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Applying artificial neural network and binary logistic models to predict propensity to pay cash dividend: Evidence from an emerging market

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Abstract. This study examines the predictors of the propensity to pay cash dividend including industry structure, natural log of revenue, firm size, big 4 auditors, and financial leverage. The paper draws upon the theory of uncertain binary choice. Pooled unbalanced panel logistic regression and artificial neural network were used to analyze data of 725 firm-year observations obtained from companies' annual accounts and financial statements from 2012 to 2021. The documented results find that industry structure, natural log of revenue (big 4 auditors, firms' size and financial leverage) significantly influence the propensity to pay (not to pay) cash dividend. The result on the interaction term shows that industry structure and log revenue has the propensity to significantly predict non-payment of cash dividend. Nagelkerke pseudo R2 indicates that the predictors explain about 36% of variability in payment of cash dividend. The ROC-curves indicate good model fits as areas under the curve are up to .85. We recommend that the management of listed companies and equity stockholders who are interested in dividend payment should consider the history of industry structure and companies' revenue while those not interested in dividend payment should consider company size, the presence of big 4 auditors and financial leverage.
Keywords: *Cash dividends, Industry structure, Independent auditors, Uncertain binary choice, Logistic regression, Artificial neural network, Algorithm, Corporate finance, Nigeria*

1. Introduction

From time-to-time, firms' equity stockholders expect return on invested equity in the form of dividend. Experience from a company's cash dividend payment pattern may affect equity investors' asset allocation decisions. The board of directors' recommendation that companies should pay dividend is an initial indubitable influence on dividend decisions before stockholders approval. Aside this, financial result is another influence on dividend payment. There are other factors unrelated to financial results that influence the board of directors in deciding whether to pay regular cash dividend or not. To delineate the study, we are interested in "regular" cash dividend because there are different types of dividends, including extra dividends, special dividends and liquidating dividends (Ross, Westerfield and Jordan, 2022). We shall simply use cash dividend in the remaining part of the paper.

a. The Nigerian context

Nigeria is a former British colony and a member of the Commonwealth. The country has an active capital market with well-articulated regulatory regimes on dividend; including Nigerian Code of Corporate Governance, NCCG (2018, as amended) and Companies and Allied Matters Act, CAMA, (2020, as amended), both of which are consistent with regards to regulation of dividend. Section 426(1) of CAMA (2020) speaks to the issue of dividend payment, and recommends that, "a company may, at a general meeting, declare dividends in respect of any year or other period only on the recommendation of the directors." Furthermore, Section 426(3) recommends that, "the general meeting has power to decrease the amount of dividend recommended by the directors but has no power to increase the recommended amount." Finally, Section 428 mandates that, "a company shall not declare or pay dividend if there are reasonable grounds for believing that the company is or would be, after the payment, unable to pay its liabilities as they become due." So, it is clear that boards of directors may or may not recommend that dividend should be paid. Anecdotal disclosures of two listed Nigerian anonymized companies go as follows.

First company:

"In respect of the current year, your Directors are pleased to recommend the dividend of 25k (twenty five Kobo) per ordinary share of 50 Kobo each for the financial year ending December 31, 2012. The payment of the dividend is subject to the approval of the shareholders at the forthcoming Annual General Meeting and if approved will be paid on June 28, 2013."

Second company:

"The Board recognizes the importance of returns generated for our esteemed shareholders' investments and support. It is based on the foregoing and the continued confidence on the prospects of our business, supported by the credible 2022 Financial year results that the Directors will propose to shareholders at the Annual General Meeting the payment of a dividend in the sum of ₦7.14 for every ordinary share of 50 kobo, representing a significant increase from the amount paid as dividend last year. The company went on to say that ₦15,639 million dividend has been recommended by the Board of Directors for approval at the forthcoming Annual General Meeting (2021: ₦1,008 million)."

We examine the influence of revenue, firm size and financial leverage on propensity to pay cash dividend, as well as non-financial considerations including industry structure and external auditors' influences. We consider the propensity to (not)pay to pay cash dividend as a behavioral choice decision which is conditional on some stimuli. We draw on knowledge-based behavior aspect of uncertain binary choice theory of Feldman (1961) and Hu, Pan, Ding and Kang (2022). Hu *et al*. (2022) opine that uncertain binary choice involves humans who are required to choose between two responses based on humans' belief degrees as influenced by some stimuli. That is to say, there are no known choice rules between stimuli and responses.

According to Hu *et al*. (2022), human behavior (response) is sensitive to some stimuli such as emotion, fatigue, learning, attention, stress, and environmental events; which are difficult to control. Hu *et al*. (2022) were influenced by psychology in preferring knowledge-based pattern of uncertain binary choice theory. Knowledge-based behavior is a purposeful behavior that involves planning and reasoning as a result of stimuli presented. It takes time to response to stimuli. The theory has practical application for our study insofar as human behavior of binary choice model (to pay or not to pay cash dividend) and stimuli (industry structure, external auditors, revenue, firm size, and financial leverage) are concerned. In a nutshell, the theory is applied to justify the use of binary logistic regression and two-sided outcome artificial neural network. Our model backs out time element in adapting the theory because, we think, there is no reasonable way to capture real-time actions and reactions in firms' yearly archival dataset.

Different authors have used different dividend decision models as their dependent variable. For examples: Jaara, Alashhab and Jaara (2018) and Uwuigbe, Olusanmi and Iyoha (2015) used dividend payout per share as their dependent variable. Jaara *et al*. (2018), Prša, Šestanović and Ramljak (2022), and Chaniago and Ekadjaja (2022) used dividend payout ratio as their dependent variable. Dewasiri, Koralalage, Azeez, Jayarathne, Kuruppuarachchi and Weerasinghe (2019), Jaara *et al*. (2018), Louziri and Oubal (2022) used dividend yield as one of their dependent variables. This study uses propensity to pay cash dividend as response variable. Flow chart 1 shows the study's conceptual framework.

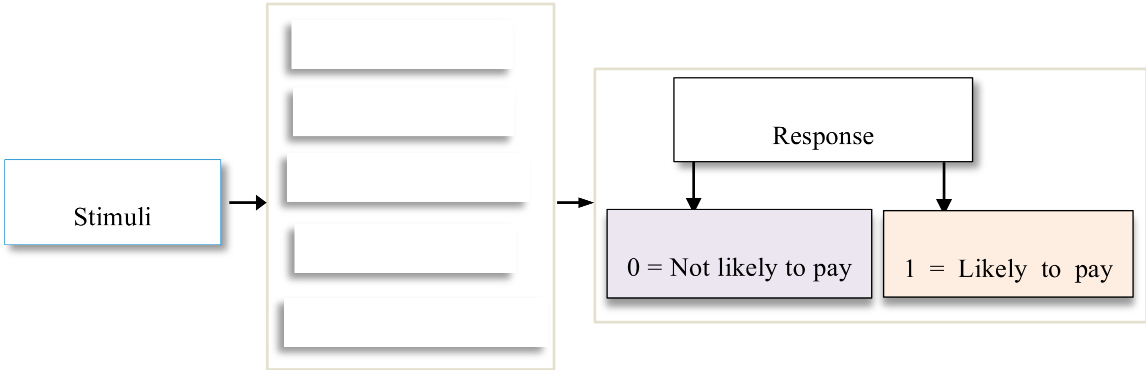


Figure 1: Conceptual Framework

The objective of this study is to examine the propensity to pay cash dividend by using industry structure (structural), external auditors (behavioral) and revenue, size and leverage (financials) as predictors. The study poses the research question of, What influences do industry structure, external auditors, revenue, firm size and leverage have on the probability to pay (or not pay) cash dividend? The study attempts to answer this question by deploying logistic regression (LR), following extant studies (Dewasiri *et al*., 2019; Franc-Dąbrowska, Mądra-Sawicka and Ulrichs, 2019; and Houqe, Monem and van Zijl, 2023) and artificial neural network (ANN, Rosenblatt, 1961); following prior studies including Intrator and Intrato (2001), Ibiwoye, Ajibola and Sogunro (2012), Elghaly and Diping (2019), Al Omari, Alkhawaldeh and Jaber (2023) and Yinka-Banjo, Akinyemi and Er-rabbany (2023). LR and ANN allow us to predict the propensity of paying (or not paying) cash dividend. Our main conclusions are based on ANN results, which also serve as a robustification strategy.

