CREDIT RISK MANAGEMENT, CASE STUDY

PRUDENTIAL BANK LTD

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DECLARATION

This thesis is a true work of the undersigned candidate and that it has not been submitted in any form to any organisation, institution or body for the award of any degree. All inclusions as well as references from works of previous authors have duly been acknowledged.

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DEDICATION

I dedicate this thesis to the late Madam Mary Maku Nyaunu, my mother.

She suddenly passed away when I was about to complete my first degree.

She could not live to enjoy the fruit of her labour.

May her soul rest in peace.

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Abstract

Technology has come to stay and its development is moving like the speed of light. Ghana, being the gateway to Africa, has necessitated the use of high level technology to enhance the turn-away time involved in all business transactions. To increase the efficiency of processing time and to meet the demands of time-sensitive customers, lending institutions must make decisions in real time or near-real time. Large banks have been utilizing credit scoring techniques to quickly and accurately assess the risk level of clients. Increasingly, midsize and smaller organizations are appreciating the need for credit scoring as well.

There are various statistical and mathematical models employed in credit scoring. In this thesis, we formulated the logistic and probit regression models to predict the probability of default of loan applicants. We used real data set (financial ratios) from a Ghanaian bank to formulate the logistic and probit regression model. At the end of the study, we found that the institution from which data was obtained can rely on current ratio, quick ratio, net profit margin, total assets turnover ratio, net sales increase and current liabilities to net sales ratio, for their credit scoring decisions. How these ratios are used to help predict effectively, the probability of default has been discussed. It was recommended that the asymmetric information gap between clients and lending institutions be bridged. We also recommend that financial expects should organize seminars and training programmes intermittently to improve the skills of credit analysts. These will go a long way into improving credit risk management.

CHAPTER ONE

1.1 HISTORICAL BACKGROUND

The word "bank" is derived from the Italian word banco, a bench covered with a green stock tablecloth. The Jews in Lombardy made transactions regarding money and bills on benches in the market-place. When a banker failed, his bench was broken by the populace; and from this circumstance we have our word bankrupt [53].

In fact, the word traces its origins back to the Ancient Roman Empire, where moneylenders would set up their stalls in the middle of enclosed courtyards called macella on a long bench called a bancu, from which the words banco and bank were derived. As a moneychanger, the merchant at the bancu did not so much go into investment. The merchant merely converted foreign currency into the only legal tender in Rome—that of the Imperial Mint [52].

But while this is the derivation generally accepted, some writers have asserted that a more accurate explanation of the use of the word "bank" is the one similar to the Italian Monte (Latin mons, metritis), a heap, or bank. Thus the Italian Monte di Pieta and the French Mont de Piete signify "a Charity Bank." Bacon and Evelyn use the word in the same sense. Bacon says: "Let it be no bank or common, but every man be master of his own money." Evelyn, referring to the Monte di Pieta at Padua, writes: "There is a continual bank of money to assist the poor." Black-stone also says: "At Florence, in 1344, government owed £60,000, and being unable to pay it, formed the principal into an aggregate sum called, metaphorically a Mount or Bank" [53].

The earliest evidence of money-changing activity is depicted on a silver drachm coin from ancient Hellenic colony Trapezus on the Black Sea, modern Trabzon, and c. 350–325 BC, presented in the British Museum in London. The coin shows a banker's table (trapeza) laden with coins, a pun on the name of the city [52].

In fact, even today in Modern Greek the word Trapeza means both a table and a bank [52].

1.1.1 Definition

A bank is a financial institution mandated by the Government to give financial services to clients. Some of these services include:

- giving out credit to clients
- accepting deposits from the public
- carrying out money transfers
- keeping valuables in save custody
- acting as trustees etc.

Many other financial activities were allowed over time. For example banks are important players in financial markets and offer financial services such as investment funds. In some countries such as Germany, banks have historically owned major stakes in industrial corporations while in other countries such as the United States, banks are prohibited from owning non-financial companies. In Japan, banks are usually the nexus of a cross-share holding entity known as the zaibatsu. In France, bank assurance is prevalent, as most banks offer insurance services (and now real estate services) to their clients.

The level of government regulation of the banking industry varies widely, with countries such as Iceland, the United Kingdom and the United States having relatively light regulation of the banking sector, and countries such as China having relatively heavier regulation (including stricter regulations regarding the level of reserves) [52].

Any financial transaction is vulnerable to chance of a default by any of the transacting parties. The banks are susceptible to multiple forms of risk but credit risk discussed in chapter two, is the most pervasive of all risk factors affecting banks and other financial intermediaries. In many developed countries small business credit scoring (SBCS) technologies have been adopted by banks and other lenders. SBCS tools enable lenders to rapidly evaluate the risks associated with different borrowers according to objective and statistically validated criteria. As a result, risk can better be managed since the credit granting process has been streamlined with processing times falling from days or weeks to minutes in some cases. Knowing that credit decisions are based on qualifications, will give borrowers' confidence a big boost.

However, due to several major developments in financial markets in recent years, it has become imperative for banks to adopt a more proactive and dynamic credit risk management policy. To cope with these developments, increasingly sophisticated mathematical and statistical tools are used to develop credit scoring models such as logistic regression, probit regression, ratio analysis, classification models, discriminant analysis, neural networks etc, to help minimise the probability of default. By systematically quantifying the risk of each application, credit scoring speeds the decision process while simultaneously bringing greater accuracy and fairness to each.

1.1.2 Traditional Banking Activities

Banks act as payment agents by conducting or checking of current accounts for customers, paying cheques drawn by customers on the bank, and collecting cheques deposited to customers' current accounts. Banks also enable customer payments via other payment methods such as:

- EFTPOS (Electronic Funds Transfer at Point Of Sale)
- ATM
- telegraphic transfer

Banks borrow money by accepting funds deposited on current accounts, by accepting term deposits, and by issuing debt securities such as banknotes and bonds. Banks lend money by making advances to customers on current accounts, by making installment loans, and by investing in marketable debt securities and other forms of money lending.

Banks provide almost all payment services, and a bank account is considered indispensable by most businesses, individuals and governments. Non-banks that provide payment services such as remittance companies are not normally considered an adequate substitute for having a bank account.

Banks borrow most funds from households and non-financial businesses, and lend most funds to households and non-financial businesses, but non-bank lenders provide a significant and in many cases adequate substitute for bank loans, and money market funds, cash management trusts and other non-bank financial institutions in many cases provide an adequate substitute to banks for lending savings to.

1.1.3 Commercial Role of Banks

The commercial role of banks is not limited to banking alone but also includes:

- Issue of banknotes (promissory notes issued by a banker and payable to bearer on demand)
- Processing of payments by way of telegraphic transfer, internet banking or other means
- Issuing bank drafts and bank cheques
- Accepting money on term deposit
- Lending money by way of overdraft, instalment loan or otherwise
- Providing documentary and standby letters of credit (trade finance), guarantees, performance bonds, securities underwriting commitments and other forms of off-balance sheet exposures
- Safekeeping of documents and other items in safe deposit boxes
- Acting as a 'financial supermarket' for the sale, distribution or brokerage, with or without advice, of insurance, unit trusts and similar financial products.

1.1.4 Economic Role of Banks

The economic functions of banks include:

(i) Issue of money, in the form of banknotes and current accounts subject to cheque or payment at the customer's order. These claims on banks can act as money because they are negotiable and or repayable on demand, and hence valued at par. They are effectively transferable by mere delivery, in the case of banknotes, or by drawing a cheque that the payee may bank or cash.

(ii) Netting and settlement of payments – banks act as both collection and paying agents for customers, participating in interbank clearing and settlement systems to collect, present, be presented with, and pay payment instruments. This enables banks to economise on reserves held for settlement of payments, since inward and outward payments offset each other. It also enables the offsetting of payment flows between geographical areas, reducing the cost of settlement between them.

(iii)credit intermediation – banks borrow and lend back-to-back on their own account as middle men

(iv)Credit quality improvement – banks lend money to ordinary commercial and personal borrowers (ordinary credit quality), but are high quality borrowers. The improvement comes from diversification of the bank's assets and capital which provides a buffer to absorb losses without defaulting on its obligations. However, banknotes and deposits are generally unsecured; if the bank gets into difficulty and pledges assets as security, to raise the funding it needs to continue to operate, this puts the note holders and depositors in an economically subordinated position.

(v) Maturity transformation– banks borrow more on demand debt and short term debt, but provide more long term loans. In other words, they borrow short and lend long. With a stronger credit quality than most other borrowers, banks can do this by aggregating issues (e.g. accepting deposits and issuing banknotes) and redemptions (e.g. withdrawals and redemptions of banknotes), maintaining reserves of cash, investing in marketable securities that can be readily converted to cash if needed, and raising replacement funding as needed from various sources (e.g. wholesale cash markets and securities markets).

1.1.5 Law of banking

Banking law is based on a contractual analysis of the relationship between the bank and the customer—defined as any entity for which the bank agrees to conduct an account.

The law implies rights and obligations into this relationship as follows:

(i) The bank account balance is the financial position between the bank and the customer: when the account is in credit, the bank owes the balance to the customer; when the account is overdrawn, the customer owes the balance to the bank.

(ii) The bank agrees to pay the customer's cheques up to the amount standing to the credit of the customer's account, plus any agreed overdraft limit.

(iii)The bank may not pay from the customer's account without a mandate from the customer, e.g. a cheque drawn by the customer.

(iv)The bank agrees to promptly collect the cheques deposited to the customer's account as the customer's agent, and to credit the proceeds to the customer's account.

(v) The bank has a right to combine the customer's accounts, since each account is just an aspect of the same credit relationship.

(vi)The bank has a lien on cheques deposited to the customer's account, to the extent that the customer is indebted to the bank.

(viii) The bank must not disclose details of transactions through the customer's account unless the customer consents, there is a public duty to disclose, the bank's interests require it, or the law demands it.

(vii)The bank must not close a customer's account without reasonable notice, since cheques are outstanding in the ordinary course of business for several days.

These implied contractual terms may be modified by express agreement between the customer and the bank. The statutes and regulations in force within a particular jurisdiction may also modify the above terms and/or create new rights, obligations or limitations relevant to the bank-customer relationship.

1.2 BANKS IN GHANA

There are several banking institutions in Ghana. These include Development Banks, Commercial Banks, Merchant Banks, Rural Banks, etc. with Bank of Ghana, serving as the central bank.

1.2.1 Development Banks

In May, 2005-2009, Bank Group's boards of directors approved the institution's Country Strategy Paper (CSP) for Ghana. The main trust of the CSP is to scale up the development impact and help improve quality of life for Ghanaians. To achieve these goals, the Bank Group's CSP for Ghana is centered on two pillars [54]:

- Improving the Investment Environment
- Promoting Pro-poor, Pro-gender Equity Policies.

The CSP is aligned with Ghana's Poverty Reduction Strategy (GPRS) for the period 2003-2005.

The major strategic focus of the Ghana Poverty Reduction Strategy(GPRS) poverty reduction based on maintaining macro-economic stability, increasing production and employment, promoting human resources development, implementing special programmes for the vulnerable and excluded, and ensuring good governance through accountability and transparency.

Line with the principles of the Paris Declaration on Aid Effectiveness, the Bank will also seek to engage in co-financing arrangements with other development partners to achieve economies of scale and ensure complementarily of interventions. In addition to project support, a new budget support programme, also to be funded from ADF-XI resources, will focus on private sector development and governance. The programme will set aside a package for institutional support, including training and technical assistance, with a view to strengthening Ghana's capacity in the emerging oil and gas sectors and to assist the government in preparing a national oil and gas strategy.

The Bank Program's focus on infrastructure and governance fully complies with the strategic orientation of the Bank Group's CSP 2005-2009 for Ghana. It is also fully aligned with the Government's Growth and Poverty Reduction Strategy (GPRS II) 2006-2009, which is anchored on the three pillars 'Private Sector Competitiveness'; 'Human Resource Development'; and 'Good Governance and Civic Responsibility'. The Program is also fully aligned with the Ghana Joint Assistance Strategy (G-JAS) 2007-2010, which covers all three pillars of the GPRS II, and complies with the Northern Development Initiative launched by the Government in November 2007.

Ghana has made considerable progress in recent years. Prudent macroeconomic policies and structural reforms, supportive international environment, massive debt relief, and donor financial support have contributed to macroeconomic stabilization, growth, a vibrant private sector and poverty reduction. However, significant challenges lie ahead, in particular, the further stimulation of private sector activity to attain sustained economic growth required to achieve the MDGs and middle-income status by 2015. The strategic orientation of the CSP is tailor-made to address these challenges.

The CSP's conception around the two pillars 'Improving the Investment Environment' and 'Promoting Pro-poor, Pro-gender Equity Policies' allows the Bank to continue to support the Government's socio-economic development agenda as spelled out in the GPRS II 2006-2009, and justifies the proposed new Bank interventions to be funded from ADF-XI during the remaining period 2008-2009 in the infrastructure and governance sectors. It is recommended that the Bank Group Boards of Executive directors approve the Bank Group's strategy for Ghana for the remaining period 2008-2009.

