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, Olusanni 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, Kuruppuaratich 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.
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-rabban (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. *FIN.LEV*, operating via node H(1:2) or 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 reinvestment. 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/clientele’s 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:

\[ H_1: \text{Industry structure is likely to significantly influence payment of cash dividend.} \]

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:

\[ H_2: \text{Big 4 auditors are likely to significantly discourage payment of cash dividend.} \]

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:

\[ H_3: \text{Log of revenue is likely to significantly influence payment of cash dividend.} \]

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 Khadia (2022) in their study of Moroccan listed companies found that total assets have negative relationships with payout ratio and dividend yield. Louziri and Khadia’s result is consistent with those of Javid and Ahmed (2009) and Al-Shubir, 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:

\[ H_4: \text{Firm size is likely to significantly discourage payment of cash dividend.} \]

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, Gaoied 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 Osobo (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.
Table 1: Sector * year crosstabulation

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 \( \ln \left[ \frac{1}{1-p} \right] = X_\beta \). Deriving \( P_t \), gives \( \frac{\exp (X_t \beta)}{1+\exp (X_t \beta)} = (1 + \exp (-X_\beta))^{-1} = A(X_\beta) \). The econometric model specification goes as:

\[
\ln \left[ \frac{1}{1-p} \right] = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + B
\]

(\( i \))

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

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:
\[
\text{PROB(CDP,1)} = \beta_0 + \beta_1 \text{STR} + \beta_2 \text{AUDIT} + \beta_3 \text{LN(REV)} + \beta_4 \text{LN(SIZE)} + \beta_5 \text{FIN.LEV} + \varepsilon
\]

\[
\text{Predicted sign:} \quad - \quad + \quad + \quad - \quad + \quad - \quad \varepsilon \quad \ldots(1)
\]

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

\[
\text{Predicted sign:} \quad - \quad + \quad + \quad + \quad \varepsilon \quad \ldots(2)
\]

Where: \text{PROB(CDP,1)} is the criterion/dependent variable, taken on the value “0” and “1”. The predictors are industry structure (\text{STR}), which proxy the combination of the ten industrial grouping; \text{AUDIT} is the external auditors (big 4 versus non-big 4) that audited a company’s annual financial statements. \text{LN(REV)} is natural logarithm of revenue, \text{LN(SIZE)} is natural logarithm of total assets. Financial leverage (\text{FIN.LEV}) is operationalized as \frac{\text{total prior charge debts}}{\text{total prior debts + total equity}}. \text{STR}^* \text{LN(REV)} is an interaction term between \text{STR} and log total revenue. \text{STR}^* \text{LN(REV)} is included in Model 2 as a preferred control variable in the additional analysis later in the paper. \beta_0 = \text{constant}, \beta_i = \beta_6 are the row vectors of logit coefficients of the regressors. \varepsilon = \text{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
--- | --- | --- | --- | --- | ---
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
Houque 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
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

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<td>72</td>
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<td>725</td>
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</tbody>
</table>

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.
Table 4: Descriptive statistics (# of observation = 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.
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.

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.
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 / 1.464 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

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<tr>
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<th>Wald</th>
<th>Sig.</th>
<th>Exp(B)</th>
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<td>$LN(REV)$</td>
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<td>.114</td>
<td>50.897</td>
<td>.000**</td>
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<td>$FIN.LEV$</td>
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<td>.000**</td>
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<td>.924</td>
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<td>(Constant)</td>
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<td>48.852</td>
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**2 Log likelihood 730.516, Sig. $p < .001$ 724.301, Sig. $p < .001$ Nagelkerke R-Square .357 .366

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 / 1.464 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 $N1$ increase in revenue has the propensity to increase cash dividend paid by about up to $N82/N114$ 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 $H_3$ shows that $LN(SIZE)$ has $(.720)^{-1} \text{ or } 1.389/(.698)^{-1}$ 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 -3.28 (Model 1) and -3.60 (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 $N1$ is likely to reduce payment of cash dividend by up to about $N33/N36$, 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 $(.511)^{-1} \text{ or } 1.957)/(.521)^{-1}$ 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 $N1$ additional borrowing will likely reduce cash dividend paid by about $N70$. 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 $N5$. 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%.

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<tr>
<td>Total</td>
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**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.