The study makes at least three major contributions to the literature. The first contribution is that it appears to be the first empirical study to predict the propensity to pay cash dividend using industry structure, independent auditors and log of revenue as predictors. Secondly, method-wise, it appears to pioneer the use state-of-the-art ANN to predict the propensity to (not)pay cash dividend in an emerging economy, which is an original contribution to the literature. Finally, this is the first instance known to the authors where the psychology of human behavior is used to model uncertainty binary logistic regression in respect of payment or non-payment of cash dividend. The practical implication of the theory is that future researchers can apply it to model the propensity to (not)pay cash dividends.

We motivate the relationships between the response variable and the predictors as follows. Firstly, the dynamics of industry structure can influence firms' ability to pay or not to pay cash dividend. For examples, firms operating in the tourism and hospitality industry (telecom industry) is unlikely (likely) not to pay (to pay) cash dividend on a regular basis because of seasonal (steady) cash flows. Therefore, we expect industry structure to influence payment of cash dividend. Secondly, big 4 auditors in particular (and, indeed, accountants in general) appear to be conservative in nature. Independent auditors are part of corporate governance mechanisms (Bhattacharya, Li and Rhee, 2016). Managements of companies will be conscious that external auditors are watching over their financial representations/disclosures. We expect big 4 auditors to restrict or discourage their clients from paying cash dividend because external auditors are obliged to report on clients going concern status (*e.g.,* Downing and Langli, 2019). By so doing, external auditors assure their own survival and prosperity. Thirdly, after meeting all operational costs and taxes, high revenue-earning companies channel residual revenues to their shareholders through payment of cash dividend. *Ceteris paribus*, companies that make high revenue are expected to pay cash dividend. Fourthly, large firms may be reluctant to pay cash dividend because of overinvestments and empire building (Farooq, Al-Jabri, Khan, Ansari and Tariq, 2022); or they may have continued to acquire additional noncurrent assets with available cash or on credit terms, of which they are obligated to settle. In either case, they need cash to settle. Therefore, it is expected that firm size will likely influence non-payment of cash dividend. Finally, highly geared companies are statutorily barred from paying dividend out of capital (see, section 428 alluded to above). In order to stay afloat, we expect financial leverage to discourage paying dividend.

Issuing from these expectations, we make the tentative unidirectional alternative hypotheses that industry structure and revenue (external auditors, firm size and financial leverage) are likely to influence payment (non-payment) of cash dividend. The above expectations morph into testable alternative hypotheses in section 2.2 of this paper.

We provide early insights of our findings. Our unbalanced logistic regression test results show that industry structure (*STR*) and natural log of revenue. *LN(REV)* are likely to significantly predict payment of cash dividend while big 4 auditors, *AUDIT(1)*, natural log of firm size, *LN(SIZE)*, and financial leverage (*FIN.LEV*) are likely to significantly predict the non-payment of cash dividend. In particular, the logit coefficients on *STR* and *LN(REV)* are positive and statistically significant at conventional levels. The exp(B) on *STR* indicates that the odds that cash dividend will be paid is 1.114 (Model 1) and 2.519 (Model 2) times higher than the odds that cash dividend will not be paid. We find that *LN(REV)* has 2.258 (Model 1) and 3.125 (Model 2) times the odds that cash dividend will be paid higher than the odds that it will not be paid. We find the logit coefficients on *AUDIT(1), LN(SIZE)* and *FIN.LEV* to be -.396/-.381, -328/-360 and -672/.652 in Models 1/2, respectively; they are statistically significant. The exp(B) on *AUDIT(1)* of about .673 indicates the odds that cash dividend will not be paid by up to 1.5 times higher than the odds that cash dividend will be paid. The exp(B) on *LN(SIZE)* of about .72 indicates the odds that cash dividend will not be paid by up to about 1.4 times higher than the odds that cash dividend will be paid. The exp(B) on *FIN.LEV* of .511 indicates that *FIN.LEV* has about 2 times the odds that cash dividend will not be paid higher than the odds that it will be paid. These test results accept the alternative hypotheses. Our control variable is likely to significantly predict non-payment of cash dividend. -2 LL of 730.516/724.301 indicate good model fit. Nagelkerke pseudo R^2 statistic of Model 1 suggests that the predictors in our model explain up to about 36% of the variability in payment of cash dividend. The results are contained in Table 7.

STR, passing via node H(1:3), predicts the payment of cash dividend. LN_REV operating via nodes H(1:1) and H(1:3) significantly predicts the payment of cash dividend. AUDIT, operating via node H(1:1) significantly predicts the payment of cash dividend. But, operating via node H(1:4) significantly predicts non-payment of cash dividend. LN_SIZE, operating via node H(1:2) significantly predicts non-payment of cash dividend. FIN.LEV, operating via node H(1:2) or node H(1:4) significantly predicts non-payment of cash dividend. ANN result for Model 2 is derived from equation (2), and presented in multilayer perceptron 2 (MPL) 2. As in the analysis for Model 1, the algorithm on STR shows that it significantly predicts the payment of cash dividend via node H(1:3). LN_REV, passing via node H(1:2) is a significant predictor of cash dividend paid. AUDIT, LN_SIZE, FIN.LEV and STR*LN_REV are significant predictors of non-payment of cash dividend. In particular, MLP 2 shows that AUDIT operating via node H(1:3); LN_SIZE, operating node H(1:1) or node H(1:4) and FIN.LEV, operating via node H(1:1), node H(1:2), H(1:3), or node H(1:4) is a significant predictor of non-payment of cash dividend. All the results are in sync with our hypotheses. The control variable, STR*LN_REV, operating via node H(1:3), is a significant predictor of non-payment of cash dividend. Figure 1 (Model 1) in Table 9 shows that among the input variables, *LN(REV)* is having the highest of importance/normalized importance, .571/100. This is followed by *FIN.LEV/AUDIT* (.097)*, LN(SIZE)*(.087)*,*and STR at .064. Diagnostic assessments of the performance of the algorithms indicate excellent model sensitivity. As we see from Table 10 and Figures 3 and 4, the areas under the curve (AUC) are .854 and .839.

The rest of the paper proceeds as follows. The next section presents theoretical and empirical reviews of related literature, together with associated hypotheses. Section 3 discusses the methodology, including population, sample selection, data sources, research design and methods. Section 4 presents the results and discussion of our findings. Section 5 concludes.

2. Literature Review

a. Theoretical literature

Due to uncertainty of payment of dividend, Black (1976) argued that "the harder we look at the dividend picture, the more it seems like a puzzle, with pieces that just do not fit together." Brealy, Myers and Allen (2008) opine that dividend policy is one stormy aspect of corporate finance. There are myriad contending theories on dividend such as those of dividend irrelevancy hypothesis (Miller and Modigliani, 1961; Frankfurter and Lane, 1992), high cash dividend policy (Lintner, 1956; and Gordon, 1963); agency cost theory (Jensen and Meckling (1976); signalling theory (Lintner, 1956; Gordon, 1963 and Bhattacharyya, 1979) and clientele effects (Black and Scholes, 1974; amongst others). The followings are some of the conceptual theories reviewed, in brief.

i. Dividend irrelevance hypothesis

Miller and Modigliani (1961), in a seminar paper, proposed the dividend irrelevance hypothesis wherein they suggested that a firm's value is independent of dividend payment. According to the theory, dividend does not affect share prices where there are no taxes, brokerage fees/commissions or other transaction costs. But Black (1976) questioned the dividend irrelevance hypothesis by arguing that in the real world dividend decision can have consequences for corporate and personal taxes, firms' creditors, cost of capital and investors' portfolio management.

ii. Theory of a bird in hand

This theory is variously referred to as bird in palm theory or theory of high cash dividend (Thanh, Ha and Ngoc, 2022). Lintner (1956) and Gordon (1963) say that equity investors prefer high dividend now to future capital appreciation because of uncertainty, imperfection and incomplete knowledge about the future as well as asymmetry of information in markets. The authors are of the view that (some) investors are risk averse; which is why they would prefer receiving dividend now instead of stock price appreciation. According to Amidu and Abor (2006), signalling theory is encapsulated in information asymmetry theory.

iii. Agency cost theory

Jensen and Meckling (1976) opined that agency cost arises from the separation of ownership and management rights because boards of directors act in their own interest rather than in the interests of shareholders who own the company (Jensen (1986)). However, La Porta, Lopez-de Silanes, Shleifer and Vishny (2000) and John and Knyazeva (2006) opined that firms, premised on the substitute model, would pay more dividends so as to decrease the cash flow available to managers in order to reduce agency costs.

