To what extent do leverage, profitability, and liquidity explain cross-sectional variation in bankruptcy risk among firms?

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Contents

1 Introduction

Understanding why some firms fail while others survive is crucial to prevent its severe consequences. Firm bankruptcies are high-cost events, causing complete loss in stakeholder investment, employees' jobs and disrupted supply chains. For this reason, researchers have long sought to identify which financial characteristics best predict corporate distress. Due to the improbable and complex nature of bankruptcies, this can prove quite challenging. Classical approaches, such as Altman's Z-score, emphasise leverage, profitability, liquidity and activity ratios as key indicators of financial fragility. This project follows the same tradition by empirically evaluating how a set of core accounting ratios influence the probability that a firm becomes bankrupt.

The methods are applied on a large cross-section of firms on the Taiwan Stock Exchange [1]. The datasets consists of firms for which both financial statement information and a binary bankruptcy indicator are observed. In this report, four variables are central to the empirical investigation. The dependent binary variable *Bankrupt*, equal to one if the firm is classified as bankrupt (based on the business regulations of the Taiwan Stock Exchange) and zero otherwise.

Moving on to the explanatory variables, *Leverage* is measured as the firm's liability-to-equity ratio. Higher liability-to-equity indicates a levered firm. From the perspective of avoiding bankruptcy, this is preferred only when the firm has a steady cash flow generation, but not when it is in decline. Highly leveraged firms face greater refinancing risk and thinner equity buffers, suggesting a positive relationship with bankruptcy. Conversely, a lower ration is sometimes preferred as it indicates that the firm is closer to be fully equity financed. Clearly, it alone cannot be used as a prediction of bankruptcy, thus we introduce *Profitability*, defined as Net Income relative to Total Assets. Profitability is a direct measure of operating performance and internal liquidity generation. Firms with higher profitability have an extra buffer against market shocks or otherwise urgent events. There is an implied negative association between profitability and corporate bankruptcy. Finally, this report's analysis uses the *Liquidity* measure based on the Current Ratio in the dataset. Liquidity captures the firm's short-term solvency position.

The goal of this project is to quantify how these financial characteristics relate to bankruptcy risk and to assess which indicators retain explanatory power when included jointly in a limited dependent variable framework. The analysis proceeds by estimating a baseline linear probability model, diagnosing its shortcomings, and then developing a more appropriate Logit specification. The results provide insight into the relative importance of leverage, profitability and liquidity in predicting financial distress and contribute to the broader literature on firm failure and credit risk.

2 Literature Review

Corporate bankruptcy prediction has been a central topic in economics for decades, with early contributions establishing the key firm-level predictors of financial distress. Altman (1968) [2], devised a formula to determine the probability that a firm will go into bankruptcy within two years. The so-called Z-score model, demonstrated that forms of leverage, profitability and liquidity ratios contain substantial information about default risk. Beaver (1966) [3] documented that high leverage and declining earnings are strong early warning signals of bankruptcy. His theory has since been empirically proved.

Since then, subsequent research has dived deeper into the insights that modern econometric techniques can provide. The first being Ohlson (1980) [4] proposing, much like in this report, a logit-based bankruptcy model. Showing increased accuracy over its predecessors of 96.1% predictive accuracy two years before bankruptcy. This showed that nonlinear probability models outperform linear specifications when the dependent variable is binary.

More recent work on the empirical investigation of determinants of corporate failure and the pricing of financially distressed stocks, confirms that leverage increases insolvency risk by reducing solvency buffers, while profitability reflects operational strength and the ability to generate internal funds (Campbell, Hilscher and Szilagyi, 2008 [5]). Liquidity ratios are argued to make firms more available to make interest payments, and thus may be able to postpone bankruptcy with the possibility of avoiding it altogether if circumstances improve. However, Liquidity measures are often noisy and unstable in practice, which weakens their empirical predictive power.