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<th>Importance</th>
<th>Normalized Importance</th>
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<tr>
<td>$STR$</td>
<td>.064</td>
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<td>$AUDIT$</td>
<td>.097</td>
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<tr>
<td>$LN(REV)$</td>
<td>.571</td>
<td>100.0%</td>
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<tr>
<td>$LN(SIZE)$</td>
<td>.087</td>
<td>15.2%</td>
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<tr>
<td>$FIN.LEV$</td>
<td>.097</td>
<td>17.0%</td>
</tr>
<tr>
<td>$STR*LN(REV)$</td>
<td>.093</td>
<td>27.4%</td>
</tr>
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</table>

Table 9: Independent variable Importance
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.
## 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 $\text{STR} \times \ln(\text{REV})$, $\text{STR} \times \ln(\text{SIZE})$, $\text{AUDIT} \times \ln(\text{REV})$, and $\text{AUDIT} \times \ln(\text{SIZE})$. 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 $\text{STR} \times \ln(\text{REV})$, 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 $\text{STR} \times \ln(\text{REV})$ and $\text{PROB(CDP,1)}$ is low, positive and significant, $p < .000$. This result is shown in Table 11. Consequently, we dropped the other interaction terms in favor of $\text{STR} \times \ln(\text{REV})$ 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, $\text{STR} \times \ln(\text{REV})$ is used as a control variable in Model 2.

<table>
<thead>
<tr>
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<tr>
<td>Area</td>
<td>Area</td>
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<tr>
<td>PROB(CDP,1)</td>
<td>Not likely to pay CD</td>
<td>.854</td>
</tr>
<tr>
<td></td>
<td>Likely to pay CD</td>
<td>.854</td>
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</table>

### Table 11: Spearman’s rho correlation matric

<table>
<thead>
<tr>
<th></th>
<th>PROB(CDP,1)</th>
<th>STR</th>
<th>AUDIT</th>
<th>LN(REV)</th>
<th>LN(SIZE)</th>
<th>FIN.LEV</th>
<th>STR $\times$ LN(REV)</th>
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<td></td>
<td></td>
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<tr>
<td>AUDIT</td>
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<td>.059</td>
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<td>STR $\times$ LN(REV)</td>
<td>.145**</td>
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**. Correlation is significant at the 0.01 level (2-tailed).

### 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 endogeneity 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 (H2), firm size (H4) and financial leverage (H5) 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 (H1, H2, H3, H4 and H5). 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


7. Appendices

<table>
<thead>
<tr>
<th>Appendix 1.</th>
<th>Spearman’s rho correlation matric</th>
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<td><em>LN(REV)</em></td>
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<tr>
<td><em>STR</em> <em>SIZE</em></td>
<td>.074*</td>
</tr>
</tbody>
</table>

** starred, * Correlation is significant at the 0.01, .05 level (2-tailed), respectively.
### Appendix 2. Spearman’s rho correlation matrix

<table>
<thead>
<tr>
<th></th>
<th>PROB(CDP,1)</th>
<th>STR</th>
<th>AUDIT</th>
<th>LN(REV)</th>
<th>LN(SIZE)</th>
<th>FIN.LEV</th>
<th>AUDIT*SIZE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PROB(CDP,1)</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td><strong>STR</strong></td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>AUDIT</strong></td>
<td>-.336**</td>
<td>.059</td>
<td>1</td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>LN(REV)</strong></td>
<td>.454**</td>
<td>-1.197**</td>
<td>-.498**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>LN(SIZE)</strong></td>
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<td>-.136**</td>
<td>-.360**</td>
<td>.852**</td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>FIN.LEV</strong></td>
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<td>.028</td>
<td>.164**</td>
<td>.156**</td>
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</tr>
<tr>
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<td>.953**</td>
<td>-.032</td>
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<td>.115**</td>
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</tr>
</tbody>
</table>

**, * Correlation is significant at the 0.01, 0.05 level (2-tailed), respectively.

### Appendix 3. Spearman’s rho correlation matrix

<table>
<thead>
<tr>
<th></th>
<th>PROB(CDP,1)</th>
<th>STR</th>
<th>AUDIT</th>
<th>LN(REV)</th>
<th>LN(SIZE)</th>
<th>FIN.LEV</th>
<th>AUDIT*REV</th>
</tr>
</thead>
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<td>1</td>
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<td></td>
<td></td>
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<tr>
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<tr>
<td><strong>AUDIT</strong></td>
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<tr>
<td><strong>LN(REV)</strong></td>
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<td>-1.197**</td>
<td>-.498**</td>
<td>1</td>
<td></td>
<td></td>
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</tr>
<tr>
<td><strong>LN TA</strong></td>
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<td>-.360**</td>
<td>.852**</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>FIN.LEV</strong></td>
<td>-.118**</td>
<td>.028</td>
<td>.164**</td>
<td>.156**</td>
<td>.241**</td>
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<td>-.237**</td>
<td>.176**</td>
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</tr>
</tbody>
</table>

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