These banks include National Investment Bank, Agricultural Development Bank, International Commercial Bank, the Trust Bank, Prudential Bank, Amalgamated Bank, Ghana Commercial Bank, ARB Apex Bank.

1.2.1.1 Agricultural Development Bank of Ghana

Agricultural Development Bank of Ghana, commonly known as Agricultural Development Bank or ADB, is a government-owned development and commercial bank in Ghana. The bank is the first development finance institution established by the Government of Ghana. As at August 2009, the bank is one of twenty six (26) licensed commercial banks in Ghana [55].

The bank was established by an Act of Parliament (Act 286) in 1965 to promote and modernize the agricultural sector through appropriate but profitable financial intermediation. Its original name then was the Agricultural Credit and Co-operative Bank and the establishing Act gave its main object as "to provide credit facilities to agriculturists and persons for connected purposes".

In order to mitigate risk and maximize profits, the bank also engages in other types of banking beyond making agricultural loans. The ranges of services offered include:

1.2.1.1.1 Development Banking

- Agricultural Credit - For production and marketing
- Agro-processing Finance- For local and foreign markets
- Cocoa Farm Maintenance and Cocoa Bean Purchase
- Export Development Finance - Finance of value-addition to agricultural products for export

- Agribusiness Finance - Financing of purchase or lease of agricultural implements, fertilizer, storage facilities, transportation, distribution and export of agricultural produce.

1.2.1.1.2 Corporate Banking

- Foreign Account Service
- Domestic Checking Account Service
- Service Desk Facilities - Upon the request of the client, ADB opens a service desk at the client's premises to facilitate transactions for client's customers and staff.
- Business Credit
- International Banking - Through the bank's vast network of correspondent banks throughout the world.

1.2.1.1.3. Personal Banking

- Checking Accounts- Balances earn interest
- Direct Salary Deposit Services - Employers deposit salaries directly into employee's accounts
- Saving Accounts - Ordinary, Money-Market or Certificate-of-Deposit accounts
- Personal Loans - Available to employed customers with direct-deposit salary services
- Local Payment Services
- Automated Teller Machines (ATM) Services.

1.2.1.1.4. International Banking

- Export Financing-Short-term financing, Export Documentation and Processing, Export Advisory Services, Letters of Credit and Letters of Collection
- Import Financing - Letters of Credit, Import Advisory Services, Conduct due diligence on foreign suppliers.

1.2.1.1.5 Home Link Services

- Ghanaians Living or working Abroad
- Global citizens married to Ghanaians.

1.2.1.1.6. Treasury Management

- Certificate of Deposit - In Cedis or International Currencies
- Bank of Ghana Treasury Bills or Bonds
- Custodial Bank Accounts
- Offshore Accounts - With all major International banks
- Cash Management Services
- Bank of Ghana Check Clearing Services
- Offshore Check Clearing Services
- Issue of Foreign Bank Drafts
- Issue of Traveller's Checks
- International Funds Transfer.

1.2.2 Commercial Banks

Commercial banks offer a wide range of corporate financial services that address the specific needs of private enterprise. They provide deposit, loan and trading facilities but will not service investment activities in financial markets [46]. While commercial banks offer services to individuals, they are primarily concerned with receiving deposits and lending to businesses [47]. These banks in Ghana include Standard Chartered Bank, Ghana Commercial Bank Ltd, International Commercial Bank, Metropolitan and Allied Bank of Ghana, Barclays Bank of Ghana etc.

1.2.3 Merchant Banks

Merchant banks are financial institutions engaged in providing financial services and advice to corporations and to wealthy individuals. The bank does not have retail offices where one can go and open a savings account. It is said to be in the business of wholesale banking [50]. The term can also be used to describe the private equity activities of banking [48]. The bank deals in international finance, long-term loans for companies and underwriting [49]. The bank does not provide regular services to the general public.

1.2.4 Rural Banks

A rural bank is a financial institution that helps rationalize the developing regions or developing country to finance their needs specially the projects regarding agricultural progress [51]. They are owned, managed and patronized by local people. Rural bank also provide financial services.There are one hundred and twenty-nine rural banks in Ghana. Some of these banks operate agencies to cater for communities located far from the bank's facilities. These banks in Ghana include Manya Krobo Rural Bank, La Community Bank, Gomoa Rural Bank Ltd, Jomoro Rural Bank etc. The banks play certain vital roles in Ghana's economy. These include:

- They provide banking services by way of funds mobilisation and credit to cottage industry operators, farmers, fishermen and regular salaried employees.
- They grant credit to customers to cater for the payments of school fees, acquisition and rehabilitation of houses, and to meet medical expenses.
- They devote part of their profit to meet social responsibilities such as donation to support education, health, traditional administration and the needy in their respective communities.
- They undertake a mix of micro finance and commercial banking activities structured to satisfy the needs of the people in the rural areas.

1.3 BANK LOAN

A loan is a resource, mostly in momentary terms given out to a qualified applicant with an agreement to pay back the money with interest at a specified date. Typically, the money is paid back in regular instalments. The loan is provided at a cost, referred to as the interest on the resource received. This provides an incentive for the bank to engage in the loan.

There are two major characteristics that vary amongst loans obtained from a banking industry. These are the security required to access the loan and the terms of the loan.

Considering the security required to access the loan, there are two types:

- Secured loans
- Unsecured loans.

1.3.1 Secured loan

A secured loan is a loan backed by a guarantee of payment for the loan. The borrower by law gives up ownership of collateral used as security to the lender. A typical example of a secured loan is a mortgage loan. This is used by clients in purchasing properties. A mortgage loan is procured by a buyer to pay off the seller of a piece of property in full. The buyer then owes the mortgage lender the total amount borrowed with interest and fees. As collateral the lender of the mortgage keeps ownership of the said property until the buyer pays the mortgage off in full. However, the buyer occupies the property as if it were already his or her own. If the borrower defaults on the mortgage loan, the bank has the legal right to sell the property to get back the money that has been lost. Another form of a secured loan is a car loan. Just as a mortgage loan is secured by housing, a car loan may be secured by the car. There are two types of auto loans. These are direct and indirect auto loans. For a direct auto loan, the bank gives the loan directly to the client. In the case of an indirect auto loan, the car dealership acts as an intermediary between the bank or financial institution and the client.

1.3.2 Unsecured loans

These are monetary loans not backed by any guarantee. Some of these include credit cards loans, personal loans, bank overdrafts, corporate bonds etc.

1.4 TYPES OF LOANS

The banks provide all manner of loans to clients depending on the need of the customer. Some of the types provided by banks to small and start up businesses, and individual clients include credit card debt, personal loans, bank overdrafts, corporate bonds, fixed rate mortgages, adjustable rate mortgage etc.

1.4.1 Credit Card Debt

Credit card is a card with electronic funds embedded on it by a financial institution. It is used by clients in making payments of items purchased anywhere, and which will be paid to the financial institution at a later date. It eliminates the risk of carrying physical money and makes possible on-line shopping. Although it is a beneficial tool to humanity, it is not a good item for individuals whose spending habits are questionable. Quite a number of people spend more on their credit cards than they deposit each month. This causes an increase in debt as clients are unable to pay the bills on their credit cards. These clients eventually run into credit card debt and finding their way out of this debt is a hell. Credit card companies make a large portion of their money from interest and fees paid by cardholders. A client only gets charged interest when he carries his debt from one month to the next. Credit card companies love these cardholders because people who pay interest help increase the credit card companies' profits. They make no money from clients who pay off their balances in full.

1.4.2 Personal Loans

As the name suggests, is the money that an individual borrows to meet personal needs. In today's economy, where every dollar counts, it is extremely crucial to make an informed decision before opting for personal loans. Lending institutions and banks that provide personal loans have their own set of policies and criteria. It is important for a client to compare the loans and ascertain which one will be a better choice. Most people begin with comparing the interest rates on personal loans.

1.4.3 Bank Overdrafts

A bank overdraft is a situation where an individual spends more than he actually has in his bank account. This money needs be paid back because it belongs to the bank. The bank deducts from client's account immediately money goes into the account. A bank overdraft is also a type of loan as the money is technically borrowed.

1.4.4 Corporate Bonds

A bond is a security issued by a borrower, mostly a company or the government in which the investor agrees to lend money to the borrower in exchange for a predetermined interest rate for a period of time(often between one and thirty years). Technically, a bond is a form of loan given out to entities like a company or the government. The public buys bonds offered by these companies or the government in an attempt to raise money for an expansion of the company. When the time agreed upon is due, the company pays back the original principal and the interest in full to the lender.

A corporate bond is a bond issued by a corporation to raise money in order to expand its business. Corporate bonds are considered higher risk than government bonds. As a result, interest rates are almost always higher, even for top-flight credit quality companies. Regarding the loan terms, there are two types:

- Short term commercial loan
- Long term commercial loan.

1.4.4.1 Short term commercial loan

Short-term commercial loans provide businesses with money to cover excess demand over a season or period [43]. Because the time allowed on short term commercial loan is quick, the risk is low and these loans can either be secured or unsecured. This type of loan is most often used for businesses in the manufacturing, retailing, distribution, or service sectors. Once the immediate needs are met, usually anywhere from three months to one year, the loan is repaid with the profits made through utilization of the loan. For nearly all start-up businesses [44], and most existing businesses, a short-term commercial loan from a bank will have to be secured by adequate collateral. Cash flow and a regular sales history are of key importance to the lender. A fixed interest rate may be available because the duration of the loan, and therefore the risk of rising rates, is limited. While some short-term loans have terms as brief as 90-120 days, the loans may extend one to three years for certain purposes.

1.4.4.2 Long term commercial loan

Long-term commercial loans are used by companies that are just starting out or need to expand and want to obtain mortgage loans. They are often used by companies to purchase business properties like plants and equipments [45]. They are issued over time periods greater than five years and usually closer to twenty years [43]. Long-term commercial loans are a trade off between the borrower and the lender. The borrower obtains the loan and, in exchange, the lender receives shares of the company.

1.4.4.3 Mortgage

A mortgage loan is a loan secured by real property through the use of a document which evidences the existence of the loan and the encumbrance of that realty through the granting of a mortgage which secures the loan. However, the word mortgage alone, in everyday usage, is most often used to mean mortgage loan

A home buyer or builder can obtain financing (a loan) either to purchase or secure against the property from a financial institution, such as a bank, either directly or indirectly through intermediaries. Features of mortgage loans such as the size of the loan, maturity of the loan, interest rate, method of paying off the loan, and other characteristics can vary considerably.

In many countries, though not all (Iran and Bali, Indonesia are two exceptions) [56], it is normal for home purchases to be funded by a mortgage loan. Few individuals have enough savings or liquid funds to enable them to purchase property outright. In countries where the demand for home ownership is highest, strong domestic markets have developed.

1.4.4.3.1 Basic Concepts and Legal Regulation

According to Anglo-American property law, a mortgage occurs when an owner (usually of a fee simple interest in realty) pledges his interest (right to the property) as security or collateral for a loan. Therefore, a mortgage is an encumbrance (limitation) on the right to the property just as an easement would be, but because most mortgages occur as a condition for new loan money, the word mortgage has become the generic term for a loan secured by such real property

As with other types of loans, mortgages have an interest rate and are scheduled to amortize over a set period of time, typically 30 years. All types of real property can, and usually are, secured with a mortgage and bear an interest rate that is supposed to reflect the lender's risk.

Mortgage lending is the primary mechanism used in many countries to finance private ownership of residential and commercial property. Although the terminology and precise forms will differ from country to country; the basic components tend to be similar:

- Property: the physical residence being financed. The exact form of ownership will vary from country to country, and may restrict the types of lending that are possible.
- Mortgage: the security interest of lender in the property, which may entail restrictions on the use or disposal of the property. Restrictions may include requirements to

purchase home insurance and mortgage insurance) or pay off outstanding debt before selling the property.

- Borrower: the person borrowing who either has or is creating an ownership interest in the property.
- Lender: any lender, but usually a bank or other financial institution. Lenders may also be investors who own an interest in the mortgage through a mortgage-backed security. In such a situation, the initial lender is known as the mortgage originator, which then packages and sells the loan to investors. The payments from the borrower are thereafter collected by a loan servicer.
- Principal: the original size of the loan, which may or may not include certain other costs; as any principal is repaid, the principal will go down in size.
- Interest: a financial charge for use of the lender's money.
- Foreclosure or repossession: the possibility that the lender has to foreclose, repossess or seize the property under certain circumstances is essential to a mortgage loan; without this aspect, the loan is arguably no different from any other type of loan.

Many other specific characteristics are common to many markets, but the above are the essential features. Governments usually regulate many aspects of mortgage lending, either directly (through legal requirements, for example) or indirectly (through regulation of the participants or the financial markets, such as the banking industry), and often through state intervention (direct lending by the government, by state-owned banks, or sponsorship of various entities). Other aspects that define a specific mortgage market may be regional, historical, or driven by specific characteristics of the legal or financial system.