The consensus across the studies is clear: the probability of insolvency of a firm is closely related to the their leverage and earnings performance, with non-linear models being more adept to modelling binary outcomes such as bankruptcy. This literature forms the theoretical foundation for the empirical model estimated in the following sections.

3 Econometric Theory

3.1 Hypothesis testing

Before presenting the statistical results, it is useful to translate the economic predictions of the model into explicit testable, statistical hypotheses. The reader may already have familiarised themselves with the theoretical motivation outlined earlier. The motivation suggested three economic channels through which firm characteristics influence bankruptcy risk.

Firstly, leverage can be a double-edged sword concerning the prediction of bankruptcy. Firms with higher leverage carry greater financial fragility, but can be compensated by significant cash flow generation, nonetheless one can expect it to face a higher probability of bankruptcy. Secondly, firms with high profitability are resilient to adverse shocks, so we assume that is correlated with a lower probability of bankruptcy. Third, liquidity may affect short-term solvency, although its empirical relevance is ambiguous due to measurement noise in accounting-based liquidity ratios.

These economic considerations lead to the following hypotheses. For leverage, the null hypothesis is that leverage has no effect on bankruptcy risk, while the alternative predicts a positive effect.

$$H_0 : \beta_{\text{Lev}} = 0 \quad \text{(leverage has no effect)}$$
$$H_1 : \beta_{\text{Lev}} > 0 \quad \text{(higher leverage increases bankruptcy risk)}$$

For profitability, the null is again that profitability has no effect, while the alternative predicts a negative effect.

$$H_0 : \beta_{\text{Prof}} = 0 \quad \text{(profitability has no effect)}$$
$$H_1 : \beta_{\text{Prof}} < 0 \quad \text{(higher profitability reduces bankruptcy risk)}$$

For liquidity, the null hypothesis is that liquidity does not influence bankruptcy, with the alternative allowing for a non-zero effect in either direction.

$$H_0 : \beta_{\text{Curr}} = 0 \quad \text{(liquidity has no effect)}$$
$$H_1 : \beta_{\text{Curr}} \neq 0 \quad \text{(liquidity affects bankruptcy risk)}$$

In addition to individual hypotheses, it is also informative to test whether the three financial ratios jointly contribute explanatory power beyond the intercept-only model.

$$H_0 : \beta_{\text{Lev}} = \beta_{\text{Prof}} = \beta_{\text{Curr}} = 0 \quad \text{(financial ratios have no joint effect)}$$
$$H_1 : \text{at least one of } \beta_{\text{Lev}}, \beta_{\text{Prof}}, \beta_{\text{Curr}} \neq 0 \quad \text{(financial ratios jointly affect bankruptcy risk).}$$

The statistical testing of these hypotheses is carried out using the Logit model, with coefficient z-statistics used for individual hypotheses and a likelihood-ratio test employed for the joint significance of all regressors.

4 Data

4.1 Data Description

The analysis is based on a cross-sectional dataset of 6,819 firms originating from the bankruptcy prediction dataset from the Taiwan Economic Journal for the years 1999-2009 [1]. The observed binary bankruptcy indicator is the heart of this data, alongside a wide range (94) of financial ratios covering profitability, leverage, liquidity, cash flow, turnover, and asset composition. There are no missing values in the data, but it is not cleansed of outliers.

For the purposes of this report, we focus on three theoretically motivated predictors of financial distress: leverage, profitability and liquidity, together with the binary bankruptcy indicator.

The dependent variable, `Bankrupt`, equals one if the firm is classified as bankrupt and zero otherwise. The three explanatory variables used in the main analysis are constructed directly from the raw dataset:

- *Leverage* (`Lev`): measured as the ratio `Liability.to.Equity`.
- *Profitability* (`Prof`): measured as `Net.Income.to.Total.Assets`.
- *Liquidity* (`Curr`): measured as `Current.Ratio`.

