is beyond the scope of this study.[4]

ES exemplify regressions' rules. The ES can regress the estimated fraud values (estimated by our model) on the NET SALES account of the focus company. If the regression is significant, then the ES may reach some tentative conclusions, about the possibility of fraud. This can be true, if it turns out to be a case of a pure definition of VF, FF and MF. The ES further reinforces its conclusion that fraud may exist, estimating its CF structure, dollar estimates and probabilities. More analysis needs to be used to further reinforce such suspicions and eventually come up with an explanation to the fraud. ES show that explanations to the VF can include: 10% inflated net sales and receivables, to increase gross profit and raise stock market values. Our methods may help ES calculate risks and correctly interpret them. Are the ratios correct? At this point one cannot be sure if there is a fraud or not. This ES tests itself, using a value and sign test as internal controls of integrity and reliability.[5]

6 Summary output for Barclays Bank PLC[6]

The regression statistics sub-analysis contains the three parts. The 1st part is the multiple R, 0.999845. The second part is the lower RS, R**2, value of 0.99969. The third part, following the RS is the even lower adjusted R-square (ARS) of 0.999632. Multiple R is the correlation between the predicted and the actual values of the focus company, Barclays Bank PLC, the coefficient of correlation. These correlate the actual and the forecasted values of this SF.

6.1 Bank ES rules[7]

This regression analysis helps ES form patterns of rules for fraud classification. The ES will apply such rules to a suspicious bank, to classify its fraud. We will form the ES rule in a step by step fashion as we discuss the output 0.999632. Following is the 1st component of this rule, dealing with RS:

For the regression of the differenced account on the DFR:

If the Industry is equal to This Industry and the Suspicious Company R-Square is Equal To
Less than the upper bound of R**2: 0.99969, And
Greater Than the Lower bound of ARS: 0.999632 , And ➔

In practice this will be one large rule, for simplicity we break it into its components. Arrow heads indicate ➔ that the rule continues. A banking knowledge base system (KBS) will store these rules.

6.2 Multiple R (R) – internal software control, the sum of square (SS) and beta values

If the multiple R is equal to one, then a change in the value of X, the independent predictor variable, the BP%DFR predicts the dependent predicted variable, the focus company, Barclays Bank PLC BP%DFR, perfectly well. Otherwise, multiple R is different from one, and the prediction is less than perfect. The present multiple R of 0.999845 tells us that there is relatively strong linear relationship. The independent variables (the BP%DFR of Barclays) and the COB industry estimate the SF very well. This means that if the BP%DFR increases, then the SF is also very likely to increase as well, in this sample of data. If this is statistically significant, it may apply to other samples.

6.3 RS: variance in the SF explained by the financial ratios

Unfortunately, we cannot interpret R in more precise terms, since it is not equal to one. The RS, the coefficient of determination, may help us determine the meaning of the relationship of the population more precisely. ES would typically apply such relationship to the population of cases.

The multiple R (R), 0.999845 squared is equal to, RS, 0.99969. The RS should be lower than R, because we square a fraction. If RS is equal or larger than R, we most likely have an error. The RS is the coefficient of determination. The RS shows how the independent variable determines the dependent variable. The independent (predictor) variables are some ratios, the BP%DFR. In contrast, the SF is the dependent (predicted) variable. R shows that BP%DFR predicts the SF (in the focus company) very well, close enough to 100%. This way ES estimate fraud damage as a function of such BP%DFR, for a cost benefit analysis.

6.4 The ARS: a function of the R and the number of observations

The ARS, 0.999632 is lower than both the multiple R and the RS.[8] We adjust the ARS for the degrees of freedom (df). The number of observations, 20, determines the df. This ARS tempers the strength of the R, which may be unrealistically high, especially if we have a small number of observations. To avoid overstating the strength of RS, we calculate the ARS. This difference between the RS and ARS will shrink as we increase the number of observations. We split these observations into two parts. The 1st half (ten observations) includes zero values of both the predictor financial ratios, BP%DFR and the predicted SFs. These zero values represent no difference in financial ratios in the absence of fraud. Thus, the difference between the fraudulent and the real financial ratios, as well as the SF itself is all equal to zero. The second half shows the differences in the financial ratios that explain the SF. In contrast to the origin values of zero, these later ten observations will usually differ from zero. Otherwise, we may not have simulated a fraud; we know this by definition and design.

7 ANOVA: testing the utility of the model

The difference between the RS and ARS will shrink as we increase the number of observations. If such differences exist, then, the ANOVA portion will explain them. Specifically, the SSE [sum of squared (SS, column) error or residual (row)], that is much greater than zero, explain some such differences. In our case, the value of SS residual is 1.1E + 10, which is very small and very close to zero, explaining the proximity of RS and ARS.