Mortgage loans are generally structured as long-term loans, the periodic payments for which are similar to an annuity and calculated according to the time value of money formulae. The most basic arrangement would require a fixed monthly payment over a period of ten to thirty years, depending on local conditions. Over this period the principal component of the loan (the original loan) would be slowly paid down through amortization. In practice, many variants are possible and common worldwide and within each country.

Lenders provide funds against property to earn interest income, and generally borrow these funds themselves (for example, by taking deposits or issuing bonds). The price at which the lenders borrow money therefore affects the cost of borrowing. Lenders may also, in many countries, sell the mortgage loan to other parties who are interested in receiving the stream of cash payments from the borrower, often in the form of a security (by means of a securitization). In the United States, the largest firms securitizing loans are Fannie Mae and Freddie Mac, which are government sponsored enterprises.

Mortgage lending will also take into account the (perceived) riskiness of the mortgage loan, that is, the likelihood that the funds will be repaid (usually considered a function of the creditworthiness of the borrower); that if they are not repaid, the lender will be able to foreclose and recoup some or all of its original capital; and the financial, interest rate risk and time delays that may be involved in certain circumstances.

1.4.4.3.2 Mortgage loan types

There are many types of mortgages accessed worldwide, but several factors broadly define the characteristics of the mortgage. All of these may be subject to local regulation and legal requirements.

- Interest: interest may be fixed for the life of the loan or variable, and change at certain pre-defined periods; the interest rate can also be higher or lower.
- Term: mortgage loans generally have a maximum term, that is, the number of years after which an amortizing loan will be repaid. Some mortgage loans may have no amortization, or require full repayment of any remaining balance at a certain date, or even negative amortization.
- Payment amount and frequency: the amount paid per period and the frequency of payments; in some cases, the amount paid per period may change or the borrower may have the option to increase or decrease the amount paid.
- Prepayment: some types of mortgages may limit or restrict prepayment of all or a portion of the loan, or require payment of a penalty to the lender for prepayment.

The popular types of mortgage loan include:

- Fixed-Rate Mortgage
- Adjustable-Rate Mortgage
- Interest-Only Mortgage
- Mortgage Buy Down.

1.4.4.3.3 Fixed-Rate Mortgage

Fixed-rate mortgages allow for repayment of a debt in equal monthly mortgage payments over a specified period of time, from 10 to 50 years. A 30-year amortization period is most common. Fixed-rate mortgages are the most common mortgage for first-time homebuyers because they're stable. Typically the monthly mortgage payment remains the same for the entire term of the loan regardless of the length of time allowing for predictability in one's monthly housing costs. Some of the benefits include [57]:

- Inflation protection.
  If interest rates increase, your mortgage and your mortgage payment won't be affected. This is especially helpful if you plan to own your home for 5 or more years.
- Long-term planning.
  One knows what one's monthly mortgage expense will be for the entire term of the mortgage. This can help you plan for other expenses and long-term goals.
- Low risk.
  One always knows what one's mortgage payment will be, regardless of the current interest rate. This is why fixed-rate mortgages are so popular with first-time buyers.

1.4.4.3.4 Adjustable-Rate Mortgage

An adjustable rate mortgage (ARM) is a mortgage loan where the interest rate on the note is periodically adjusted based on a variety of indices [58]. Among the most common indices are the rates on 1-year constant-maturity Treasury (CMT) securities, the Cost of Funds Index (COFI), and the London Interbank Offered Rate (LIBOR). A few lenders use their own cost of funds as an index, rather than using other indices. This is done to ensure a steady margin for the lender, whose own cost of funding will usually be related to the index. Consequently, payments made by the borrower may change over time with the changing interest rate (alternatively, the term of the loan may change). Adjustable rate mortgages are characterized by their index and limitations on charges (caps). In many countries, adjustable rate mortgages are the norm, and in such places, may simply be referred to as mortgages.

1.4.4.3.5 Interest-Only Mortgage

An interest only mortgage is a mortgage option in which you are only expected to pay the interest on one's mortgage. If one does this, nothing will be applied to the principal of the loan. An interest only loan payment option can be attached to both an adjustable rate mortgage and a fixed rate mortgage. Generally the interest only payment option is only available for a set time, after which you must pay off the entire loan, refinances or your payments will go up to start paying down the principal [59]. Interest-only payments do not contain principal. Many of the interest-only mortgages available today feature an option for interest-only payments.

1.4.4.3.6 Mortgage Buy Down

Borrowers who want to pay a lower interest rate initially often opt for mortgage buy downs. The interest rate is reduced because fees are paid to lower the rate, which is why it's called a buy down. Buyers, sellers or lenders can buy down the interest rate for the borrower [56].

Mortgage buy downs are often not the first choice for home buyers because it does require some money up front. The first three years' worth of interest charges on the mortgage to be exact [60].The choice of a mortgage buy down, lowers one's interest rate for the first three years of the loan, thus reducing the monthly payments during that time. This time is used to hopefully increase one's income to the point where one will be able to better afford a mortgage when it returns to its regularly scheduled interest rate in the fourth year.

1.5 PROBLEM STATEMENT

In Ghana, loan applicants often wait days, or even weeks for loan approvals. Credit analysts use their own judgements in evaluating applicants. These judgements are often poorly made due to lack of symmetric information gab between lenders and borrowers. The information asymmetries also serve to reduce competition in the firm lending market so firms with good credit history often pay handsomely for access to credit, even when the bank or firm lending to them had established their creditworthiness.

1.6 OBJECTIVES

The main objective of this thesis is to formulate a logistic and probit regression model to predict the probability of default of loan applicants. Specifically, the thesis through the established model(s) would identify the very factors attributing to the probability of default.

Any of these models is expected to help reduce credit granting processing time and simultaneously bringing greater accuracy and fairness to each applicant.

1.7 JUSTIFICATION

Logistic or probit regression models are important tools for financial or lending institutions. The absence of a trusted model to help evaluate credit worthiness of clients in an economy such as Ghana's has lead to frustrations for parties involved in loan transactions. Formulating a model to calculate the probability of default is a core ingredient of the client's repayment evaluation and will lead to an accurate and a faster evaluation of the client's ability to pay back credit. When these models are used to take decisions on clients applying for credit, the cost of processing of loans and the overestimated amount of risks of default will be reduced.

1.8 LIMITATION

It should be noted that these models cannot be used to take decisions on loan applicants outside the bank from which data was obtained since different banks do not share the same data (financial ratio).

1.9 ORGANISATION

The structure of this thesis is as follows: A brief introduction, problem statement, objectives, justification and limitations have been discussed in chapter 1; Chapter 2 discusses literature review; Chapter 3 gives the methodology of the logistic and probit regression models; Chapter 4 discusses the application of the methodology discussed in chapter 3 to build our models and how they can be used to help predict the probability of default; Chapter 5 deals with the conclusion and recommendation.

CHAPTER TWO

LITERATURE REVIEW

2.1 EMPERICAL STUDIES ON CREDIT RISK MANAGEMENT

Credit analysis has been a great concern to lending institutions worldwide. Regulators, banks and bondholders, pension, fund trustees and other fiduciary agents have increasingly used ratings-based criteria to constrain behaviour. The importance of ratings-based regulations has traditionally been particularly visible in the United States, where it can be traced back to the 1930s [17].

Recent times, small firms are being established. These firms contribute greatly to the development of the economy of Ghana; yet, financing them is a problem due to the high defaulting rates. This problem has drawn the attention of researchers both in academia and industry.

In 1968, Altman [19] assessed the analytical quality of ratio analysis using the discriminant function with ratios called the Z- score model. He found that 95% of the data used was correctly predicted.

In 2007, François Coppens et al., [20] assessed the performance of credit rating systems in the assessment of collateral used in eurosystem monetary policy operations. Preference was given to backtesting techniques as they happened to be the early warning tools for identifying performance problems in credit assessment systems. This could be useful in the context of the Eurosystem Credit Assessment Framework, in which various credit assessment sources can be employed to assess the credit quality standards of eligible collateral.

In 2002, Kuldeep [22] discussed and compared various methods for forecasting financial distress and credit ratings using financial data relevant to a debt issue ratings obtained from the publications of a premier credit rating agency in India.

Findings clearly showed that financial performance data of the company before the issue, has significant effect on credit rating by expert. Artificial Neural Networks (ANN) model was found superior to discriminant analysis model.

In 2006, the Basel Committee on Banking Supervision [21], researched into credit risk concentration. He concluded that Multi-factor models and possible refinements and extensions have the potential to offer a credible alternative to simulation-based assessments of economic capital, at least for diagnostic purposes.

In the same year, 2006, Wong [23], researched into credit risk analysis for financial corporations. He compared the performance of several statistical models. He found that 70% of his data set was correctly predicted and concluded that the logit regression analysis is the preferred model. It is therefore the model to help in credit risk analysis in the US financial corporations.

Also in 2006, Kuldeep and Sukanto [24] conducted a comparative study of prediction performances of an artificial neutral network (ANN) model against a linear discriminant analysis (LDA) with regards to forecasting corporate credit ratings from financial statement data. They found that since ANN models can better deal with complex data sets and do not require restraining assumptions like linearity and normality, it is the preferred approach in corporate credit rating forecast that uses large financial data set.

Despite the fact that outcomes of discriminant analysis can be predicted effectively, some difficulties arise when the assumptions underpinning it are violated and when the sample size used in the research is small. In 1966, Horrigan [26] and in 1970, Orgler [27] used multiple linear regression in their analysis. However, this method is not appropriate when the dependent variable of a model is categorical in nature. It is appropriate to represent such a qualitative dependent variable by a dummy. In short, to avoid problems such as biased and inconsistent estimates, generalized linear models (GLM) such as logistic, probit and poisson regressions were developed.

The development of generalized linear models (GLM) has contributed immensely to the economic world and most especially, in the area of credit scoring. For example in 1980, Ohlson [28] used the logistic regression model in his paper. This Ohlson did to avoid the problems faced when the discriminant analysis was used. By using logistic and probit regression model, a significant, consistent, and unbiased estimation was obtained. Based on this conviction, other researchers such as; Gilbert et al., [29] and Hayden [30] used it in their researches.

In 2005, Young-Chan [31], researched into corporate credit rating analysis. His study applied support vector machines (SVMs) to the corporate credit rating problem in an attempt to suggest a new model with better explanatory power and stability. To serve this purpose, he used a grid-search technique with 5-fold cross-validation to find out the optimal parameter values of RBF kernel function of SVM. In addition, to evaluate the prediction accuracy of SVM, the he compared its performance with those of multiple discriminant analysis (MDA), case-based reasoning (CBR), and three-layer fully connected back-propagation neural networks (BPNs). The experiment results show that SVM outperforms the other methods.

In 2000, Comeo and Hill [37], used weibit, gombit, logit and probit models to determine whether the underlying probability distribution of dependent variables affected the predictive ability. They concluded that there is little or no difference between the models.

In 1997,Pompe [38],compared classification trees with linear discriminant analysis and neural network. The 10-fold cross validation results revealed that decision trees performed better than the logistic regression but not as the neural networks.

In 1980[39], Dombolena and Khoury included the stability measures of the ratios to the discriminant analysis model with ratios. The stability measures included standard error of estimates, coefficient of variations and standard deviation of ratios over the past few years. The standard deviation was found to be the strongest measures of stability and accuracy of ratios was found to be 78% five years prior to failure.

Gilbert et al., [40],in 1990 showed that in bankruptcy model developed with bankrupt random samples firms that failed from other financially upset firms when stepwise logistic regressions was used, can be distinguished.

Mehta [41], included the time varying states to optimize credit policy, suggested by Cyert et al., in 1970. Dynamic relationships when evaluating alternatives were taken into account.

Charalombous et al., [42], in 2000, compared neural networks algorithms, which included feed forward networks, radial basis function, learning vector quantization and back propagation with logistic regression. The neural networks produced a better prediction results.

2.2 CONCEPTS OF CREDIT RISK MANAGEMENT

Risk is the probability of an event inimical to an entity. It can be positive or negative depending on the event or the circumstance under which risk was taken. In this study, focus was given to risk associated with credit scoring.

There are probable risks faced by lending and financial institutions. Some of which are interest rate risk (It is the possibility of a reduction in the value of a security resulting in a rise in interest rate), mortgage risk (It is the possibility that a borrower in a mortgage agreement will fail to make timely principal and interest payments in accordance with the terms of the mortgage), currency risk (It is a risk that arises from a change in price of one currency against another), liquidity risk (It is a risk that arises from the difficulty of selling an asset), credit risk, etc. Amongst the various forms of risk, exposure to credit risk continue to be the leading source of major problems faced by financial and other lending institutions. It is the risk most likely to accelerate an institution's failure. Hence, it is the risk most supervisors of lending and financial institutions would not fail to pay the closest attention.

Whereas credit is the benefit enjoyed by a borrower intended to be repaid at a later date, credit risk is the likelihood that a borrower will fail to pay back credit in a speculated period of time. Increasingly, lending and other financial institutions are faced with other forms of credit risk apart from the usual loans. These include interbank transactions, foreign exchange transactions, trade financing, bonds, extension of commitments and guarantees etc.