There are internal and market theory of dividend policy. The internal theory says that undistributed profits will be consumed in the company as an extra benefit or, if retained, such retained earnings will be invested. This is the well-known Jensen and Meckling's (1976) agency costs theory. The external theory says that capital markets are imperfect because of information asymmetry where insiders are better informed about the firm's future cash flows than outside investors. Agency costs can also arise between current shareholders and future shareholders in the sense that when a company is awash with cash current shareholders would prefer cash dividend to re-investment. This conflict manifests itself when future potential shareholders prefer reinvestment as they want to meet a prosperous company by the time they invest. However, payment of cash dividend can reduce conflict of interests between owners (shareholders) and directors (agents) because dividend payment is thought to align the interests of both parties (Easterbrook, 1984).

iv. Signalling theory

There is the ever-present information asymmetry that exists between agents who manage a company and outside equity stockholders who own the company. While managers control the day-to-day operations of the company and have a lot of insider information, outside and dispersed stockholders do not. According to signalling theory ((Lintner, 1956; and Gordon, 1963), investors can infer information about earnings ability of companies through the signals emitted from dividend announcements by managers. Given asymmetric information, dividend announcements serve as one of the effective means to communicate information to equity stockholders, as well as to signal managers' performance to shareholders. Also, Bhattacharyya (1979) opined that managers have confidential information about the distribution of cash flows and they signal this to the market through the choice of dividend payout ratio. However, due to their maturity and less information asymmetry large firms do not need to signal with dividend (Bhattacharya, 1979; and John and Williams, 1985).

v. Clienteles effects theory

Clientele effects theory says that different investor-groups have different needs for cash because of tax motives. Consequently, each group of equity shareholders tends to prefer investing in the shares of companies that satisfy their varying needs. Brav, Graham, Harvey and Michaely (2005) argued that retail investors who use dividends to meet daily needs may prefer dividend payments when compared to institutional or wholesale investors who do not. According to Black and Scholes (1974), equity investors who pay high taxes prefer that companies retain their profits in order to avoid paying high taxes. On the other hand, equity investors who pay low taxes may prefer to receive cash dividend. There is an offshoot of clientele effect theory, which is called catering theory.

vi. Catering theory of dividend

Catering theory explains the proclivity towards dividend payout. In promoting the clientele theory, Baker and Wurgler (2004a) argue that the propensity to pay dividend varies when managers do so in order to cater to investors' needs, for example, the needs of institutional shareholders versus retail shareholders. Therefore, as firms pay dividends investors reciprocate by paying above-market prices for the firms' ordinary shares (e.g., Baker and Wurgler, 2004b). Catering theory sees dividend policy as a tool for catering to different investor/clienteles' yearnings (Franc-Dąbrowska *et al*., 2019).

vii. Calming theory

Hauser (2013) and Jabbouri (2016) opined that companies increase dividend payouts during periods of economic crises, with the aim to calm down investors' anxiety. Frankfurter and Lane (1992) hold the view that dividend payouts can be a method of calming investors; that dividends play a monitoring role on managers; and that paying dividend encourages company managers to take risk. Frankfurter and Lane (1992) further hold that dividend payouts can increase the attractiveness of equity issue as they enhance the future stability of companies. In order words, managers can use dividend payouts as a way of calming or reassure investors. Therefore, dividend payouts might convey reassuring information about a firm's future earnings prospects (Allen and Michaely, 2003).

b. Review of relevant empirical literature and development of hypotheses

This section adopts a brief thematic review of the empirical literature.

i. Industry structure

Industry structure (Baumol, 1982) can be a source of variation in studies of a country's economic/commercial landscape, particularly relating to cash dividend paid by all industries put together. For example, Brawn and Šević (2018) documented empirical evidence that industry sector is one key factor determining dividend payments. These lead to our first alternative hypothesis that:

H_1: Industry structure is likely to significantly influence payment of cash dividend.

ii. Independent auditor

It appears that there is lack of consensus on the impact of independent auditors on cash dividend paid. Prior studies (Asien, 2022; Francis and Yu, 2009; Bhattacharya, Li. and Rhee, 2016; Khan and Ahmad, 2017; and Downing and Langli, 2019) investigated the nexus between dividend paid and external auditors. In particular, Downing and Langli (2019) opined that independent auditors are required to raise issues about a firm's going concern status, and that independent auditors can also communicate weaknesses in firms' accounting and internal control processes. Khan and Ahmad (2017) made a null hypothesis that audit type has no impact on dividend payouts in pharmaceutical companies listed on the Pakistani stock exchange, PSX. However, the authors found audit type to be a positive significant determinant of dividend payouts of pharmaceutical companies. Bhattacharya, Li, and Rhee (2016) investigated, using big 4 auditors as one of their alternative measures of corporate governance, the relation between corporate governance and dividend policy at varying levels of idiosyncratic risk. Asien (2022) find that big 4 auditors help firms to reduce actual cash taxes paid because of aggressive tax planning devises rendered by external auditors to their clients. This leads to the second alternative hypothesis that:

H_2: Big 4 auditors are likely to significantly discourage payment of cash dividend.

iii. Revenue

Extant research documents evidence suggesting that operating revenues have positive, statistical and economical influence on cash dividend paid. For example, Hossain *et al*. (2014), who investigated the determinants of dividend paid per share of companies listed on Dhaka Stock Exchange (DSE), Bangladesh during 2007–2011, found that the log of total sales influences dividend paid per share. Other empirical studies such as those of Hossain *et al*. (2014) and Akpan and Amran (2014) suggested that turnover can serve as a potential proxy to measure firm performance. Therefore, we make the third alternative hypothesis that:

H_3: Log of revenue is likely to significantly influence payment of cash dividend.

iv. Firm size

Prior empirical studies found a positive relationship between firm size and propensity to pay cash dividend. That is, larger firms are more likely to pay dividend than smaller firms. Denis and Osobov (2008) found positive influence of firm size on propensity to pay dividend. Farooq *et al*. (2022) documented evidence that firm size positively but insignificantly influence propensity to pay dividend among listed on the PSX. Fama and French (2001) investigated the influence of company size on the probability of paying dividend, and found that the total assets of firms who were paying dividends were considerably higher than those who were not paying. Fatemi and Bildik (2012) suggest that large firms have a greater propensity to pay dividend. Uwuigbe *et al*. (2015) investigated the relationship between corporate governance mechanisms (such as board size, ownership structure, CEO duality, independence of the board and firm size) and dividend payout ratios of firms listed on the Nigerian Exchange Group (NGX) Limited. Using OLS regression, the authors found that natural log of total assets positively and significantly affect dividend payout ratios of 50 Nigerian firms from 2006 to 2011. Dissanayake and Dissabandara (2021) examined how Sri Lankan companies' corporate board characteristics, and found that firm size positively influenced propensity to pay dividend. On the contrary, Louziri and Khadija (2022) in their study of Moroccan listed companies found that total assets have negative relationships with payout ratio and dividend yield. Louziri and Khadija's result is consistent with those of Javid and Ahmed (2009) and Al-Shubiri, Al-Taleb and Al-Zoued (2012). In our study, we posit that large firms may be reluctant to pay cash dividends because of the need to continue expanding their empire. Thus, we hypothesize in the alternative that:

H_4: Firm size is likely to significantly discourage payment of cash dividend.

v. Financial leverage

Arko, Joshua, Charles and Amidu (2014) identify leverage as one major determinant of corporate dividend. Shapovalova (2023) found empirical evidence that leverage negatively and significantly influence the likelihood not to pay dividend among Russian firms. Also, Dissanayake and Dissabandara (2021) found leverage to negatively affect propensity to pay dividend. Naceur, Goaied and Belanes (2006) and Al-Malkawi (2007) argued that companies with high debt ratios are likely to pay fewer dividends because of the fact that their cash flows are meant for prior charge debt investors. Thus, the prospects of paying dividends could force highly leveraged firms to seek costly external financing. Houqe *et al*. (2023) and Denis and Osobov (2008) also found that a higher level of leverage significantly reduces the chances of paying dividends. Among other factors, Li, Twite, He and Shi (2009) investigated the probability of dividend payout, and found that firms with lower (higher) financial leverage are more likely to pay (not to pay) cash dividends. Also, Farooq *et al*. (2022) documented evidence that financial leverage negatively and insignificantly influence propensity to pay dividend. We build on this stream of literature to make our fifth alternative hypotheses that:

H_5: High financial leverage is likely to significantly discourage payment of cash dividend.