These variables are chosen as they appear as the fundamentals of Bankruptcy scoring in the pertinent literature. They are great predictors of financial distress and align with our economic hypotheses introduced in Section 3. Extreme values in the liquidity ratio were retained for transparency, but their distributional properties are discussed below.

4.2 Descriptive Statistics

Before estimating the econometric models, this study examined the descriptive statistics of the main variables of interest.

As outlined in the introduction, bankruptcy is a high-cost but rare event. This is reflected in the data with `Bankrupt`-cy having a mean of 0.032, implying that only 3.2% of firms in the dataset are classified as bankrupt. This is unsurprising but means we have to account for the unbalanced class in the discussions.

The first independent variable, Leverage (`Lev`), has a mean of 0.28 and displays substantial right-skewness of around 27.45 and kurtosis of 1208. Most firms exhibit moderate leverage, but a small number of them have exceptionally high liability-to-equity ratios, consistent with the notion that financial distress is concentrated in a limited subset of firms and foreshadowing that leverage may be a strong indicator of bankruptcy.

Profitability (`Prof`) is more evenly distributed, with a mean of 0.81 and less extreme skewness. We infer that most firms are relatively profitable, and that the profitability measure is less affected by outliers than leverage or liquidity.

Finally, liquidity (`Curr`) shows extremely high variance and heavy-tailed behaviour with skewness of 82.54, kurtosis of 6812. This reflects the known instability of accounting-based liquidity ratios, particularly when current liabilities approach zero. As a result, liquidity contributes little explanatory power in the empirical models, a point discussed further in

Section 6.

The take-away from the dataset is that bankruptcy is a low-frequency event, we have some meaningful variation and skewness in leverage and profitability, and liquidity measures must be interpreted cautiously due to their extreme dispersion. The econometric approach that ensues takes these data characteristics into consideration in its discussions.

5 The Model to be Estimated

5.1 The Benchmark and LDV Models

The objective of the empirical analysis is to identify which firm-level financial characteristics predict bankruptcy.

Let $Bankrupt_i$ denote a binary indicator equal to one if firm i is classified as bankrupt and zero otherwise. We decide to model a linear probability model (LPM) to the dependent variable as a benchmark. The model, having to capture a binary and bounded variable, can serve only as a baseline diagnostic tool. The main specification adopts a nonlinear limited dependent variable model.

We transform the binary indicator to an unobserved continuos index $Bankrupt_i^*$ that captures the firm's underlying financial condition:

$$Bankrupt_i^* = \alpha_0 + \alpha_1 Lev_i + \alpha_2 Prof_i + \alpha_3 Curr_i + u_i,$$

where Lev_i denotes leverage (Liability-to-Equity ratio), $Prof_i$ denotes profitability (Net-Income-to-Total-Assets ratio), and $Curr_i$ denotes liquidity (Current Ratio). The observed binary outcome is generated by the threshold rule:

$$Bankrupt_i = \begin{cases} 1 & \text{if } Bankrupt_i^* > 0, \\ 0 & \text{otherwise.} \end{cases}$$

Under the logit specification, the disturbance term u_i follows a logistic distribution, yielding the conditional bankruptcy probability

$$P(Bankrupt_i = 1 \mid X_i) = \Lambda(\alpha_0 + \alpha_1 Lev_i + \alpha_2 Prof_i + \alpha_3 Curr_i),$$

where $\Lambda(\cdot)$ denotes the logistic cumulative distribution function. Coefficients capture the direction of each effect, while economic magnitudes are obtained using average marginal effects due to the nonlinear nature of the model.

We motivate our model choice by economic theoretical considerations and diagnostic evidence by this study. The findings in Section 6, which follows later in the report, show that the baseline OLS model exhibits severe functional-form misspecification with RESET test rejection and heteroskedasticity, demonstrating that the LPM is inappropriate for binary outcomes.

Therefore, we choose the logit model that naturally enforces probability bounds, accommodates nonlinear effects, and provides interpretable marginal responses. A probit model is also estimated as a robustness check, differing only in the assumption that u_i follows a standard normal distribution rather than a logistic one.