Considering the little confidence lately in credit market, it makes a lot of meaning to employ a better credit risk management practices to minimize exposure to credit risk.

Credit risk management identifies, measures, monitors and reports potential credit risk exposures in an institution [34]. It also ensures that there are adequate funds against unexpected losses as proposed by the Basel Committee, an institution created by the central bank Governors of a group of ten nations. The Basel Committee has issued a document on this proposal to encourage banking supervisors globally to promote sound practices with regards to managing risk. The recommendation on banking laws and regulations issued by the Basel Committee on banking supervision is what we call Basel II. In practice, Basel II [34] attempts to achieve this by putting in place stringent risk and capital management requirements to guarantee that banks and other lending institutions reserve capital suitable enough to protect the institution against credit risk exposure.

According to Basel II, financial institutions should assess the credit exposure for each applicant applying for credit and for each credit facility using the following criteria:

1. **Probability of Default (PD):** It is the probability that an applicant will default within the next 12 months [35].

2. **Loss given Default (LGD):** It is the amount of capital a financial or lending institution loses when a client defaults [33]. Calculation of the loss given default is done by comparing actual total losses to the total potential exposure at the time of default.

3. **Exposure at Default (EAD):** It is a total value that a financial or lending institution is exposed to at the time of default [36]. Each exposure is given an EAD value and is identified within the bank's internal system. Exposure at default along with loss given default (LGD) and probability of default (PD) is used to calculate the credit risk capital of financial institutions. The expected loss as a result of a client's default is usually measured over a year. The calculation of EAD is done by multiplying each credit obligation by an appropriate percentage. Each percentage used coincides with the specifics of each respective credit obligation.

The minimum capital requirements (MCR) are given as [16].

$$MCR = EAD \times LGD \times PD - b \times EL \qquad (\beta).$$

where the expected loss (EL) is

$$EL = PD \times EAD \times LGD \qquad (\mu)$$

and b is the proportion of the expeeted loss of loan covered by minimum capital requirement

Once these components PD, LGD and EAD are obtained, calculation of the minimum capital requirement is simple as in equation (ß). The main issues faced by financial and lending institutions are [34]: the necessary information needed to evaluate the components PD, LGD and EAD for each applicant, and the execution of a risk rating system to correctly build a statistically valid model.

CHAPTER THREE

METHODOLOGY

3.1 GENERALIZED LINEAR MODELS

The generalized linear model (GLM) is a generalization of ordinary least squares regression.

It relates the random distribution of the measured variable of the experiment to the systematic portion of the experiment (the linear predator) through a function called the link function.

Generalized linear models were formulated as a way of unifying various other statistical models like linear regression, logistic regression, poisson regression etc under one framework. This allows them to develop a general algorithm for maximum likelihood estimation in all these models.

In GLM, each outcome, Y, of the dependent variables, is assumed to be generated from a distribution function in the exponential family (a large range of probability distributions).The mean, μ, of the distribution depends on the independent variables, X, through[14], [16]:

$$E(Y) = \mu = g^{-1}(X\beta) \quad (3.1)$$

where $E(Y)$ is the expected value of Y

$X\beta$ is the linear predator, and

g ,is the link function.

The variance is a function, V, of the mean:

$$Var(Y) = V(\mu) = V\left(g^{-1}(X\beta)\right) \quad (3.2)$$

The unknown parameters, β, are estimated with maximum likelihood techniques.

The GLM consists of three components [32]:

3.1.1 The Distribution Function

The exponential family distributions parameterized by θ and τ can be expressed as[14], [16]:

$$f_Y(y;\theta,\tau) = \exp\left(\frac{a(y)b(\theta)+c(\theta)}{h(\tau)} + d(y,\tau)\right) \quad (3.3)$$

Where;

f is the probability mass function,

τ is the dispersion parameter,

θ is the mean of the distribution,

a, b, c, d and h are unknown functions

3.1.2 The Linear Predator

This incorporates the information about the independent variables into the model. The symbol η (eta) is used to denote a linear predator. It is related to the expected value of the data through the link function.

η is expressed as a linear combination of the unknown parameters β and the independent variables X [14],[16].

Thus, $$\eta = X\beta \quad (3.4)$$

3.1.3 The Link Function

This provides the relationship between the linear predator and the mean of the distribution function. Some of the commonly used link functions are shown in Table 3.0.

Table 3.0: The Link Function

Distribution	Name	Link function	Mean function
Normal	Identity	$X\beta = \mu$	$\mu = X\beta$
Binomial	Probit	$X\beta = \Phi^{-1}(\mu)$	$\mu = \Phi(X\beta)$
Binomial	Logit	$X\beta = \ln\left(\frac{\mu}{1-\mu}\right)$	$\mu = \frac{\exp(X\beta)}{1+\exp(X\beta)}$
Gamma	Inverse	$X\beta = \mu^{-1}$	$\mu = X\beta$
Poisson	Log	$X\beta = \ln(\mu)$	$\mu = \exp(X\beta)$
Gaussian	Inverse squared	$X\beta = \mu^{-2}$	$\mu = (X\beta)^{\frac{1}{2}}$

3.1.4 Binary Choice Models

In binary models, the dependent variable takes only two possible values. And in credit scoring, the dependent variable is identified using the dummy variables 1 to represent a state of a defaulting firm and 0 representing a non defaulting firm as in equation(3.5) [25]:

$$Y_i = \begin{cases} 1, if\ firm\, i\, defaults \\ 0, if\ otherwise \end{cases} \qquad (3.5)$$

Where, Y_i denotes whether firm i is in a state of default, and its probability of default is θ. When the response data, are binary (taking on only values of 0 and 1), the distribution function is generally chosen to be the binomial distribution and the interpretation of the mean is the probability, p, of Y_i taking on the value 1 [14].

Thus,

$$P(Y=1) = F(x_i\beta_i) = \theta. \qquad (3.6)$$

Here, F is the cumulative distribution function (inverse link function),

β_i, is the unknown parameter vector of the model,

x_i, represent the independent variables in the model.

This type of variable can be considered to be a Bernoulli (or binary) probability distribution with a probability θ. The Bernoulli probability function is [16]:

$$f(y,\theta)=\theta^{y}(1-\theta)^{1-y}, \quad (y=0,1),$$

$$E[y]=\theta \tag{3.7}$$

$$Var[y]=\theta(1-\theta)$$

3.2 MAXIMUM LIKELIHOOD ESTIMATION (MLE)

Maximum likelihood estimation is normally used for fitting a statistical model. It calculates the logit coefficients. MLE seeks to maximize the log likelihood, which reflects how likely it is (the odds) that the observed values of the dependent variables may be predicted from the observed values of the independents [4]. It is an iterative algorithm which starts with an initial arbitrary ''guesstimate'' of what the logit coefficients should be. The algorithm determines the direction and size change in the logit coefficients which increase the log likelihood. After the initial function is estimated, the residuals are tested and a re-estimate is made with an improved function, and the process is repeated until convergence is reached.

As mentioned before to estimate the unknown parameters, we need to write the likelihood function. The likelihood function through the observed data is defined to be:

$$L(y_i,\theta)=\prod_{i=1}^{n}\theta^{y_i}(1-\theta)^{1-y_i} \tag{3.8}$$

where, θ is the probability that each independent variable x_i takes the value one as dependent variable.

MLE is defined to be the natural logarithm of the likelihood function. Thus,

$$l(y_i,\theta)=\sum_{i=1}^{n}\{y_i\ln(\theta)+(1-y_i)\ln(1-\theta)\}, \qquad (3.9)$$

where the parameters have their usual meaning.

Prove

Suppose Y is a random variable with a probability density function $f(y_i,\theta)=\theta^{y_i}(1-\theta)^{1-y_i}$, where θ is a .continuous parameter.

The likelihood function is written as

$$L(y_i,\theta)=\prod_{i=1}^{n}\theta^{y_i}(1-\theta)^{1-y_i}$$

$$L(y_i,\theta)=\theta^{y_1}(1-\theta)^{1-y_1}\theta^{y_2}(1-\theta)^{1-y_2}\ldots\theta^{y_n}(1-\theta)^{1-y_n}$$

The log likelihood function is defined to be $l(\theta)=\ln(L(y_i,\theta))$

$$l(\theta)=\ln L=y_1\ln\theta+(1-y_1)\ln(1-\theta)+y_2\ln\theta+\ldots y_n\ln\theta+(1-y_n)\ln(1-\theta)$$

$$l(\theta)=\sum_{i=1}^{n}\{y_i\ln(\theta)+(1-y_i)\ln(1-\theta)\}.$$

Hence, the proof.

Illustration

Let the probability density or mass function be

$$f(x,\theta)=\theta^{x}\ell^{-\theta}$$

The likelihood function $L(x_i,\theta)$ is

$$L(x_1,x_2,\ldots,x_n,\theta)=\prod_{i=1}^{n}\theta^{x}\ell^{-\theta}$$

$$=\theta^{x_1}\ell^{-\theta}\theta^{x_2}\ell^{-\theta}\ldots\theta^{x_n}\ell^{-\theta}$$

$$= \theta^{x_1 + x_2 + \dots x_n} \ell^{-\theta-\theta-\dots-\theta}$$

$$= \theta^{\sum_{i=1}^{n} x_i} \ell^{-n\theta}$$

The log likelihood function $l(\theta) = \ln(L(x_i, \theta))$ is

$$l(\theta) = \sum_{i=1}^{n} x_i \ln \theta - n\theta$$

The score function $s(\theta) = l'(\theta)$ is

$$S(\theta) = \frac{\partial l(\theta)}{\partial \theta} = \frac{1}{\theta} \sum_{i=1}^{n} x_i - n$$

For maximum $l(\theta)$, $S(\theta) = 0$.

Thus,

$$\frac{1}{\theta} \sum_{i=1}^{n} x_i - n = 0$$

$$\hat{\theta} = \overline{x_i}$$

3.3 GOODNESS OF FIT MEASURES

The goodness of fit of a statistical model describes how well a model fits a set of data. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question. Such measures are used in statistical hypothesis testing.

3.3.1 Likelihood Ratio Test

The likelihood-ratio test uses the ratio of the maximized value of the likelihood function for the full model (L_1) over the maximized value of the likelihood function for the simpler model (L_0). The likelihood-ratio test statistic equals:

$$D = -2\ln\left(\frac{L_0}{L_1}\right) = -2(\ln L_0 - \ln L_1), \tag{3.10}$$

where D is assumed to be distributed as chi-square with p-1 degrees of freedom.

The likelihood-ratio test, also called the model chi-square test, tests the significance of the overall model. When the simpler model (L_0) is the baseline model with the constant only (model at step zero), the likelihood test tests the significance of the model as a whole. A well-fitting model is significant at $p \le 0.05$ level of significance [4]. When this likelihood test is significant, it means then at least one of the independent variables is significantly related to the dependent variable. That means, the null hypothesis that all the independent variable effects are zero, is rejected.

3.3.2 Wald Statistic Test

The Wald statistic test is an alternative test commonly used to test the significance of the individual logistic coefficients for each independent variable (that is, to test the null hypothesis in logistic regression that a particular logit coefficient is zero). The Wald statistic is the square of the logistic coefficients divided by its standard error. The test statistic is:

$$W = \frac{\hat{\beta}^2_i}{Se(\beta_i)}, \quad i = 1,2,\ldots,n+1, \tag{3.11}$$

where, $\hat{\beta}_i$ is the maximum likelihood estimate of ith logit coefficient.

$Se(\hat{\beta}_i)$ is the standard error of the ith logit coefficient. It is defined as:

$$Se(\hat{\beta}_i) = \sqrt{\text{cov}_i} \tag{3.12}$$

The hypothesis tested by the Wald statistic is defined as:

$H_0 : \beta_i = 0, i = 1,2,\ldots,n$
$H_1 : \beta_i \ne 0.$

The decision is taken by comparing the value of the Wald statistic with the standard normal table value.

Since the Wald statistic is known to be sensitive to the violations of large-sample assumption of the logistic regression, the likelihood ratio test is considered more reliable for small samples. Therefore the likelihood ratio test of individual model parameters is preferred.

3.3.3 Pearson's Chi-square Test

Pearson's chi-square (χ^2) test, being the best- known of several chi-square tests, is a statistical procedure whose results are evaluated by reference to the chi-square distribution. It is the original and most widely used chi-square test for cases where the events cover an outcome of a categorical variable [9]. The test statistic is calculated by finding the difference between each observed and theoretical frequency for each possible outcome, squaring them, dividing each by the theoretical frequency and taking the sum of the results. Thus

$$\chi^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i}, \tag{3.13}$$

where,

O_i is the observed frequency ,

E_i, is the theoretical frequency for each possible outcome

n, is the number of outcomes

χ^2, is the chi-square statistic.

The chi- square statistic can then be used to calculate the p-value by comparing the value of the statistic to a chi- square distribution. The number of degrees of freedom is equal to the number of possible outcomes, minus one.