The ANOVA helps us evaluate the utility of the entire model. It tests individual coefficients allowing us to conclude that a linear relationship between the independent and the dependent variables exists. The ANOVA decomposes the variability of the dependent variable, The emulate fraud, measured by SS total, 3.55E + 13 into its components, the regression SS, 3.55E + 13 and the residual part, 1.1E + 10. If the SSR (regression) is large relatively to the SSE (residual), the RS is high – signifying a good fit and a good model, as is our present case. A value of F, 17225.41, shows the significance of the model. This F value is statistically significant at the 0.05 level. This means that the BP%DFR, Xs independent variables, explain the variation in Y dependent variable, the SF dollar amount for Barclays Bank PLC. Therefore, the model is useful for estimating the cost for this kind of fraud damages.[9]

8 ANOVA predictors-test of the intercept constant and the beta slope(s)

The test of the intercept and/or individual beta coefficients allows us to decide about the linearity assumption. We decide whether a linear relationship exists between the independent predictor financial ratios and their predicted dependent variable, the SF in the focus company, Barclays Bank PLC. Consequently, we perform the t-test for the intercept constant, –13.1994 and the predictor beta value for Barclays Bank PLC is –1E + 07. Our test criterion is the P-value.

To evaluate the statistical significance of the intercept coefficient, –13.1994, we compare it to its standard error. The standard err column, 8,288.838, for the intercept, along with the relatively small differences between the t-stat and the P-value columns, –0.00159 and 0.998749, confirm our notion from the theory. We cannot reject the null hypothesis, since this P-value, of 0.998749, is greater or equal to 0.05. Thus, we cannot reject the null hypothesis, that the intercept value is zero, concluding that it is zero, when the value of the other variables is also zero. Namely, in the absence of any differences among the financial ratios the model assumes no fraud. Therefore, the focus and the peer companies (DFR equal zero), at the origin, the forecasted fraud (intercept) must also equal zero. However, if we are farther away from the origin, the intercept can be used together with the other variables and then the entire model is statistically significant at the 0.05 level, as the ANOVA demonstrated. Thus, the origin and its vicinity are outside our relevant range. When we apply this model, we know that the fraud is greater than zero.

8.1 ES form patterns of rules for ANOVA and intercept's upper and lower bounds

Using the ANOVA bounds of the Intercept, the ES can continue forming the rules as follows:

➔If The ANOVA is statistically significant at the 5% level, & The Suspicious Company's Intercept is:
Less Than Intercept Coefficient Upper 95% Bound Of: 17558.35, And
Greater Than Intercept Coefficient Lower 95% Bound Of:-17584.7, And ==>

Expert Systems (ES) Form Patterns Of Rules For Predictor (Independent) Variables: The X1-3 Coefficients Or Slopes, & Their 95% Upper And Lower Confidence Interval (CI) Bounds

We will plug the X1-3 coefficients or slopes of the variables in the final regression equation. To complete the regression equation we need the residual. Therefore, we will do that in the after the residual output analysis. In the meantime, we can complete the fraud pattern ES rule, using the 95% upper and lower bounds of this variable together with the RS and the intercept, as follows:

=> the 1st Best Predictor is: X1 = NET SALES/TOTAL ASSETS , And
its Coefficient (Slope) value is Greater Than 95% lower Bound of: -1.5E+07;

The 2nd Best Predictor is: X2 = SG & A/SALES (same as above but for X2 Bounds), And
The 3rd Best Predictor is X3 = NET SALES/EMPLOYEES

Then, it is most likely due to a: 10% inflated net sales and receivables to increase gross profit and stock market value type of the perpetrated fraud.

At this point, the ES will also fire an explanation as to support its decision (Rushinek and Rushinek, 2001).[10] To complete the calculation of the estimated fraud, we need to include the residual value, in addition to the values of the financial ratios. Thus, we will replace the X symbols by their values, and add the residual to the sum, that should produce the SF in a given year. In contrast to the insignificant intercept, the slopes are all significant. Thus, we reject the null hypothesis that the slopes are all equal to zero. We can plug our parameters into the model after we figure out the residual value.

9 Conclusions

This study develops a 'finger print' definition for a specific class of frauds, with a specific rate, for the banking industry. The regression parameters define parts of the fraud finger print. Some of these parameters include such variables as the upper and lower bounds of the coefficients of the best fraud predictor variables, and its statistical significance. These finger prints define ES rules for a case based reasoning (CBR) knowledge base (KB). The KB should eventually contain all the possible combinations of fraud finger prints for the banking industry. We also define the fraud rate of over or under statements of financial accounts and its time periods, as well as its amounts and their pattern, since they may affect the fraud finger print. Such finger prints together with other fraud characteristics should help an ES diagnose fraud patterns by benchmarking a suspicious bank against its banking peers. The resulting anomalies will fire the ES rules that will help trace the source of the bank fraud.

It is evident that past market meltdowns could not rely on financial reports. The problem is the failure of financial reports to report a crucial fact: a company's actual financial condition. Ultimately, we intend to supplement existing ES software that will be able to discriminate between fraudulent and fraud free banks. Further research needs to create and test systems that will be able to flag and pinpoint the sources, accounts and amounts of bank frauds. This should be done in a preventive nature before financial firms are a threat to the system.

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Notes

1 We simulate a 10% inflated based fraud.

2 We use a real peer compared to a simulated phony partner.

3 This is a simulation predictor ratio.

4 This is an estimate of potential fraud prevention benefits.

5 Further studies need to test the reliability of the expert system.

6 The regression analysis is between the actual and simulated fraud data.

7 In this case the expert system uses real and simulated data.

8 Actual financial ratios and simulated ratios were used.

9 The model needs to be tested over extended time.

10 Experts will continually add their expertise to the system via the web.