5.2 Multicollinearity Diagnosis

Table 1: Correlation Matrix for Main Regressors

	Lev	Prof	Curr
Lev	1.000	-	-
Prof	**-0.160**	1.000	-
Curr	**-0.004**	**0.015**	1.000

Multicollinearity among the regressors is assessed using variance inflation factors (VIFs). The correlation matrix in Table 1 shows that multicollinearity is not a concern for the main regressors. The reader can observe that Leverage (Lev) and profitability (Prof) are slightly negatively correlated at –0.16, sharing our economic intuition that highly leveraged firms often have lower net income relative to assets, but far below levels that threaten model stability. Liquidity (Curr) is essentially uncorrelated with both variables $corr < 0.02$, reflecting the noisy and weakly informative nature of this ratio in the dataset.

Moreover, the Variance inflation factors are $VIF_i \approx 1.00$ for all regressors. This confirms that the regressors are statistically independent enough to be used jointly in a logit or OLS specification. As a result, any inference in the empirical models is not distorted by multicollinearity, and coefficient estimates remain identifiable and interpretable.

6 Empirical Results

6.1 Baseline OLS Benchmark

To serve as a useful point of reference, we begin with a simple linear probability model (LPM) to regress the bankruptcy indicator on leverage alone. The model was declared as follows:

$$Bankrupt_i = \beta_0 + \beta_1 Lev_i + u_i.$$

We find that the coefficient on leverage is positive and statistically significant over the 5% mark, with a value of 2.04. This reflects our economic theory, showing that leverage is good predictor of bankruptcy, indicating that levered firms are more likely to be bankrupt. However, the explanatory power of the model is extremely low, with $R^2 \approx 0.028$, and the fitted values are not restricted to the $[0, 1]$ interval (as seen from the residual magnitude). These features already suggest that the LPM is not appropriate for modelling a binary outcome.

To finish off the evaluation of the adequacy LPM model, we compute the heteroskedasticity-robust (HC1) standard errors, to account for heteroskedasticity when assessing the significance of leverage. We run the Ramsey RESET tests of functional form, adding squared and cubed fitted values as additional regressors to detect functional-form misspecification. Finally, we also run the Breusch-Pagan tests to detect any heteroskedasticity. Table 2 summarises the results from the code presented below.

```
# robust standard errors
coeftest(ols1, vcov = vcovHC(ols1, type = "HC1"))

# functional form test (RESET)
resettest(ols1, power = 2:3, type = "fitted")

# Breusch-Pagan
bptest(ols1)
```

Table 2: Diagnostic tests for the baseline LPM

Test	**Statistic**	**df**	**p-value**
HC1 robust SE for β_{Lev}	–	–	3.96×10^{-5}
Ramsey RESET (powers 2–3)	39.31	(2, 6815)	$< 2.2 \times 10^{-16}$
Breusch–Pagan test	22.34	1	2.29×10^{-6}

The robust (HC1) standard errors, which confirmed the significance of leverage, with p-val = $3.961 \cdot 10^{-05} << 0.05$, even when accounting for heteroskedasticity, confirming our intuition of positive association between leverage and bankruptcy risk and it not being an artifact of the error structure.

However, the model diagnostics reveal substantial misspecification. The Ramsey RESET test strongly rejects the null of correct functional form with p-val = $2.2 \cdot 10^{-16} << 0.05$. This strongly indicated that certain non-linear dynamics are not being captured correctly, and hints towards the use of more complex models. It's in the nature of LPMs to impose constant marginal effects and to not respect the bounded nature of binary outcomes.

Moreover, the Breusch-Pagan test detects significant heteroskedasticity p-val = $2.286 \cdot 10^{-6} << 0.05$. Here we can see how the classical OLS assumption is being violated since the variance of the error term is linked to the predicted probability.