3.4 BINARY LOGISTIC REGRESSION

The binary logistic regression is a type of generalized linear model whose dependent variable is dichotomous. This variable can take the value 1 with a probability of success θ, or the value 0 with probability of failure 1-θ. This type of variable is a binary or Bernoulli variable. The independent variables can take any form. The relationship between the dependent and the independent variables is not a linear function but it does assume a linear relationship between the independent variables and the log odds of the dependent variable [4], [15]. Therefore the link function of the binary logistic regression function is obtained using the logit transformation of θ:

$$\theta = \frac{\ell^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_i x_i)}}{1+\ell^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_i x_i)}} , \qquad (3.14)$$

where, α is the constant of the equation , $\beta_1, \beta_2, \ldots, \beta_i$ are the coefficients of the independent variables and $x_1, x_2, \ldots, x_i$ are the variables.

The transformation, also called the odds, is the ratio of the probability of success to the probability of failure. That is,

$$odds = \frac{\theta}{1-\theta} \qquad (3.15)$$

But,

$$\frac{\theta}{1-\theta} = \frac{a}{b} = \ell^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_i x_i)} \qquad (3.16)$$

where

$$a = \frac{\ell^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_i x_i)}}{1+\ell^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_i x_i)}} \qquad (3.17)$$

and

$$b = 1 - \frac{\ell^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_i x_i)}}{1-\ell^{(\alpha+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_i x_i)}} \qquad (3.18)$$

In logistic regression, the dependent variable is a logit, which is the natural logarithm of the odds. Therefore, from (3.16), logit variable, the natural log of the odds of the dependent variable occurring or not, is then found to be:

$$\log it(odds) = \ln(odds) = \ln(\ell^{(\alpha+\beta_1 x_1+\beta_2 x_2+...+\beta_i x_i)}) = \alpha + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_i x_i \qquad (3.19)$$

Substituting (3.6) and (3.15) into (3.19), we have:

$$\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_2 x_2 + ... + \beta_i x_i \qquad (3.20)$$

This is the binary logistic regression equation.

The parameters of this model can be found with the help of statistical software such as the SPSS or the STATA. Goodness-of-fit tests such as the likelihood ratio test are available as indicators of model appropriateness, whereas the Wald test also tests the significance of individual independent variables. The Pseudo R^2, measures the strength of association between the dependent and independent variables.

The model in equation (3.20), can be used to predict the probability of a firm defaulting or not.

3.4.1 Variable Selection In The Model

A well-fitting model is a model with significant logit coefficients. To make a global statement about the significance of an independent variable, both the correlation and the parameter estimates (logit coefficients), should be significant [4]. Decision on which logit coefficient is significant to the model, is one of the challenges faced in logistic regression model building.

This decision as to which logit coefficient is significant, is done using the Wald test or by comparing the p-value with the cut-off value (0.05).Significance is established if $p \leq 0.05$, taking also into consideration a higher value of the pseudo R^2.

If the significant variables in the model are more than necessary, then another [16] selection criterion, called the backward stepwise selection method, is used. This method automatically excludes some of the significant variable.

3.4.2 Backward Elimination

(i) Estimate the parameters for the full model that includes all eligible variables.

(ii) Based on the MLEs of the model in (1), calculate the p-value or the Wald's statistic for all the variables and find their significance.

(iii)Choose the variable with the largest significance. If that significance is less than the probability for a variable removal, then stop backward; otherwise, go to the next step

(iv)Modify the current model by removing the variable with the largest significance from the model. Estimate the parameters for the modified model. If all the variables in the backward list are removed then stop backward; otherwise, go back to step 2

3.4.3 Backward Stepwise (BSTEP) Algorithm

(i) Estimate the parameters for the full model that includes the final model from previous method and all eligible variables. Only variables listed on the BTEP variable list are eligible for entry and removal. Let the current model be the full model.

(ii) Based on the Maximum Likelihood Estimations (MLEs) of the current model, calculate the Wald's statistic for each variable in the BSTEP list and find its significance.

(iii)Choose the variable with the largest significance. If that significance is less than the probability for a variable removal, then go to step 5. If the current model without the variable with the largest significance is the same as the previous model, stop BSTEP; otherwise go to the next step.

(iv)Modify the current model by removing the variable with the largest significance from the model. Estimate the parameters for the modified model and go back to step 2.

(v) Check to see any eligible variable is not in the model. If there is none, stop BSTEP; otherwise, go to the next step.

(vi)Based on the MLEs of the current model, calculate score statistic for every variable not in the model and find its significance.

(vii) Choose the variable with the smallest significance. If that significance is less than the probability for a variable entry, then go to the next step; otherwise, stop BSTEP.

(viii) Add the variables with the smallest significance to the current model. If the model is not the same as any previous models, estimate the parameters for the new model and go back to step 2; otherwise, stop BSTEP.

3.5 BINARY PROBIT REGRESSION

The binary probit regression, like the binary logistic regression, has a binary dependent variable. The independent variable takes any form.

Therefore, its underlying assumptions are similar to that of the binary logistic regression. In addition, the inverse of any continuous cumulative distribution function (CDF) can be used for the link since the CDF's range is [0, 1] .This is the range for a binomial mean. The normal CDF Φ is a popular choice and yields the probit model [14].

The link function (the relationship between the mean and the linear predator) for the probit model is:

$$\Phi^{-1}(P(Y=1)) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i \,, \qquad (3.21)$$

Where,

Φ^{-1} is the inverse standard normal cumulative function.

α is the constant parameter,

$\beta_1, \beta_2, \ldots, \beta_i$ are the probit coefficients, and

$x_1, x_2, \ldots x_i$ are the independent variables.

This equation is (15) is the binary probit regression equation. The coefficients can be found with the help of the SPSS or STATA software. The variables which contribute significantly to the model are selected just as the binary logistic regression, but forward stepwise algorithm, discussed below, is used to further select variables when the significant variables obtained are too many. If the value of the linear predator is known, then the probability of a firm defaulting can be found.

3.6 PROPERTIES OF MODELS

(i) The maximum likelihood estimator $\hat{\beta}$ is a consistent estimator for β. Consistency means that $\hat{\beta}$ converges in probability to β:

$$\lim_{n\to\infty} \mathrm{P}\left\{\left\|\hat{\beta}-\beta\right\|>\varepsilon\right\}=0, \tag{3.22}$$

Where $\varepsilon > 0$

(ii) The $\hat{\beta}$ is approximately normally distributed with mean vector is β and variance matrix is equal to the information matrix:

$$\hat{\beta} \sim \mathrm{N}\left(\beta, I(\beta)^{-1}\right).$$

The information function is:

$$\mathrm{I}(\beta) = -E\left[\frac{\partial^2 l}{\partial \beta_i \beta_j}\right] \tag{3.23}$$

(iii) The inverse information matrix is the Crammer Rao lower bound. Then $\hat{\beta}$ is also asymptotically efficient which means that it is an unbiased estimator with minimum variance.

3.7 ASSUMPTIONS OF MODELS [4]

(i) They do not need to assume a linear relationship between the dependent and the independent variables.

(ii) The dependent variable needs not be normally distributed but its distribution should be within the range of exponential family of distributions, such as binomial, normal, gamma, Poisson, etc

(iii) The dependent variable need not be homoscedastic for each level of independents; that is, there is no homogeneity of variance assumption: variance need not be the same within categories.

(iv). Normally distributed error terms are not assumed.

(v) They do not require that the independents be interval and unbounded.

CHAPTER FOUR

DATA ANALYSIS AND RESULTS

4.1 PRESENTATION OF DATA

The data used in this thesis was provided by a Ghanaian Bank. It consists of ten independent variables. These variables are financial ratios obtained from firms in the service provision industry .The dependent variable is a categorical one. The dummy variable 1 represents defaulted firms whereas 0 represents non-defaulted firms. The total number of observations is 80. 29 of them are defaulted whereas 51 are non-defaulted firms. These can be found in the appendix. Most collateral do not easily have observable market price. The lack of price information obliged us to depend on credit ratios as the independent variables for our model.

4.1.1 VARIABLES

(i) Current Ratio(x_1): $\frac{Current\ Assets}{Current\ Liabilities}$,

where $QuickAsset = CurrentAssets - Inventories$

The current ratio is a financial ratio that measures whether or not a firm has enough resources to pay its debt over the next 12 months. In short, it is mainly used to give an idea of a firm's ability to pay back its short term obligations. The higher the current ratio, the more capable the firm is of paying its obligations. A ratio under 1 suggests that the firm is not in good financial health to pay off its obligations. If the ratio is equal to one, it means the firm could survive for one year. A firm is considered to have a good short term financial strength it has a current ratio greater than two [5], [11], [12].

(ii) Quick Ratio(x_2): $\frac{Quick\ Assets}{Current\ Liabilities}$

Quick ratio, also known as the ''acid-test ratio'' or the ''quick assets ratio'', is a measure of the amount of liquid assets available to offset a firm's current debt The higher the value of the quick ratio, the better the position of the firm [5],[11],[12].

(iii). Return on Assets Ratio(x_3): $\frac{Net\ Profit}{Total\ Assets}$

This is an important ratio for firms deciding whether or not to initiate a new project.

The basis of this ratio is that if a firm is going to start a project, they expect to earn a return on it. If the return is above the rate that the firm borrows, then the project is accepted. If not, it is rejected [5],[11],[12].

(iv). Net Profit Margin(x_4): $\frac{Net\ Profit}{Net\ Sales}$

Net Profit Margin, also called Net Margin, is the ratio of the Net Profit to Net Sales. This number is an indication of how effective a company is at cost control. The higher the net profit margin, the more effective the firm is at converting revenue into actual profit. The net profit margin is a good way of comparing firms in the same industry, since such firms are generally subject to similar business conditions. However, the net profit margins are also a good way to compare companies in different industries in order to gauge which industries are relatively more profitable [5],[11],[12]

(v). Net Working Capital Ratio(x_5): $\frac{Net\ Working\ Capital}{Total\ Assets}$, where

$$NetWorkingCapital = CurrentAssets - CurentLiabilities$$

The Net Working Capital Ratio is the ratio of the difference between a firm's Current Assets and its Current Liabilities to its Total Assets. It is commonly used to measure a firm's liquidity. When Current Assets are greater than Current Liabilities, the firm has a positive net working capital. That means the firm has excess funds to pay bills when they fall due. When Current Assets are less than Current Liabilities, the firm has a negative Working Capital [5],[11],[12].

(vi). Fixed Assets Turnover Ratio(x_6): $\frac{Net\ Sales}{Fixed\ Assets}$

The Fixed Assets Turnover Ratio measures the firm's effectiveness in generating Net Sales revenue from investments such as Property, Plant and Equipment, back into the firm .The higher the Fixed Assets Turnover Ratio, the more effective the firm's investments in Net Property, Plant, and Equipment have become [5],[11],[12].

(vii). Total Assets Turnover Ratio(x_7): $\frac{Net\ Sales}{Total\ Assets}$

The Total Assets Turnover Ratio is the ratio of Net Sales to Total Assets. It does not only measure a firm's effectiveness in generating sales revenue from investments back into the firm, but also measures the efficiency of managing all the firm's assets. The higher the Total Assets Turnover Ratio is, the more the effective use of the firm's investments become [5],[11],[12].

(viii). Fixed Assets to Total Assets Ratio(x_8): $\frac{Fixed\ Assets}{Total\ Assets}$

Fixed Assets to Total Assets Ratio is a measure of the extent to which fixed assets are financed with owners' capital. A high ratio indicates an inefficient use of working capital which reduces the firm's ability to carry accounts receivable and maintain inventory. A high ratio also means a low cash reserve. This will often limit the firm's ability to respond to increased demand for its products and services [5],[11],[12].

(ix). Net Sales Increase(x_9): $\frac{Current\ Year's\ Net\ Sales - Prior\ Year's\ Net\ Sales}{Prior\ Year's\ Net\ Sales}$

The Sales Increase is the ratio of the difference between the current year's Net Sales and the prior Net Sales, to the prior year's Net Sales.[11],[12],

(x). Current Liabilities to Net Sales Ratio(x_{10}): $\frac{Current\ Liabilities}{Net\ Sales}$

The Current Liabilities to Net Sales Ratio measures a firm's risk. The lower the ratio, the less risky the firm becomes .The higher the ratio, the higher the probability that the firm will default [5], [11], [12].

(xi). The category of firms (y): A period of three years was agreed upon within which applicants are expected to pay back credit. Any applicant, who settles payments after the period agreed upon has elapsed, was considered to have defaulted. This information was obtained from the credit officer. The dummy variable 1 represents a defaulting firm, whereas 0 represents a non-defaulting firm. A table of Category of Firms and Their Financial Ratios can be found in appendix. However, a summary of formulae for the computation of the credit ratios can be found in table 4.1 below.