3. Methodology

a. Population, sample selection and data sources

Nigerian Exchange Group (NGX) Limited (www.ngxgroup.com/data/company-profile) classifies companies according to 11 industrial sectors (population). From this population, we draw a sample of 10 industrial sectors, excluding the financial services sector because of reasons given by Asien (2022). For the purpose of the present study, we refer to the 10 industrial sectors collectively as "industry structure" (*STR*, for short). We identified companies in the sample based on the sectorial groupings they belong to. We used alphabetical listing to initially screen the companies in each sectorial grouping, going from top to bottom of the page. Thereafter, we traced the companies to their web addresses provided at www.ngxgroup.com/data/company-profile. Companies whose annual report and/or audited annual financial statements were downloadable from their website were included in the sample.

Following Asien (2022), where a company did not have a website, or if it had one but its annual report and/or audited annual financial statements could not be downloaded, we resorted to other proprietary free internet sources which we obtained from Google search engine. We identified seven hundred and forty-four firm-year observations. After deleting nineteen firm-year observations that had incomplete data on all our variables, we were left with seven hundred and twenty-five firm-year observations, which constituted the study's sample.

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Agriculture	4	5	5	5	5	5	5	4	5	5	48
Conglomerate	5	5	5	5	5	5	5	4	4	4	47
Constr/real estate	2	2	2	2	2	2	2	2	2	2	20
Consumer goods	15	16	16	16	16	16	16	16	17	17	161
Health care	6	6	6	6	6	6	6	6	6	6	60
ICT	3	4	5	5	5	5	6	5	5	5	48
Industrial goods	9	8	10	10	10	10	11	10	10	8	96
Natural resources	3	3	3	3	4	4	4	3	4	4	35
Oil & Gas	7	9	9	9	9	9	9	10	8	7	86
Services	12	12	13	13	13	13	12	12	12	12	124
Total	66	70	74	74	75	75	76	72	73	70	725

Table 1 : Sector * year crosstabluation

Year by sector cross-tabulation are contained in Table 1. It can be seen from the table that consumer goods sector has highest total firm-year observations of 161. The services sector is next with 124 firm-year observations, and 96 and 86 for industrial goods and oil and gas, respectively. HealthCare sector has 60 firm-year observations, conglomerate, ICT and agricultural sectors have 47, 48 and 48 firm-year observations, respectively. Natural resources with 35 firm year observations, comes at the rare.

b. Model specification and statistical methods

i. Model specifications

Mimicking Mackinnon and Davidson (2002) and Hu *et al*. (2022), we estimate the following logit model to capture the natural logarithm of the odds that companies will pay cash dividend $ln\left[\frac{1}{(1-Pt)}\right] = X_t\beta$. Deriving P_t, gives $\frac{\exp(Xt\beta)}{1+\exp(Xt\beta)} = (1 + \exp(-X_t\beta))^{-1} = \Lambda(X_t\beta)$. The econometric model specification goes as:

$$ln\left[\frac{1}{(1-p}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots + B_n X_n \qquad (i)$$

Where: $ln\left[\frac{1}{(1-p)}\right]$ is a dummy coded variable. The predictors are $X_1, X_2, X_3 \ldots X_n$.

We consider the likelihood of paying cash dividend to be a logit function of industry structure, independent auditors that audit the company's financial statements, natural log of revenue, firm size and financial leverage. Mimicking Fama and French (2001), Dewasiri *et al*. (2019), Justyna Franc-Dąbrowska *et al*. (2019), Hauser (2013), Shapovalova (2023), and Houqe *et al*. (2023), we specify our study's econometric model as:

$$PROB(CDP,1) = \beta_0 + \beta_1 STR + \beta_2 AUDIT + \beta_3 LN(REV) + \beta_4 LN(SIZE) + \beta_5 FIN.LEV + \varepsilon \quad \ldots(1)$$

Predicted sign: β_1: +; β_2: −; β_3: +; β_4: −; β_5: −

$$PROB(CDP,1) = \beta_0 + \beta_1 STR + \beta_2 AUDIT + \beta_3 LN(REV) + \beta_4 LN(SIZE) + \beta_5 FIN.LEV + B_6 STR^{*} LN(REV) + \quad \ldots(2)$$

Predicted sign: β_1: +; β_2: −; β_3: +; β_4: −; β_5: _; B_6: ?

Where: *PROB(CDP,1)* is the criterion/dependent variable, taken on the value "0" and "1". The predictors are industry structure (*STR*), which proxy the combination of the ten industrial grouping; *AUDIT* is the external auditors (big 4 versus non-big 4) that audited a company's annual financial statements. *LN(REV)* is natural logarithm of revenue, *LN(SIZE)* is natural logarithm of total assets. Financial leverage (*FIN.LEV*) is operationalized as $\frac{\text{total prior charge debts}}{\text{total prior debts + total equity}}$. *STR*LN(REV)* is an interaction term between *STR* and log total revenue. $STR^{*}LN(REV)$ is included in Model 2 as a preferred control variable in the additional analysis later in the paper. β_0 = constant, $\beta_1 - \beta_6$ are the row vectors of logit coefficients of the regressors. $\acute{\varepsilon}$ = residual error term. All variables are pooled from 2012 to 2021.

ii. Methods

We deploy data analytic tools of pooled unbalanced panel data binary logistic regression and artificial neural network (Kohonen, 1984; Ripley, 1996; Rumelhart and McClelland, 1986; Wasserman, 1989; and Yinka-Banjo, Akinyemi and Er-rabbany, 2023) to run our analyses. Binary logistic regression has traditionally been used by majority of prior researchers to model a dichotomous criterion variable. Comparatively, according to Ripley (1996), ANN has proven to produce good prediction results in classification and regression problems concerning categorical (criterion variables). Intrator and Intrator (2001) have found out that artificial neural networks outperformed logistic regression model, leading the authors to suggest that logistic regression models are appropriate as a first approximation. Consequently, our ANN results complement those of binary logistic results. Moreover, ANN is also used for robustification purposes.

Some carefully selected (in terms of criterion and predictor variables) prior studies that utilized our two methods, either singly or a combination of both, places of study and findings are presented in Table 2.