An augmented specification including a quadratic leverage term fails to improve model adequacy:

$$Bankrupt_i = \beta_0 + \beta_1 Lev_i + \beta_2 Lev_i^2 + u_i,$$

In addition, RESET diagnostics continues to reject at the 5% level with a p-val $< 2.2\times10^{-16}$), thus the model adequacy does not improve with quadratic terms. The Breusch–Pagan test again indicates heteroskedasticity with p-val $= 9.42 \times 10^{-5}$.

Overall, both diagnostic tests and the instability of coefficients with robust standard errors reinforce that the LPM is not appropriate for modelling bankruptcy. The findings motivate the use of nonlinear models, such as nonlinear limited dependent variable (LDV) models, that are more suited to the modelling binary dependent variables. The models impose functional forms consistent with the binary support of the outcome and allow for non-constant marginal effects.

6.2 Transition to Limited Dependent Variable Models

The `bankrupt` variable is a binary, bounded variable. Up until now, this report has found that the LPM model is inadequate to model the variable. This was determined through diagnostic tests and strong evidence of heteroskedasticity. The analysis then proceeds with limited dependent variable models. We adopt a logit specification as a primary estimator and a probit model as robustness check. The aim of this section is to overcome the shortcomings of the LPM model.

6.3 Logit Model Results

As discussed in Section 5, and proceeding from our most recent findings, we model bankruptcy as a binary outcome using the Logit specification that relates the probability of firm failure to the three core economic ratios discussed in the report: leverage (Lev), profitability (Prof) and liquidity (Curr):

$$P(Bankrupt_i = 1 \mid X_i) = \Lambda(\alpha_0 + \alpha_1 Lev_i + \alpha_2 Prof_i + \alpha_3 Curr_i)\,,$$

where $\Lambda(\cdot)$ is the logistic CDF.

Table 3: Logit Estimates for Bankruptcy

Variable	Estimate	Std. Error	z-value	p-value
Intercept	7.232	2.050	3.528	0.0004
Lev	21.240	5.861	3.623	0.0003
Prof	-21.070	1.366	-15.421	< 0.0001
Curr	-2.76×10^{-9}	1.18×10^{-7}	-0.023	0.981
Model Fit: Null deviance = 1943.7; Residual deviance = 1577.1; AIC = 1585.1				

Table 3 reports the estimated coefficients. The reader can immediately observe that Leverage enters with a large, positive, and highly statistically significant coefficient with p-val $<< 0.05$. Similarly, Profitability is highly statistically significant with again p-val $<< 0.05$, but this time with a strongly negative coefficient. This is undeniable evidence that, within this sample, Leverage and Profitability are strong predictors of bankruptcy, aligning with the economic intuitions presented in the Econometric Theory of Section 3. The coefficient of leverage indicates that firms with higher liability-to-equity ratios face substantially higher bankruptcy risk and the coefficient of profitability indicates that profitable firms are considerably less likely to default.

However, Liquidity (measured by the current ratio and within our sample) is statistically and economically insignificant. We have seen the heavy-tailed distribution of the varibale `Curr` documented in Section 4. Therefore this result is unsurprising, the extreme dispersion in reported current assets makes the ratio uninformative for predicting financial distress in this dataset.

Moreover, model fit improves remarkedly relative to the intercept-only model. The residual deviance decreases from 1943.7 to 1577.1, and the Akaike Information Criterion (AIC) is 1585.1. Together, these metrics indicate that the regressors substantially enhance explanatory power compared to the null model.

6.4 Marginal Effects

One of the drawbacks behind LDVs is that we lose the interpretability of the coefficients. Rather, they do not directly represent effect magnitudes. Therefore, we compute the Average Marginal Effects (AMEs) to express results in probability units. The results are shown in Table 4.