Table 4.1 SUMMARIES OF FORMULAE FOR COMPUTATIONS OF CREDIT RATIOS

CREDIT RATIO	FORMULA
Current Ratio(x_1)	$\frac{Current\ Assets}{Current\ Liabilities}$, where $QuickAsset = CurrentAssets - Inventories$
Quick Ratio(x_2)	$\frac{Quick\ Assets}{Current\ Liabilities}$, Where $QuickAssets = CurrentAssets - Inentories = Accounts\ Receivable + Cash$
Return on Assets Ratio(x_3)	$\frac{Net\ Profit}{Net\ Sales}$
Net Profit Margin(x_4)	$\frac{Net\ Profit}{Net\ Sales}$
Net Working Capital Ratio(x_5)	$\frac{Net\ Working\ Capital}{Total\ Assets}$, where $NetWorkingCapital = CurrentAssets - CurentLiabilities$
Fixed Assets Turnover Ratio(x_6)	$\frac{Net\ Sales}{Fixed\ Assets}$
Total Assets Turnover Ratio(x_7)	$\frac{Net\ Sales}{Total\ Assets}$
Fixed Assets to Total Assets Ratio(x_8)	$\frac{Fixed\ Assets}{Total\ Assets}$
Net Sales Increase(x_9)	$\frac{Current\ Year's\ Net\ Sales - Prior\ Year's\ Net\ Sales}{Prior\ Year's\ Net\ Sales}$
Current Liabilities to Net Sales Ratio(x_{10})	$\frac{Current\ Liabilities}{Net\ Sales}$

4.1.2 Descriptive Statistics

Descriptive statistics are used to describe the basic features of the data gathered from a study. They provide summaries of the sample and the measures. Together with simple graphics analysis, they form the basis of virtually every quantitative analysis [1].The mean, being the location parameter of the distribution, tells little a bout the data when left in isolation. The standard deviation which remains the most common measure of statistical dispersion, measures how widely spread the values in data sets are from the mean [6]. The smaller the standard deviation, the closer the data points are to the mean. The larger the standard deviation, the less representative the mean is. Table shows the descriptive statistics.

Table 4.2: Descriptive statistic

Variable	Observation	Mean	Std. Dev.	Min	Max
x_1	80	4.49425	11.03623	0.41	89.1
x_2	80	2.706	6.359727	0.03	27.67
x_3	80	0.12625	0.1057388	0.01	0.61
x_4	80	0.049625	0.1080956	0	0.72
x_5	80	0.44825	0.4320917	0.05	2.37
x_6	80	12.34575	18.24462	0.29	148.72
x_7	80	4.270125	3.607712	0.71	13.53
x_8	80	0.2757125	0.2221597	0.27	0.78
x_9	80	0.22175	0.2697105	0.03	2.17
x_{10}	80	0.367875	0.3752626	0.04	1.29

Table 4.3: Skewness/Kurtosis tests for Normality

Variable	Pr(Skewness)	Pr(Kurtosis)
x_1	0.033	0.000
x_2	0.000	0.000
x_3	0.000	0.000
x_4	0.000	0.000
x_5	0.000	0.000
x_6	0.000	0.000
x_7	0.000	0.077
x_8	0.002	0.328
x_9	0.000	0.000
x_{10}	0.000	0.220

Apart from the features mentioned above, the range, which also gives an idea about the variability, is the difference between the maximum and minimum values in the data set.

A fundamental task in most statistical analysis is to characterize the location and variability of a data set. A further characterization of the data includes skewness and kurtosis. Skewness is a measure of symmetry, or more precisely, the lack of symmetry of a distribution or a data set. A data set is symmetric if it looks the same to the left and right of the centre point. A positive skewness value indicates a right skewed data whereas a zero skewness value indicates a symmetric distribution in data set.

Kurtosis is a measure of whether the data are peaked or flat relative to a normal distribution. That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak [3]. Standard normal distribution has a kurtosis of zero. Bar graphs are the common types of graph best suited for a qualitative independent variable [8]. Since there are no uniform distance between levels of a qualitative variable, the discrete nature of the individual bars are well suited for this type of independent variable. Figure 4.1 shows a graph of the independent variable.

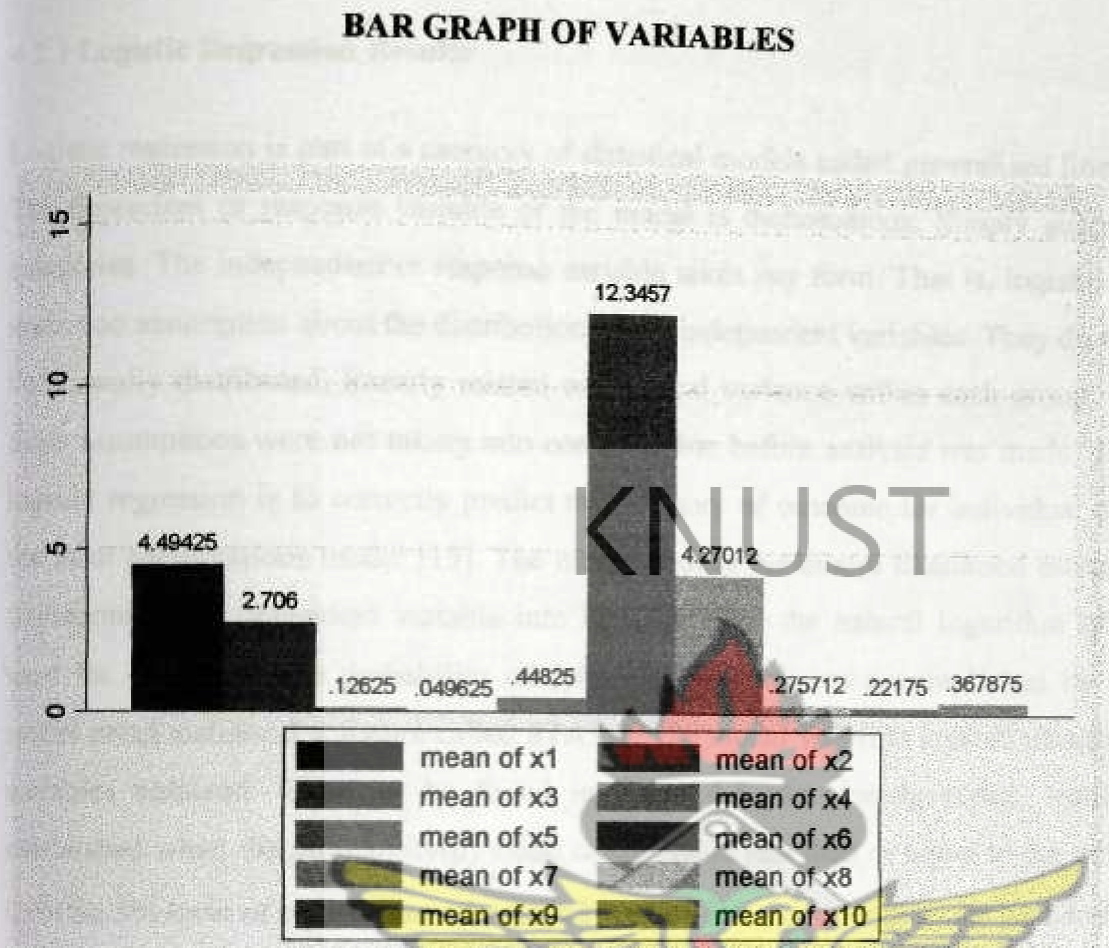

Figure 4.1: A graph of the mean of variables against variables

4.2 CREDIT SCORING MODELS RESULTS

4.2.1 Logistic Regression Results

Logistic regression is part of a category of statistical models called generalised linear models. The dependent or response variable of the model is dichotomous. Simply put, it has two categories. The independent or response variable takes any form. That is, logistic regression makes no assumption about the distribution of the independent variables. They do not have to be normally distributed, linearly related or of equal variance within each group. Therefore, these assumptions were not taking into consideration before analysis was made. The goal of logistic regression is to correctly predict the category of outcome for individual cases using the most parsimonious model [15]. The model applies maximum likelihood estimation after transforming the dependent variable into logit variable; the natural logarithm of the odds, used for estimating the probability of default. This goal was accomplished by creating a model using statistical software called STATA. The model was first created using all eligible variables obtained. This can be found in Table 4.4. As already stated, significance is established when the probability(p) value calculated is less than or equal to the cut-off value 0.05(the 5% level of significance chosen)taking also into consideration the pseudo R^2 value as it measures the strength of association between the dependent and independent variables. The higher the value, the better. From Table 4.4, the highest probability value is 0.947.It is therefore considered not to contribute significantly to the model. Hence, the variable x_6 is removed. The model was recreated without the variable x_6. This can be found in Table 4.6. Clearly, x_5 is the variable with the highest probability value (0.169). It was also removed. The current model was also created again without the variable x_5 as shown in Table 4.8. Amongst the probability of the variables, x_3 has the highest probability value (0.423).It must therefore be removed. Using the same approach, x_8, x_9 and x_7 were removed. The model obtained after removing the last variable x_7 was considered to be a well-fitted model because it is a model with significant logit coefficients. This selection criterion is the backward elimination method. Table 4.16 gives a summary of the parameters of the best model found. The significant variables obtained are few and as such there was no need for backward stepwise selection method to add or delete any significant variable. Table 4.4 gives a summary of the parameters of the best model found.

Table 4.4 Logistic regression model parameters (when all variables were used)

Table 4.1 depicts the logistic regression model created using all the financial ratios.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	2.88371	1.185595	0.015	.5599867	5.207433
x_2	-6.125412	2.46661	0.013	-10.95988	-1.290945
x_3	31.14164	25.8229	0.228	-19.47032	81.7536
x_4	-352.507	158.2202	0.026	-662.6129	-42.40108
x_5	-14.00404	14.31913	0.328	-42.06901	14.06094
x_6	-.007874	.1177441	0.947	-.2386481	.2229001
x_7	.8524176	.4372566	0.051	-.0045895	1.709425
x_8	5.474693	5.367893	0.308	-5.046185	15.99557
x_9	-33.1771	16.17058	0.040	-64.87085	-1.483343
x_{10}	10.24314	4.04154	0.011	2.321869	18.16441

Table 4.5 Logistic regression statistics (when all variables were used)

Table 4.5 depicts the logistic regression statistics when all the financial ratios were used.

Log-likelihood	-22.316579
Pseudo R^2	0.5740
Chi-square statistic	60.14
P-value	0.0000
Number of observations	80

Table 4.6 Logistic regression model parameters (when x_6 was removed)

Table 4.6 depicts the logistic regression model created when the Fixed Assets Turnover ratio was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	2.856757	1.111813	0.010	.6776433	5.03587
x_2	-6.068395	2.307082	0.009	-10.59019	-1.546597
x_3	32.14714	21.16998	0.129	-9.345254	73.63953
x_4	-350.2134	154.1868	0.023	-652.4141	-48.01283
x_5	-14.65252	10.6516	0.169	-35.52928	6.224234
x_7	.8300479	.2764232	0.003	.2882684	1.371827
x_8	5.746077	3.556703	0.106	-1.224932	12.71709
x_9	-33.37591	15.94114	0.036	-64.61997	-2.13186
x_{10}	10.22762	4.046195	0.011	2.297227	18.15802
constant	3.43017	3.184148	0.281	-2.810645	9.670984

Table 4.7 Logistic regression statistics (when x_6 was removed)

Table 4.7 depicts the logistic regression statistics when the Fixed Assets Turnover ratio was removed.

Log-likelihood	-22.316579
Pseudo R^2	0.5740
Chi-square statistic	60.14
P-value	0.0000
Number of observations	80

Table 4.8 Logistic regression model parameters (when x_5 was removed)

Table 4.8 depicts the logistic regression model created when the Net Working Capital was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	1.638899	.4997688	0.001	.65937	2.618428
x_2	-3.876762	1.296056	0.003	-6.416986	-1.336539
x_3	5.612873	7.00331	0.423	-8.113363	19.33911
x_4	-190.3276	75.82487	0.012	-338.9416	-41.71354
x_7	.716028	.2637467	0.007	.1990939	1.232962
x_8	1.74173	1.814979	0.337	-1.815562	5.299023
x_9	-14.66808	7.62752	0.054	-29.61774	.2815852
x_{10}	6.285675	2.28912	0.006	1.799083	10.77227
constant	-.7137271	1.074607	0.507	-2.819918	1.392464

Table 4.9 Logistic regression statistics (when x_5 was removed)

Table 4.9 depicts the logistic regression statistics when the Net Working Capital was removed.

Log-likelihood	**-23.461213**
Pseudo R^2	**0.5522**
Chi-square statistic	**57.85**
P-value	**0.0000**
Number of observations	**80**

Table 4.10 Logistic regression model parameters (when x_3 was removed)

Table 4.10 depicts the logistic regression model created when the Return on Asset Ratio was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	1.520084	.4658355	0.001	.6070629	2.433104
x_2	-3.443036	1.147008	0.003	-5.69113	-1.194942
x_4	-160.6202	61.15631	0.009	-280.4844	-40.75606
x_7	.7320809	.2550601	0.004	.2321723	1.23199
x_8	1.17551	1.663635	0.480	-2.085154	4.436175
x_9	-15.14354	7.440933	0.042	-29.7275	-.55958
x_{10}	5.883129	2.251455	0.009	1.470358	10.2959
constant	-.5249274	1.038559	0.613	-2.560466	1.510611

Table 4.11 Logistic regression statistics (when x_3 was removed)

Table 4.11 depicts the logistic regression statistics when the Return on Assets Ratio was removed.