Prior Studies, and market studied	Criterion variable	Predictor variable	Result	
			Sign	*Sig. p*
Dewasiri *et al*. (2019): Sri Lanka	Logistic regression	Industry	–	Significant
Bhattacharya, Li & Rhee (2016), and Khan & Ahmad (2017): US	Logistic regression	Big 4 Auditors	+	Significant
Franc-Dąbrowska *et al*. (2019): European food industry	Logistic regression	Revenue	+	Significant
Farooq *et al*. (2022): Pakistan	Logistic regression	*SIZE* (ln total assets)	+	Insignificant
Dewasiri *et al*. (2019): Sri Lanka	Logistic regression	*SIZE* (ln total assets)	+	Significant
Dissanayake & Dissabandara (2021): Sri Lanka	Logistic regression	*SIZE* (ln total assets)	+	Insignificant
Houqe *et al*. (2023): US	Logistic regression	Financial leverage	−	Significant
Shapovalova (2023): Russia	Logistic regression	Financial leverage	−	Significant
Farooq *et al*. (2022): Pakistan	Logistic regression	Financial leverage	–	Insignificant
Elghaly & Diping (2021): Egypt	Logistic regression	Financial leverage	−	Significant
Dewasiri *et al*. (2019): Sri Lanka	Logistic regression	Financial leverage	−	Significant
Dissanayake & Dissabandara (2021): Sri Lanka	Logistic regression	Financial leverage	−	Significant
Al Omari *et al*. (2023): Jordan	Artificial neural network	N/A	N/A	N/A
Elghaly & Diping (2021): Egypt	Artificial neural network	N/A	N/A	N/A

Table 2: Selected prior empirical works

Our analytic software is IBM Statistical Product and Service Solutions (SPSS) version 26.

4. Empirical results and discussion

a. Descriptive statistics

Count

	YEAR										
AUDIT	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Total
Big 4	43	42	44	44	44	42	45	44	44	42	434
Non-Big 4	23	28	30	30	31	33	31	28	29	28	291
Total	66	70	74	74	75	75	76	72	73	70	725

Tableau 3: Audit* Year crosstabulation

Table 3 presents yearly distribution of big 4 and non-big 4 cross-tabulations. We can see that big 4 auditors have the highest overall firm-year observations (434) while non-big 4 auditors have 291.

Table 4 shows descriptive statistics of all variables. The mean of the response variable is .64, which is closer to “1”. *STR* is a dummy coded variable, with 10 (1) as the maximum (minimum); the mean is 5.67 while the standard deviation is 2.812. *AUDIT* is another dummy coded variable, with “1” = big 4 auditors, and 0 otherwise; mean of *AUDIT* is .40, which is closer to non-big 4 auditors with standard deviation at .491.

	PROB(CDP,1)	*STR*	*AUDIT*	*LN(REV)* ₦'000	*LN(SIZE)* ₦'000	*FIN.LEV* ₦'000	*STR*LN(REV)*
Mean	.64	5.67	.40	16.0389	16.6554	.4177	89.403
Std. Dev.	.481	2.812	.491	2.55840	1.96602	2.55140	45.546
Minimum	0	1	0	.00	11.32	-4.27	.00
Maximum	1	10	1	21.23	21.54	67.11	176.80

Tableau 4: Descriptive statistics (# of obsevation = 725)

Mean (maximum) *LN(REV)* is ₦16.04 (₦21.23), with standard deviation at ₦2.56. Some of the companies did not earn revenue at all during the period. Mean, maximum, and minimum of *LN(SIZE)* is ₦16.65, ₦21.54, and ₦11.32, respectively; with standard deviation at ₦1.97. Mean, maximum and minimum *FIN.LEV* is ₦.418, ₦67.11, and ₦-4.27, with standard deviation at ₦ 2.55. Mean, maximum and minimum *STR*LN(REV)* is 89.4023, 176.80, and 0.00, respectively; with standard deviation at 45.546.

b. Spearman's rho correlation analysis

The Spearman's rank bivariate correlation is shown in Table 5. Except for *STR*, the table shows *prima facie*, that the predictors are significantly correlated with *PROB(CDP, 1*). *STR* appears to be weakly and positively but insignificantly correlated with *PROB(RCDP,1)*. *AUDIT* and *FIN.LEV* (*LN(REV)* and *LN(SIZE*) are negatively (positively) and significantly correlated with *PROB(RCDP,1)*. The strength and significance of correlations are moderate: for *AUDIT* (rho = -.336), *LN(REV*) (rho = .454) and *LN(SIZE)* (rho = .314*)*. *FIN.LEV* is weakly correlated at .118 with *PROB(RCDP,1)*. Table 5 shows that the highest inter-correlation coefficient is .852 between *LN(SIZE)* and *LN(REV)*. *STR* has low negative significant inter-correlations with *LN(REV)* and *LN(SIZE)* with rho = .197 and .136; respectively. *STR* is weakly inter-correlated with *AUDIT* (rho = .059) and *FIN.LEV* (rho = .028). *LN(REV)* and *LN(SIZE)* each has low (moderate) positive and significant inter-correlations with *FIN.LEV*, rho = .156 (rho = .241), respectively.

	PROB(CDP,1)	*STR*	*AUDIT*	*Ln(REV)*	*Ln(SIZE)*	*FIN.LEV*
PROB(CDP,1)	1					
STR	.001	1				
AUDIT	-.336**	.059	1			
LN(REV)	.454**	-.197**	-.498**	1		
LN(SIZE)	.314**	-.136**	-.360**	.852**	1	
FIN.LEV	-.118**	.028	.164**	.156**	.241**	1
# of Obs.	725	725	725	725	725	725

****, **, *. Sig. $p < .01, .05, .10$; respectively*

Tableau 5: Spearman's rho correlation

The inter-correction coefficients assure us that there are no high inter-correlations among the predictors, leading to the conclusion that multicollinearity is not a problem in this study. Tabachnick and Fidell (2007) suggested a threshold of .90 before collinearity can become a source of concern.

c. Pooled unbalanced panel data logistic regression result

Table 6 is the omnibus test of model coefficient, with Sig. $p < .01$. This indicates that some of the predictors are statistically significant in predicting propensity to pay cash dividend.

	Model 1			***Model 2***		
	Chi-square	df	Sig.	Chi-square	df	Sig.
Step	219.217	5	.000	225.433	6	.000
Block	219.217	5	.000	225.433	6	.000
Model	219.217	5	.000	225.433	6	.000

Table 6 : Omnibus Tests of Model Coeffcients

The pooled unbalanced panel data binary logistic regression results are presented in Table 7. At conventional significance levels the predictors are likely to significantly influence (non)payment of cash dividend. *STR* and *LN(REV)* is consistently positive and significant in favor of propensity to pay cash dividend. *LN(SIZE)* and *FIN.LEV* are consistently negative and statistically significant, meaning that the variables are likely to significantly predict non-payment of cash dividend. *AUDIT(1)* is significantly negative, $p < .01$ in Model 1 and $p < .1$ in Model 2). -2 LL of 730.516 and 724.301, $p < .001$, indicate good model fit.

	Model 1					Model 2				
	B	S. E.	Wald	Sig.	Exp(B)	B	S. E.	Wald	Sig.	Exp(B)
STR	.108	.033	10.709	***.001*****	1.114	.924	.331	7.789	***.005*****	2.519
AUDIT(1)	-.396	.201	3.896	***.048****	.673	-.381	.201	3.575	***.059******	.683
LN(REV)	.815	.114	50.897	***.000*****	2.258	1.139	.178	41.084	***.000*****	3.125
LN(SIZE)	-.328	.108	9.247	***.002*****	.720	-.360	.107	11.395	***.001*****	.698
FIN.LEV	-.672	.187	12.893	***.000*****	.511	-.652	.189	11.931	***.001*****	.521
*STR*LN(REV)*						-.051	021	6.135	***.013****	.950
(Constant)	-7.227	1.034	48.852	***.000*****	.001	-11.920	2.240	28.307	***.000*****	.000
-2 Log likelihood	730.516, Sig. p < ***.001***					724.301, Sig. p < ***.001***				
Nagelkerke R-Square	.357					.366				

**, *, ***. p < .01, .05, .10, (2-tailed)

$PROB(CDP,1) = \beta_0 + \beta_1 STR + \beta_2 AUDIT(1) + \beta_3 LN(REV) + \beta_4 LN(SIZE) + \beta_5 FIN.LEV + \varepsilon$ ...(1)

$PROB(CDP,1) = \beta_0 + \beta_1 STR + \beta_2 AUDIT(1) + \beta_3 LN(REV) + \beta_4 LN(SIZE) + \beta_5 FIN.LEV + \beta_6 STR{*}LN(REV) + \varepsilon$ ...(2)

Table 7: Pooled panel data logistic regression of probability of paying cash dividends (# of firm-year observations = 725)

Nagelkerke pseudo R^2 statistic indicates that the model explains up to about 36% of the variability in cash dividend paid. Next is the presentation of the results in more details, according to our hypotheses.