Table 4: Average Marginal Effects from Logit Model

Variable	**AME**	**SE**	**p-value**
Lev (Leverage)	0.551	0.154	3.44×10^{-4}
Prof (Profitability)	-0.546	0.0435	3.45×10^{-36}
Curr (Liquidity)	-7.16×10^{-11}	3.06×10^{-9}	0.981

The AME for leverage is approximately 0.551, meaning that a one-unit increase in the liability-to-equity ratio raises the probability of bankruptcy by 55 percentage points on average. This effect is economically large and statistically significant.

Profitability exhibits an AME of approximately -0.546, indicating a similarly sized inverse, and highly significant, effect. A higher net income relative to assets substantially reduces failure risk.

Liquidity again has an AME extremely close to zero and is statistically insignificant. This confirms that liquidity ratios do not contribute predictive information in this sample and setting.

From the marginal effects we draw interpretability that otherwise could not be made. The results concur and reinforce our previous findings: leverage sharply increases, and profitability sharply decreases the likelihood of bankruptcy, while liquidity remains statistically insignificant in this setting. This strongly suggests that these effects are economically meaningful and consistent with established financial distress theory.

6.5 Model Diagnostics

As in LPM's, LVM's can use the percent correctly predicted as the goodness-of-fit. However, the percent correctly predicted can be misleading as it can be large, although the model totally fails to correctly predict one of the outcomes of y. Thus, to evaluate the adequacy of the Logit specification, we also examine pseudo-R^2 measures and the ROC curve.

Table 5: Classification Table for the Logit Model (Threshold = 0.5)

	Actual	
Predicted	0	1
0	6580	195
1	19	25

Table 5 shows a classification table using a threshold of 0.5. It shows that almost all non-bankrupt firms are correctly predicted, with a specificity $\approx$ 99.7%. However, the model identifies only about 11% of actual bankruptcies. This high-performance is exactly why we cannot base our goodness-of-fit measure solely on the percent of correctly predicted, and why we had to investigate our variable in Section 4, where we found that `bankruptcy` was severely imbalanced with only 3% of failures in the sample. This performance is then to be expected, with relatively high number of false negatives (195). ROC-based metrics therefore provide a more reliable evaluation than raw accuracy.

McFadden's pseudo-R^2 equals 0.189, representing a substantial improvement in model fit relative to the null specification (McFadden [6], 1974). Although pseudo-R^2 values cannot be interpreted in the same way as OLS R^2, values between 0.15-0.35 are commonly viewed as indicative of a reasonably well-fitted discrete-choice model.

The second measure of adequacy chosen is the ROC curve. It produced an Area Under the Curve (AUC) of 0.897, indicating excellent discriminatory ability. Meaning that the model is highly capable of distinguishing bankrupt from non-bankrupt firms with high accuracy. Together, these diagnostics confirm that the Logit model captures the underlying structure of bankruptcy risk well and is a substantial improvement over the linear probability model.

6.6 Probit Robustness Check

To assess robustness to the functional form of the link function, we re-estimate the model using a Probit specification:

$$P(Bankrupt_i = 1 \mid X_i) = \Phi(\beta_0 + \beta_1 Lev_i + \beta_2 Prof_i + \beta_3 Curr_i)\,,$$

where $\Phi(\cdot)$ is the normal CDF.

Table 6: Probit Model Coefficients

Variable	**Estimate**	**Std. Error**	**p-value**
Intercept	2.716893	0.868490	0.00176
Lev	9.819758	2.244859	1.22×10^{-5}
Prof	-9.287766	0.658393	$< 2 \times 10^{-16}$
Curr	-0.005121	0.024399	0.83376

Table 7: Probit Model Fit Statistics

Statistic	**Value**	**Notes**
Null deviance	1943.7	Intercept-only model
Residual deviance	1571.5	Full model
Degrees of freedom	6818 / 6815	Null / Residual
AIC	1579.5	Used for model comparison

Table 8: Average Marginal Effects from Probit Model

Variable	**AME**	**SE**	**p-value**
Lev	0.5666062	0.13255265	1.915026×10^{-5}
Prof	-0.5359097	0.04457488	2.700528×10^{-33}
Curr	-5.748753×10^{-7}	0.00000000	0.0000000

Table 6 presents the estimated Probit coefficients. The signs and magnitudes of the coefficients closely follow those of the Logit model, with Leverage again entering positively and significantly, as well as Profitability entering negatively and significantly. Once again, the Probit model also finds the liquidity variable to be statistically insignificant in its current form and within this sample dataset. Suggesting that liquidity is extremely noisy in this dataset.