Log-likelihood	-23.789269
Pseudo R^2	0.5459
Chi-square statistic	57.20
P-value	0.0000
Number of observations	80

Table 4.12 Logistic regression model parameters (when x_8 was removed)

Table 4.12 depicts the logistic regression model created when the Fixed Assets to Total Assets ratio was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	1.54964	.477768	0.001	.6132316	2.486048
x_2	-3.589247	1.180052	0.002	.6132316	2.486048
x_4	-165.0346	59.6525	0.006	-281.9514	-48.11786
x_7	.703224	.2422614	0.004	.2284004	1.178048
x_9	-14.67861	7.149595	0.040	-28.69156	-.6656668
x_{10}	6.082456	2.413917	0.012	1.351265	10.81365
constant	-.0745167	.8076306	0.926	-1.657444	1.50841

Table 4.13 Logistic regression statistics (when x_8 was removed)

Table 4.13 depicts the logistic regression statistics when Fixed Assets to Total Assets Ratio was removed.

Log-likelihood	-24.04582
Pseudo R^2	0.5410
Chi-square statistic	56.68
P-value	0.0000
Number of observations	80

Table 4.14 Logistic regression model parameters (when x_9 was removed)

Table 4.14 depicts the logistic regression model created when the Net Sale Increase was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	.9694226	.3617702	0.007	.260366	1.678479
x_2	-2.677163	.993924	0.007	-4.625218	-.7291075
x_4	-158.4184	67.85681	0.020	-291.4153	-25.42145
x_7	.4145163	.2004706	0.039	.0216011	.8074316
x_{10}	4.918567	1.819349	0.007	1.352709	8.484425
constant	-.3826363	.7877943	0.627	-1.926685	1.161412

Table 4.15 Logistic regression statistics (when x_9 was removed)

Table 4.15 depicts the logistic regression statistics when the Net Sales Increase was removed.

Log-likelihood	-26.735273
Pseudo R^2	0.4897
Chi-square statistic	51.30
P-value	0.0000
Number of observations	80

Table 4.16 Logistic regression model parameters (when x_7 was removed)

Table 4.16 depicts the logistic regression model created when the Total Assets to Turnover Ratio was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	.7955728	.2341709	0.001	.3366063	1.254539
x_2	-2.368391	.7115702	0.001	-3.763043	-.9737395
x_4	-100.8711	33.71709	0.003	-166.9554	-34.78686
x_{10}	3.188354	1.216013	0.009	.8050125	5.571696
Constant	1.220762	.5491122	0.026	.1445223	2.297003

Table 4.17 Logistic regression statistics (when x_7 was removed)

Table 4.17 depicts the logistic regression statistics when the Total Assets to Turnover ratio was removed.

Log-likelihood	-31.55829
Pseudo R^2	0.3976
Chi-square statistic	41.66
P-value	0.0000
Number of observations	80

The logistic regression equation of the model was found to be:

$$\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = 1.220762 + 0.7955728x_1 - 2.368391x_2 - 1.008711x_4 + 3.188354x_{10}$$

If the values of the ratios x_1, x_2, x_4 and x_{10} of a firm are given, then the value of the log-odds, λ say, can be found. Thus,

$$\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \lambda$$

$$\frac{P(Y=1)}{1-P(Y=1)} = \ell^{\lambda}$$

The probability of default is:

$$P(Y=1) = \frac{\ell^{\lambda}}{1+\ell^{\lambda}}$$

Suppose a risk classification of 0.4 is chosen by a credit officer. A firm can be considered to have defaulted if it has a probability of default greater than 0.4 and should not be granted any loan. Loan should be granted to firms whose probability of default is less than 0.4.

Consider a firm whose credit ratio x_1, x_2, x_4 and x_{10} are respectively 2.86, 5.31, 2.42 and 2.67. The value of the log-odds is -3.00823 and the probability of default is approximately 0.0471. This value is less than 0.4.Therefore, credit should be granted to that firm. Similarly, a firm whose credit ratios x_1, x_2, x_4 and x_{10} are 2.86, 1.06, 0.42 and 1.3 respectively, will have a log-odds to be 4.707.The probability of default is approximately 0.991. Clearly, this value is greater than the risk classification value of 0.4. Hence, credit should not be granted to such firm.

In this study, the output of the logistic regression model, produced by STATA, has log-likelihoods, pseudo R^2, chi-square statistic, p-value, number of observations, confidence interval and standard error. These can be found in Table 4.17. The iteration log-likelihood is not too interesting to talk about but does contain information on how well the model converges. The final log-likelihood was found to be -31.55829. This can be used in comparisons of nested models. The pseudo R^2 summarizes the strength of the relationship between dependent and independent variables. Its value is 0.3976.That means, 39.76% variability in the dependent variable can be explained by the independent variables. The confidence interval is the boundary within which the estimated coefficients of the financial ratios are expected to be. Regarding the standard error, the model found is an estimated one and as such it is not hundred percent accurate. The margin of error for each coefficient of the variable is the standard error. The probability (p) for each for each coefficient of the variables to fall within the confidence interval is also calculated.

The fit of the entire model can be found using the chi-square test, likelihood-ratio test or by comparing the p-value with the level of significance (0.05).

The hypothesis of the entire significance is defined to be:

$H_0: \beta_1 = \beta_2 = ... = \beta_5 = 0$ (All logistic regression coefficients except the constant ere zero)

H_1: At least one of the coefficients is not 0

The accepting or rejecting can be determined by comparing the p-value with the 0.05 level of significance used in this study. From Table 4.17, the p-value was found to be 0.0000. Clearly, the fit of the model is proved since the p-value obtained is less than the 0.05 with 95% confidence interval. This means H_0 was rejected. Therefore, the coefficients of the independent variables are significant.

The fit of the individual logistic model parameter can be found.

The hypothesis for the individual logistic regression coefficients is defined as:

$H_0 : \beta_i = 0, where\, i = 1,2,...,5$

$H_1 : \beta_i \neq 0.$

The accepting or rejecting can be determined by comparing the individual p-value obtained in Table 4.16 with the 0.05 level of significance. Clearly, the p-values of

the ratios x_1, x_2, x_4 and x_{10} are less than 0.05 with 95% confidence interval. This means H_0 was rejected. Therefore, individual logistic model parameter is significant to the model found.

4.2.2 Probit Regression Results

Probit regression, like the logistic regression, is a generalized linear model. The dependent variable is categorical but the independent variable takes any form.

Therefore, its underlying assumptions are similar to that of the logistic regression. These assumptions were not taken into consideration before analysis was made.

The probit regression model uses the standard normal cumulative distribution to obtain the odds. The model was created in this study using the backward selection approach. The output in Table 4.6.1 and Table 4.6.2 were obtained by first using all the variables. Just as the logistic regression model was formulated, the variables x_6 x_5, x_3, x_8, x_9 and x_7 were removed one at a time using the backward elimination mentioned earlier on until the step at which each variable in the model has significance lower than or equal to 0.05. Table 4.6.13 gives a summary of the parameters of the best model.

Table 4.6.1: Probit regression model parameters (when all variables were used)

Table 4.6.1 depicts the probit regression model created using all the financial ratios.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	1.209207	.4263165	0.005	.3736417	2.044772
x_2	-2.572141	.8704569	0.003	-4.278205	-.866077
x_3	14.78176	13.26938	0.265	-11.22574	40.78927
x_4	-136.084	55.00635	0.013	-243.8944	-28.27351
x_5	-6.785702	7.373384	0.357	-21.23727	7.665864
x_6	.019911	.0573671	0.357	-.0925266	.1323485
x_7	.4000263	.1934945	0.039	.0207839	.7792686
x_8	3.130351	2.815614	0.266	-2.388152	8.648853
x_9	-16.22548	7.951801	0.041	-31.81073	-.6402407
x_{10}	4.489623	1.595338	0.005	1.362818	7.616427
constant	1.073249	1.596214	0.501	-2.055274	4.201772

Table 4.6.2 probit regression statistics (when all variables were used)

Table 4.6.2 depicts the probit regression statistics when all the financial ratios were used.

Log-likelihood	-22.916025
Pseudo R^2	0.5626
Chi-square statistic	58.94
P-value	0.0000
Number of observations	80

Table 4.6.3 Probit regression model parameters (when x_6 was removed)

Table 4.6.3 depicts the probit regression model created when the Fixe Assets Turnover ratio was removed

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	1.239323	.4204357	0.003	.415284	2.063362
x_2	-2.631791	.8582193	0.002	-4.31387	-.9497121
x_3	11.70013	9.515056	0.219	-6.949035	30.34493
x_4	-135.8831	54.92316	0.013	-243.5305	-28.23569
x_5	-4.918017	4.831659	0.309	-14.38789	4.55186
x_7	.4486678	.1413968	0.002	.1715352	.7258003
x_8	2.380128	1.736434	0.170	-1.02322	5.783476
x_9	-15.37807	7.462144	0.039	-30.0036	-.7525373
x_{10}	4.402605	1.536172	0.004	1.391763	7.413447
constant	.8357443	1.413959	0.554	-1.935565	3.607054

Table 4.6.4 Probit regression statistics (when x_6 was removed)

Table 4.6.4 depicts the probit regression statistics found when the Turnover ratio was removed

Log-likelihood	-22.975485
Pseudo R^2	0.5614
Chi-square statistic	58.82
P-value	0.0000
Number of observations	80

Table 4.6.5 Probit regression model parameters (when x_5 was removed)

Table 4.6.5 depicts the probit regression model created when the Net Working Capital was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	.9151278	.2504279	0.000	.4242981	1.405958
x_2	-2.124771	.6412222	0.001	-3.381544	-.8679989
x_3	3.25334	4.326219	0.452	-5.225893	11.73257
x_4	-97.49851	33.02014	0.003	-162.2168	-32.78024
x_7	1.028152	.142266	0.003	.1408507	.6985233
x_8	1.028152	1.086098	0.344	-1.100561	3.156864
x_9	-9.225732	4.455065	0.038	-9575	-.4939649
x_{10}	3.418724	1.100305	0.002	1.262167	5.575282
constant	-.4802752	.6182999	0.437	-1.692121	.7315703

Table 4.4.6 Probit regression statistics (when x_5 was removed)

Table 4.4.6 depicts the probit regression statistics found when the Net Working Capital was removed.

Log-likelihood	-23.523758
Pseudo R^2	0.5510
Chi-square statistic	57.73
P-value	0.0000
Number of observations	80

Table 4.6.7 Probit regression model parameters (when x_3 was removed)

Table 4.6.7 depicts the probit regression model created when the Return on Assets Ratio was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	.8554974	.2359479	0.000	.393048	1.317947
x_2	-1.898062	.5626742	0.001	-3.000883	-.7952404
x_4	-82.95802	24.92477	0.001	-131.8097	-34.10638
x_7	.4332939	.1391897	0.002	.1604872	.7061006
x_8	.6932258	.9942331	0.486	-1.255435	2.641887
x_9	-9.435047	4.347849	0.030	-17.95668	-.9134194
x_{10}	3.227964	1.09259	0.003	1.086527	5.369401
constant	-.3671286	.6012812	0.541	1.545618	.8113609

Table 4.6.8 Probit regression statistics (when x_3 was removed)

Table 4.6.8 depicts the probit regression statistics found when the Return on Assets Ratio was removed.

Log-likelihood	-23.825087
Pseudo R^2	54.52
Chi-square statistic	57.12
P-value	0.0000
Number of observations	80

Table 4.6.9 Probit regression model parameters (when x_8 was removed)

Table 4.6.9 depicts the probit regression model created when the Fixed Assets to Total Assets Ratio was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	.8688741	.2403717	0.000	.3977541	1.339994
x_2	-1.975114	.5747215	0.001	-3.101548	-.848681
x_4	-85.66346	24.74157	0.001	-134.156	-37.17086
x_7	.4175752	.1328177	0.002	.1572573	.6778931
x_9	-9.061484	4.19191	0.031	-17.27748	-.8454913
x_{10}	3.316493	1.166475	0.004	1.030243	5.602742
constant	-.1141154	.4693431	0.808	-1.034011	.8057802

Table 4.6.10 Probit regression statistics (when x_8 was removed)

Table 4.6.10 depicts the probit regression statistics found when the Fixed Assets to Total Assets Ratio was removed.