In Model 1 (Model 2), the exp(B) on *STR* indicates that the odds that cash dividend will be paid is 1.114 (2.519) times higher than the odds that cash dividend will not be paid. In Models 1 and 2, Wald = 10.709 and 7.789, logit coefficients are .108(.924), $p < .01$ level (2-tailed). This result accepts our first alternative hypothesis (H_1) that industry structure is likely to influence the payment of cash dividend. *AUDIT(1)* is negative and statistically significant . In Model 1 and Model 2, Wald = 3.896 and 3.575, logit coefficients are -.396 and -.381, $p < .05$ ($p < .1$). The logit coefficient of Model 1 (Model 2) suggests that big 4 auditors are likely to discourage payment of cash dividend by up to 37% (38%). In economic terms, if a company is audited by big 4 auditors, then its cash dividend paid will likely fall by up to ₦38. In Model 1/Model 2, the result shows that big 4 auditors have 1.486 (3dp) or $(.673)^{-1}$ / 1.464 or $(.683)^{-1}$ times the odds that cash dividend will not be paid higher than the odds that they will be paid. This result accepts our second alternative hypothesis (H_2). In Model 1 (Model 2), *LN(REV)* has Exp(B) of 2.258 (3.125). This means the natural log of revenue has 2.258 (3.125) times the odd that cash dividend will be paid that higher than the odds that it will not be paid.

In Model 1(Model 2), Wald is 50.897(41.084), logit coefficient is .815 (in Model 1) and 1.139 (in Model 2); both significant at $p < .01$. The test results indicate that *LN(REV)* has the propensity to predict payment of cash dividend by up to about 82% in Model 1, and 114% in

Model 2. In economic terms, a ₦1 increase in revenue has the propensity to increase cash dividend paid by about up to ₦82/₦ 114 in Model 1/Model 2. The test result accepts our third alternative hypothesis (H_3) that log revenue is likely to influence payment of cash dividend. In Model 1/Model 2, the test on H_4 shows that *LN(SIZE)* has $(.720)^{-1}$ or 1.389/$(.698)^{-1}$ or 1.433 times the odds that cash dividend will not be paid higher than the odds that it will be paid. In Model 1 and Model 2, Wald = 9.247, $p < .01$ and 11.395, $p < .1$; respectively. Logit coefficients of -.328 (Model 1) and -.360 (Model 2), suggest that additions to firm size is likely to discourage payment of cash dividend by up to about 33% and 36%, respectively. Economically interpreted, this result suggests that acquisition of total assets by ₦1 is likely to reduce payment of cash dividend by up to about ₦33/₦36, in Model 1/Model 2. This result accepts our fourth alternative hypothesis that firm size is likely to discourage payment of cash dividend.

Finally, the result on financial leverage shows that in Model 1/Model 2, *FIN.LEV* has $(.511)^{-1}$ or 1.957)/$(.521)^{-1}$ or 1.919 times the odds that cash dividend will not be paid higher than the odds that it will be paid. In Model 1 and Model 2, Wald = 12.893 and 11.931, $p < .01$. The logit coefficient is -.672 in Model 1 and -.652 in Model 2. The economic import of this result is that a ₦1 additional borrowing will likely reduce cash dividend paid by about ₦70. These suggest that financial leverage has the propensity to influence non-payment of cash dividend, which accept our fifth alternative hypothesis (H_5). Although we have no hypothesis for our control variable, we find that the interaction between industry structure and natural log revenue, *STR*LN(REV)* is likely to significantly predict non-payment of cash dividend. The result on *STR*LN(REV)* shows that the exp(B) is $(.950)^{-1}$ or 1.053 times the odds that cash dividend will not be paid higher than the odds that it will be paid. Wald = 6.135, $p < .05$; logit coefficient = -.051. The economic interpretation is that any interaction of industry structure and revenue will likely reduce cash dividend paid by merely ₦5. Using Model 1 as reference point, among these results, *LN(REV)* appears to have the greatest influence on cash dividend paid, followed by *FIN.LEV*, *AUDIT*, *LN(SIZE)* and *STR*, accordingly.

i. Artificial neural network analysis

The case processing summary of artificial neural network analysis is presented in Table 8. Out of the 725 firm-year observations, training is 68% while testing is 32%, in Model 1. In Model 2, training is 69.8% while testing is 30.2%.

		Model 1		***Model 2***	
		N	Percent	N	Percent
Sample	Training	493	68.0%	506	69.8%
	Testing	232	32.0%	219	30.2%
Total		725	100.0%	725	100.0%

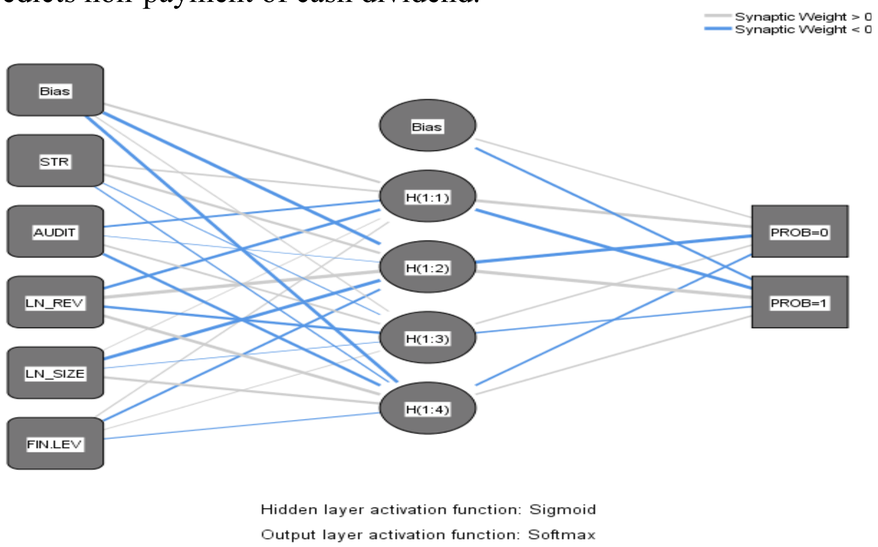
Table 8 : Case Processing Summary

Following prior studies (e.g., that of Elghaly and Diping, 2021), our ANN algorithms apply Sigmoid hidden layer activation function and Softmax output layer activation function.

A large value of these activation functions indicates that the respective activation function value will be close to 1; otherwise it will be closer to 0. Results of ANN derived from equation (1) are presented in multilayer perceptron 1 (MPL) 1. As an initial step, notice that all synaptic weights < .0, indicating the significance of our tests. The inputs into the MPL 1 algorithm are STR, AUDIT, LN_REV, LN_SIZE and FIN.LEV. STR, passing via node H(1:3), predicts the payment of cash dividend; it predicts otherwise while passing via node H(1:4). The algorithm passing via node H(1:3) accepts our hypothesis.