Log-likelihood	- 24.073019
Pseudo R^2	0.5405
Chi-square statistic	56.63
P-value	0.0000
Number of observations	80

Table 4.6.11 Probit regression model parameters (when x_9 was removed

Table 4.6.11 depicts the probit regression model created when the Net Sales Increase was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	.5070944	.1659871	0.002	.1817658	.8324231
x_2	-1.422826	.4773674	0.003	-2.358449	-.4872032
x_4	-78.70766	29.71147	0.008	-136.9411	-20.47424
x_7	.2286372	.1063351	0.032	.0202242	.4370502
x_{10}	2.671629	.9082142	0.003	.8915622	4.451696
constant	-.2910815	.4661255	0.532	-1.204671	.6225076

Table 4.6.12 Probit regression statistics (when x_9 as removed)

Table 4.6.12 depicts the probit regression statistics found when the Net Sales Increase was removed.

Log-likelihood	-26.853748
Pseudo R^2	0.4874
Chi-square statistic	51.07
P-value	0.0000
Number of observations	80

Table 4.6.13 Probit regression model parameters (when x_7 was removed)

Table 4.6.13 depicts the probit regression model created when the Total Assets to Turnover Ratio was removed.

Variables	Coefficients	Std. Err	P>|z|	[95% Conf.	Interval]
x_1	.4457784	.1178203	0.000	.2148548	.6767019
x_2	-1.338462	.3735919	0.000	-2.070689	-.6062358
x_4	-54.43643	15.00397	0.000	-83.84367	-25.0292
x_{10}	1.798699	.6678316	0.007	.4897733	3.107625
constant	.689575	.3185684	0.030	.0651924	1.313958

Table 4.6.14 Probit regression statistics (when x_7 was removed)

Table 4.6.14 depicts the probit regression statistics when the Total Assets to Turnover Ratio was removed.

Log-likelihood	-31.681058
Pseudo R^2	0.3953
Chi-square statistic	41.41
P-value	0.0000
Number of observations	80

The probit regression equation of the model was found to be:

$$\Phi^{-1}(P(Y=1)) = 0.68957 + 0.4457784x_1 - 1.338463x_2 - 54.43643x_4 + 1.798699x_{10}$$

If the values of the ratios x_1, x_2, x_4 and x_{10} of a firm are given, then the value of the linear predator, say t, can be found. Thus,

$$\Phi^{-1}(P(Y=1)) = t$$

The probability of default is:

$$P(Y=1) = \Phi(t)$$

Using the standard normal distribution table, the probability of default can be found.

The pseudo R^2 was found to be 0.3953. This means, 39.53% variability in the dependent variable can be explained by the independent variables.

The significance of the entire model was found by comparing the calculated chi-square statistic (41.41) obtained in Table 4.3 with the tabulated value. The chi-square table value with 5 degrees of freedom and 0.05 level of significance, i.e. $\chi^2_{(0.05,5)}$, was found to be (11.07). Clearly, the tabulated value (11.07) is less than the calculated value (41.41) obtained. Therefore, we fail to accept the null hypothesis that includes only the constant term in the model. Hence, we conclude that the model is significant.

There is also a chance to test for the significance of the individual probit model parameters.

Like the logistic regression model, all the p-values of the ratios x_1, x_2, x_4 and x_{10}, found in Table 4.30, are less than 0.05 with 95% confidence interval. This means, individual probit regression model parameter, is important in predicting the probability of default.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

In this study, real data set (financial ratios) from a Ghanaian bank was used to formulate the logistic and probit regression model. At the end of the study, the logistic and probit regression models were found to be respectively

$$\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = 1.220762 + 0.7955728x_1 - 2.36839x_2 - 1.008711x_4 + 3.188354x_{10}$$

and

$$\Phi^{-1}(P(Y=1)) = 0.68957 + 0.4457784x_1 - 1.338463x_2 - 54.43648x_4 + 1.798699x_{10}.$$

Clearly, among the data used, current ratio, quick ratio, net profit margin and current liabilities to net sales ratio were the financial ratios found to have contributed significantly in formulating the models. By comparing the Pseudo R^2 values of these two models, the logistic regression model gave a better variation as it showed a higher variability between the logit and the financial ratios. The comparison can be found in tables 4.17 and 4.6.14. This model result can help predict whether or not a new applicant will default.

After careful analysis of our study, we recommend the following:

- The Bank of Ghana should make the use of models to access credit worthiness of clients a policy for all banks, to reduce the probability of default. This will avert any future occurrence of credit crises in Ghana.
- The model's parameters should be adjusted periodically to reflect the model's performance over time.
- The asymmetric information gap between clients and the banks should be bridged.
- Financial experts should organize training programmes and seminars periodically to improve the skills of credit analysts.

These recommendations will go a long way into helping reduce credit risk in Ghana when implemented.

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APPENDIX

The Category of Firms and Their Financial Ratios

Firm	Y	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
1	1	89.1	24.02	0.61	0.16	0.96	148.72	3.96	0.027	2.17	0.99
2	0	2.86	1.06	0.17	0.06	0.42	7.52	2.67	0.36	0.3	0.28
3	0	7.92	1.24	0.25	0.09	0.62	9.88	2.89	0.29	0.17	0.34
4	1	1.72	1.31	0.05	0	0.36	7.46	1.1	0.16	0.05	0.28
5	0	3.33	3.32	0.09	0	0.5	4.31	1.24	0.29	0.07	0.94
6	1	0.41	0.22	0.01	0.01	0.37	3.34	2.47	0.74	0.08	0.21
7	0	1.06	0.03	0.06	0.02	0.05	1.9	4.02	0.13	0.27	0.25
8	0	1.65	1.07	0.3	0.11	0.17	1.42	2.7	0.56	0.11	0.79
9	1	1.7	0.9	0.1	0.03	0.4	19.19	3.68	0.1	0.1	1.29
10	0	2.1	1.2	0.08	0	0.49	27.5	2.27	0.07	0.03	0.09
11	1	1.7	0.4	0.03	0.01	0.16	26.45	13.53	0.58	0.39	0.04
12	0	28.88	27.67	0.16	0.02	0.76	30.48	6.5	0.21	0.26	0.16
13	0	2.1	1.5	0.05	0.07	0.47	2.26	1.82	0.08	0.26	0.05
14	0	1.5	0.9	0.05	0.05	0.05	0.29	0.71	0.64	0.3	0.19
15	1	1.2	0.7	0.04	0.01	0.14	8.57	5.76	0.13	0.11	0.04
16	0	2	1	0.27	0.06	2.37	2.74	2.85	0.25	0.76	0.27
17	1	1.5	0.3	0.17	0.02	0.29	5.97	9.68	0.08	0.2	0.17
18	0	1.6	0.8	0.25	0.03	0.28	5.8	9.5	0.07	0.21	0.16
19	0	1.4	0.7	0.24	0.04	0.29	5.9	9.4	0.06	0.2	0.15
20	1	1.7	0.6	0.27	0.05	0.27	5.7	9.3	0.05	0.23	0.2
21	0	0.41	0.22	0.01	0.01	0.37	3.34	2.47	0.74	0.08	0.21
22	0	1.06	0.03	0.06	0.02	0.05	1.9	4.02	0.13	0.27	0.25
23	0	1.65	1.07	0.3	0.11	0.17	1.42	2.7	0.56	0.11	0.79
24	1	1.7	0.9	0.1	0.03	0.4	19.19	3.68	0.1	0.1	1.29
25	0	2.1	1.2	0.08	0	0.49	27.5	2.27	0.07	0.03	0.09
26	1	1.7	0.4	0.03	0.01	0.16	26.45	13.53	0.58	0.39	0.04
27	0	2.86	1.06	0.17	0.06	0.42	7.52	2.67	0.36	0.3	0.28
28	0	7.92	1.24	0.25	0.09	0.62	9.88	2.89	0.29	0.17	0.34
29	1	1.72	1.31	0.05	0	0.36	7.46	1.1	0.16	0.05	0.28
30	0	3.33	3.32	0.09	0	0.5	4.31	1.24	0.29	0.07	0.94
31	1	1.7	0.9	0.1	0.03	0.4	19.19	3.68	0.1	0.1	1.29
32	0	2.1	1.2	0.08	0	0.49	27.5	2.27	0.07	0.03	0.09
33	1	1.7	0.4	0.03	0.01	0.16	26.45	13.53	0.58	0.39	0.04
34	0	28.88	27.67	0.16	0.02	0.76	30.48	6.5	0.21	0.26	0.16
35	0	2.1	1.5	0.05	0.07	0.47	2.26	1.82	0.08	0.26	0.05
36	0	7.92	1.24	0.25	0.09	0.62	9.88	2.89	0.29	0.17	0.34
37	1	1.72	1.31	0.05	0	0.36	7.46	1.1	0.16	0.05	0.28
38	0	3.33	3.32	0.09	0	0.5	4.31	1.24	0.29	0.07	0.94
39	1	0.41	0.22	0.01	0.01	0.37	3.34	2.47	0.74	0.08	0.21
40	0	1.06	0.03	0.06	0.02	0.05	1.9	4.02	0.13	0.27	0.25
41	0	1.5	0.9	0.05	0.05	0.05	0.29	0.71	0.64	0.3	0.19
42	1	1.2	0.7	0.04	0.01	0.14	8.57	5.76	0.13	0.11	0.05
43	0	2	1	0.27	0.06	2.37	2.74	2.85	0.25	0.76	0.28

44	1	1.5	0.3	0.17	0.02	0.29	5.97	9.68	0.08	0.2	0.17
45	0	1.6	0.8	0.25	0.03	0.28	5.8	9.5	0.07	0.21	0.15
46	1	1.7	0.9	0.1	0.03	0.4	19.19	3.68	0.1	0.1	1.27
47	1	2.1	1.2	0.08	0	0.49	27.5	2.27	0.07	0.03	0.09
48	1	1.7	0.4	0.03	0.01	0.16	26.45	13.53	0.58	0.39	0.08
49	0	9.66	1.06	0.17	0.06	0.42	7.52	2.67	0.36	0.3	0.24
50	0	3.20	1.24	0.25	0.09	0.62	9.88	2.89	0.29	0.17	0.34
51	1	1.32	1.91	0.33	0	0.84	8.46	1.1	0.16	0.05	0.67
52	0	3.33	3.32	0.09	0	0.5	4.31	1.24	0.29	0.07	0.94
53	1	1.7	0.9	0.1	0.03	0.4	19.19	3.68	0.1	0.1	1.29
54	0	3.1	1.5	0.1	0.09	0.30	24.8	2.61	0.08	0.06	0.10
55	1	1.7	0.4	0.03	0.01	0.16	26.45	13.53	0.58	0.39	0.04
56	0	28.88	27.67	0.16	0.02	0.76	30.48	6.5	0.21	0.26	0.16
57	0	2.1	1.5	0.05	0.07	0.47	2.26	1.82	0.08	0.26	0.05
58	0	7.92	1.24	0.25	0.72	0.60	9.57	2.45	0.78	0.35	0.48
59	1	1.72	1.31	0.05	0	0.36	7.46	1.45	0.51	0.03	0.26
60	0	1.06	0.03	0.06	0.02	0.05	1.9	4.02	0.13	0.27	0.25
61	0	1.65	1.07	0.3	0.11	0.17	1.42	2.7	0.56	0.11	0.79
62	0	3.33	3.32	0.09	0	0.5	4.31	1.24	0.29	0.07	0.94
63	1	0.41	0.22	0.01	0.01	0.37	3.34	2.47	0.74	0.08	0.21
64	0	3.33	3.32	0.09	0	0.5	4.31	1.24	0.29	0.07	0.94
65	0	2	1	0.27	0.06	2.37	2.74	2.85	0.25	0.76	0.28
66	0	2.1	1.5	0.05	0.07	0.47	2.26	1.82	0.08	0.26	0.05
67	0	2.1	1.2	0.08	0	0.49	27.5	2.27	0.07	0.03	0.09
68	0	1.1	1.3	0.05	0.04	0.21	2.21	1.86	0.06	0.22	0.04
69	0	1.5	0.9	0.05	0.05	0.05	0.29	0.71	0.64	0.3	0.19
70	0	1.6	0.8	0.25	0.03	0.28	5.8	9.5	0.07	0.21	0.15
71	1	1.7	0.9	0.1	0.03	0.4	19.19	3.68	0.1	0.1	1.29
72	0	0.41	0.22	0.01	0.01	0.37	3.34	2.47	0.74	0.08	0.21
73	0	1.06	0.03	0.06	0.02	0.05	1.9	4.02	0.13	0.27	0.25
74	0	1.2	0.7	0.04	0.01	0.14	8.57	5.76	0.13	0.11	0.05
75	1	1.5	0.3	0.17	0.02	0.29	5.97	9.68	0.08	0.2	0.17
76	1	1.7	0.4	0.03	0.01	0.16	26.45	13.53	0.58	0.39	0.04
77	0	11.34	27.67	0.16	0.02	0.76	30.48	6.5	0.21	0.26	0.12
78	0	8.34	1.24	0.25	0.09	0.62	9.88	2.89	0.29	0.17	0.34
79	1	1.72	1.31	0.05	0	0.36	7.46	1.1	0.16	0.05	0.26
80	0	1.66	3.32	0.09	0.65	0.5	4.31	1.24	0.29	0.07	0.87