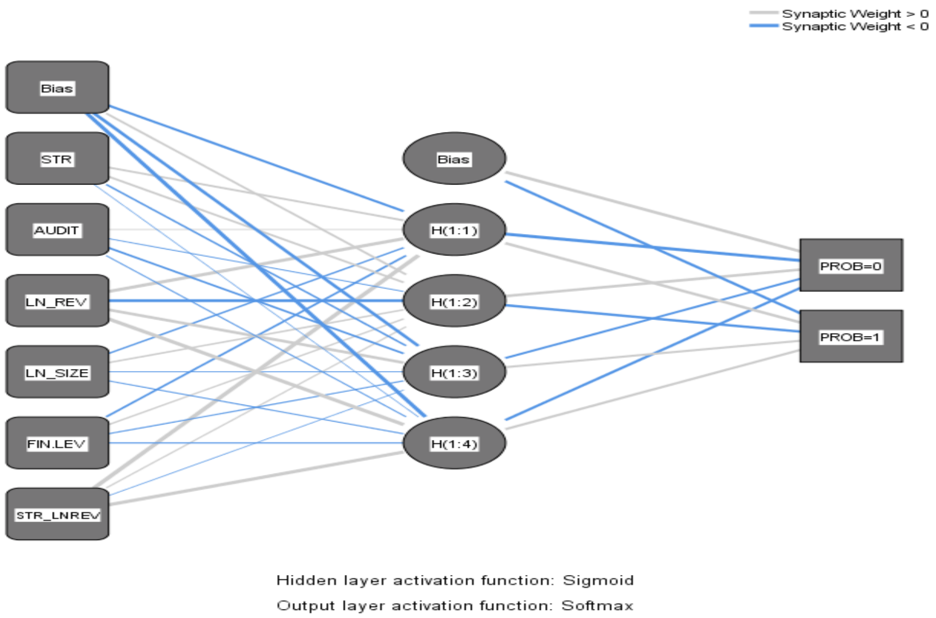
LN_REV operating via nodes H(1:1) and H(1:3) significantly predicts the payment of cash dividend, consistent with our hypothesis. AUDIT, operating via node H(1:1) significantly predicts the payment of cash dividend. But, operating via node H(1:4) significantly predicts non-payment of cash dividend, which is consistent with our hypothesis. Clearly, LN_SIZE, operating via node H(1:2) significantly predicts non-payment of cash dividend, which is in sync with our hypothesis. FIN.LEV, operating via node H(1:2) or node H(1:4) significantly predicts non-payment of cash dividend.

Diagram 1. Network structure showing Multilayer Perceptron for Model 1, MPL 1



The ANN result for Model 2 is derived from equation (2), and presented in multilayer perceptron 2 (MPL) 2. The inputs into MPL 2 algorithm are STR, AUDIT, LN-REV, LN-SIZE, FIN.LEV and STR*LN_REV. As in the analysis for Model 1, the algorithm on STR shows that it significantly predicts the payment of cash dividend via node H(1:3), which is consistent with our hypothesis. LN_REV, passing via node H(1:2) is a significant predictor of cash dividend paid. AUDIT, LN_SIZE, FIN.LEV and STR*LN_REV are significant predictors of non-payment of cash dividend. In particular, MLP 2 shows that AUDIT operating via node H(1:3); LN_SIZE, operating node H(1:1) or node H(1:4) and FIN.LEV, operating via node H(1:1), node H(1:2), H(1:3), or node H(1:4) is a significant predictor of non-payment of cash dividend. These results are in sync with our hypotheses. The interaction term, STR*LN_REV, via node H(1:3), is a significant predictor of non-payment of cash dividend. Based on the results from Model 1, our hypotheses are supported.

Diagram 2. Network structure showing Multilayer Perceptron for Model 2, MPL 2



Using our baseline equation in Table 9, Figure 1 shows that *LN(REV)* have the highest of importance/normalized importance, .571/100, followed by *FIN.LEV/AUDIT* (.097/17.0%), *LN(SIZE)*(.087),and *STR* at .064.

	Model 1		***Model 2***	
	Importance	Normalized Importance	Importance	Normalized Importance
STR	.064	11.2%	.062	17.5%
AUDIT	.097	17.0%	.014	3.9%
LN(REV)	.571	100.0%	.353	100.0%
LN(SIZE)	.087	15.2%	.135	38.2%
FIN.LEV	.097	17.0%	.340	96.2%
*STR*LN(REV)*			.093	27.4%

Table 9 : Independent variable Importance

Figure 1. Importance of predictors (Model 1)

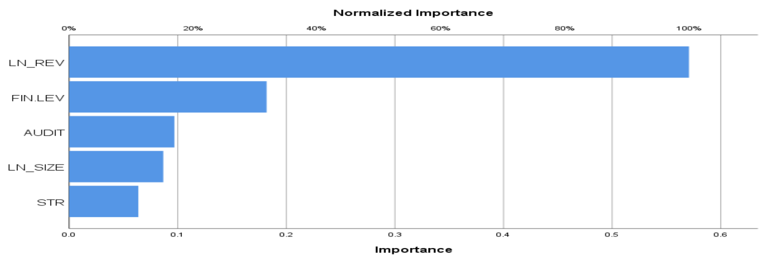


Figure 2.
Importance of predictors
(Model 2)

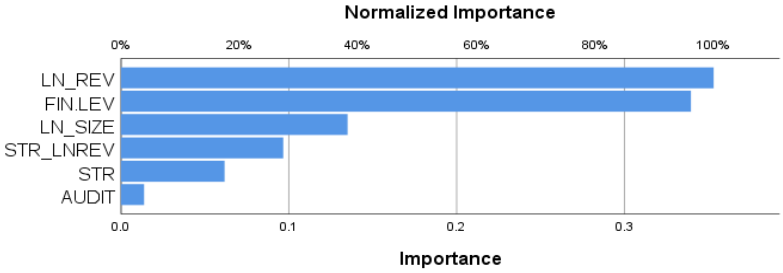


Figure 3.
Plot of ROC Curve
(*Model 1)*

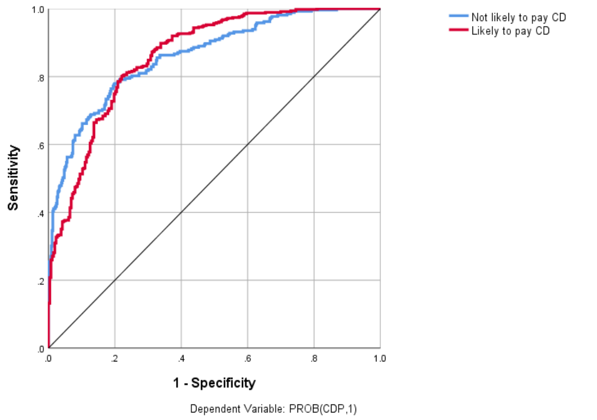
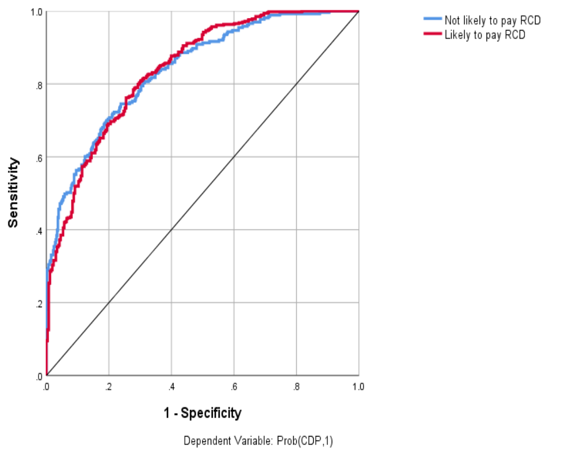


Figure 4.
Plot of ROC Curve
(*Model 2)*



Diagnostic assessments of the performance of the algorithms indicate excellent model sensitivity. As we see from Table 10 and Figures 3 and 4, the areas under the curve (AUC) are .854 and .839.

		Model 1	***Model 2***
		Area	Area
PROB(CDP,1)	Not likely to pay CD	.854	.839
	Likely to pay CD	.854	.839

Table 10 : Area Under the Curve

ii. Additional analysis

It is possible that some of our predictors may have high interaction among themselves. We investigated this by running correlation coefficient tests involving additional interaction terms, including *STR**Ln(REV)*, *STR**Ln(SIZE)*, *AUDIT**Ln(REV),* and *AUDIT**Ln(SIZE)*. In each run, we alternated each interaction term separately while retaining our original predictors in Model 1. The exercises resulted in very high inter-correlation values for most of the predictors. The less severe inter-correlation is between *STR**LN(REV)*, whose correlation value is .918. (See appendices 1-3 at the end of paper for the alternative correlation values). The bivariate correlation (rho = .145) between *STR**LN(REV)* and *PROB(CDP,1)* is low, positive and significant, $p < .000$. This result is shown in Table 11. Consequently, we dropped the other interaction terms in favor of *STR**LN(REV)* while running the additional analysis. The result is what we saw in Model 2 of Table 7 in section 4.3.1. To be clear, *STR**LN(REV)* is used as a control variable in Model 2.

	PROB(CDP,1)	*STR*	*AUDIT*	*LN(REV)*	*LN(SIZE)*	*FIN.LEV*	*STR*LN(REV)*
PROB(CDP,1)	1						
STR	.001	1					
AUDIT	-.336**	.059	1				
LN(REV)	.454**	-.197**	-.498**	1			
LN(SIZE)	.314**	-.136**	-.360**	.852**	1		
FIN.LEV	-.118**	.028	.164**	.156**	.241**	1	
*STR*LN(REV)*	.145**	.918**	-.102**	.110**	.103**	.068	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table 11 : Spearman’s rho correlation matric

iii. Endogeneity concerns

Endogeneity is an often ignored problem in building statistical models (Avery, 2019), and it manifests itself in any, or all, of three subtle ways: (1) in situations of causality where a company decides to pay cash dividend and predictor variables begin to react to the decision.

For examples: A company borrowing to pay dividend; or where industry structure attracts some external auditors. Endogeneity would bring about significant inter-correlation between the unobserved factors that contribute to both the endogenous independent variables and the dependent variable. Endogeneity of this sort leads to inefficient regression estimates; (2) by omitting some (important) variables in a regression model. In our company level study, for example, these include profitability, firm risk, growth opportunities, firm's age, liquidity, and so on, including, but not limited to, a gamut of corporate governance variables. Therefore, these and other variables not included in our study could have significant impact on cash dividend paid. However, it is instructive to note that it is practically impossible to capture in a model every conceivable important variable; otherwise that would create problems of its own. In virtually all studies, it is not easy "to completely rule out omitted variables and measurement errors." (Kashyap, 2019). (3) Where there are errors in measurement variables.

One way our study addressed the endogeniety problem is to use the "enter" model to run a more efficient model parameters instead of the less powerful conditional step-wise logistic technique which has been criticized by Avery (2019) and Kashyap (2019). Binary logistic regression is a nonparametric statistical technique which does not assume normal distribution. Also, it does not assume linearity between criterion and predictor variables. Kashyap (2019) has demonstrated that endogeneity does not matter all the time. In the instant case, it would not matter for logistic regression.

5. Conclusion

This study examines the predictors of cash dividend paid, using 725 firm-year observations' data of Nigeria's listed firms from 2012–2021. We formulated and tested the hypotheses that: industry structure and revenue are likely to drive the payment of cash dividend whereas big 4 auditors, firm size and 5) financial leverage are likely to do otherwise. Our hypotheses were tested using the statistical techniques of pooled unbalanced data logistic regression and artificial neural network, the latter originally used in biology (Hain and Jurowetzki, 2022).

Our unbalanced logistic regression test results, particularly from Model 1, show that industry structure (*STR*) and natural log of revenue are likely to significantly predict payment of cash dividend whereas big 4 auditors (*AUDIT*); firm size, *LN(SIZE)*, and financial leverage (*FIN.LEV*) are likely to significantly predict that cash dividend will not be paid.

In Model 1 and Model 2, respectively, the logit coefficients on *STR* and *LN(REV)* are .108/.924 and .815/1.139; $p < .00$. The exp(B) on *STR* indicates that the odds that cash dividend will be paid is 1.114 (in Model 1) and 2.519 (in Model 2) times higher than the odds that cash dividend will not be paid. We find that *LN(REV)* has 2.258 (in Model 1) and 3.125 (in Model 2) times the odds that cash dividend will be paid higher than the odds that it will not be paid. We find big 4 auditors (H_2), firm size (H_4) and financial leverage (H_5) to significant discourage payment of cash dividend paid. The logit coefficients on *AUDIT(1), LN(SIZE)* and *FIN.LEV* are -.396/-.381, -328/-360 and -672/.652 in Model 1/Model 2, respectively. The exp(B) on *AUDIT(1)* indicates the odds that cash dividend will not be paid by up to 1.5 times higher than the odds that cash dividend will be paid. The exp(B) on *LN(SIZE)* of about .72 indicates the odds that cash dividend will not be paid by up to about 1.4 times higher than the odds that cash dividend will be paid. The exp(B) on *FIN.LEV* of .511/.521 indicates that *FIN.LEV* has about 2 times the odds that cash dividend will not be paid higher than the odds that cash dividend will be paid. These results accept all our alternative hypotheses (H_1, H_2, H_3, H_4 and H_5). Our control variable, the interaction between *STR* and *LN(REV)* –$STR^*LN(REV)$– is likely to significantly predict non-payment of cash dividend. -2 LL of 730.516 and 724.301 indicate good model fit. Nagelkerke pseudo R^2 statistic of Model 1 indicates that our model predictors explain up to about 36% of the variability in payment of cash dividend. Results are contained in Table 7.

Our ANN algorithm in Model 1 finds that STR and LN_REV significantly predict payment of cash dividend whereas AUDIT, LN_SIZE and FIN.LEV and STR*ln(REV) significantly predict otherwise. The ANN test results robustify the acceptance of the alternative hypotheses that industry structure (H_1) and log of revenue (H_3) are likely to influence the payment of cash dividend whereas big 4 auditors (H_2), firm size (H_4) and financial leverage (H_5) are likely to significantly discourage the payment of cash dividend.

We recommend that company management and equity stockholders who are interested in dividend payment should consider the history of industry structure and companies' revenue while those not interested in dividend payment should consider company size, the presence of big 4 auditors and financial leverage.

The study contributes to the literature in several respects. It appears to be the first empirical study to predict the propensity to pay cash dividend using industry structure, independent auditors and log of revenue as predictors. Secondly, method-wise, it appears to pioneer the use state-of-the-art ANN to predict the propensity to (not)pay cash dividend in an emerging economy. Finally, it is the first instance known to the authors where the psychology of human behavior is used to model uncertainty binary logistic regression in respect of payment or non-payment of cash dividend. The practical implication of the theory is that future researchers can apply it to model the propensity to (not)pay cash dividends.

As a limitation, we did not investigate the issue of endogeniety further because, as we have seen, endogeneity does not matter in logistic regression.

6. References

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7. Appendices

Appendix 1. Spearman's rho correlation matric

	PROB(CDP,1)	*STR*	*AUDIT*	*LN(REV)*	*LN(SIZE)*	*FIN.LEV*	*STR*SIZE*
PROB(CDP,1)	1						
STR	.001	1					
AUDIT	-.336**	.059	1				
LN(REV)	.454**	-.197**	-.498**	1			
LN TA	.314**	-.136**	-.360**	.852**	1		
FIN.LEV	-.118**	.028	.164**	.156**	.241**	1	
*STR*SIZE*	.074*	.953**	-.032	.019	.115**	.090*	1

**, *. Correlation is significant at the 0.01, .05 level (2-tailed), respectively.

Appendix 2. Spearman's rho correlation matric

	PROB(CDP,1)	*STR*	*AUDIT*	*LN(REV)*	*LN(SIZE)*	*FIN.LEV*	*AUDIT*SIZE*
PROB(CDP,1)	1						
STR	.001	1					
AUDIT	-.336**	.059	1				
LN(REV)	.454**	-.197**	-.498**	1			
LN(SIZE)	.314**	-.136**	-.360**	.852**	1		
FIN.LEV	-.118**	.028	.164**	.156**	.241**	1	
*AUDIT*SIZE*	.074*	.953**	-.032	.019	.115**	.090*	1

**, *. Correlation is significant at the 0.01, 05 level (2-tailed), respectively.

Appendix 3. Spearman's rho correlation matric

	PROB(CDP,1)	*STR*	*AUDIT*	*LN(REV)*	*LN(SIZE)*	*FIN.LEV*	*AUDIT*REV*
PROB(CDP,1)	1						
STR	.001	1					
AUDIT	-.336**	.059	1				
LN(REV)	.454**	-.197**	-.498**	1			
LN TA	.314**	-.136**	-.360**	.852**	1		
FIN.LEV	-.118**	.028	.164**	.156**	.241**	1	
*AUDIT*LN(REV)*	-.250**	.019	.951**	-.315**	-.237**	.176**	1

**. Correlation is significant at the 0.01 level (2-tailed).