The model fit statistic, recorded in Table 7, match those of the Logit model, with a null deviance of 1943.7 and a residual deviance of 1571.5. In fact, the Akaike Information Criterion is slightly lower for the Probit (AIC = 1579.5) than for the Logit model (AIC = 1585.1), suggesting marginally better in-sample fit, although the difference is negligible.

Similarly to the Logit model, the average marginal effects (Table 8) of the Probit model show that leverage increases the probability of bankruptcy by approximately 0.567, while profitability decreases it by approximately 0.536. Both effects are statistically significant at the 5% level considered in this report. Liquidity again has a marginal effect extremely close to zero and is insignificant.

The results are nearly identical to those obtained from the Logit model, showing that our findings are not sensitive to the assumed distribution of the latent error term.

Together, the Probit results fully corroborate the main findings. We conclude that leverage is a strong predictor of bankruptcy, profitability sharply reduces bankruptcy risk, and liquidity carries no explanatory power in this setting.

6.7 Hypothesis Testing

For individual coefficients, the tests are based on the model's z-statistics, while joint significance is assessed using a likelihood-ratio (LR) test comparing the full model to an intercept-only specification.

The logit model estimates (which closely coincide with the probit model estimates), cover the main economic hypotheses. For leverage, the null hypothesis $H_0 : \beta_{Lev} = 0$ is strongly rejected in favour of the alternative $H_1 : \beta_{Lev} > 0$. For profitability, the null $H_0 : \beta_{Prof} = 0$ is rejected in favour of $H_1 : \beta_{Prof} < 0$. Liquidity is found to be statistically insignificant, and the null $H_0 : \beta_{Curr} = 0$ cannot be rejected.

```
linearHypothesis(logit1, c("Lev = 0", "Prof = 0", "Curr = 0"))
```

A final joint likelihood-ratio test, ran with the code above, rejects the null that all slope coefficients are zero. This indicates that the set of firm characteristics provides significant explanatory power.

The hypothesis tests confirm the expected signs implied by financial distress theory, where highly levered and unprofitable firms are substantially more likely to enter bankruptcy, while liquidity adds no independent predictive power after controlling for leverage and profitability.

7 Conclusion

This study investigates to what extent do key economical indicators of financial fragility determine corporate bankruptcy. Basing the analysis on a cross-sectional dataset of 6,189 firms originating from the Taiwan Economic Journal for the years 1999-2009 [1], this report has followed a classical statistical approach to assessing the significance of the factors. The empirical strategy began with a baseline OLS model, diagnosing its adequacy and then transitioning to limited dependent variable models better suited for binary outcomes.

The baseline OLS regression provided a useful descriptive starting point but failed all key diagnostic tests, showing strong evidence of functional form misspecification, heteroskedasticity and extremely low explanatory power. These findings the theoretical limitations of OLS in binary settings and pushed the study to adopt more complex, non-linear models.

The LDV models, firstly the logit specification, yielded clear and economically meaningful results, that followed from the economic theory covered in Section 3. The conclusions drawn were that Leverage is strongly correlated with an increased the likelihood of bankruptcy, while profitability sharply reduced it. These effects were both found to be statistically significant and economically large, as reflected in the estimated marginal effects. Liquidity on the other hand, displayed no significant predictive power. This we attributed to the variable's extreme distributional properties in the dataset, discussed in Section 4.

The logit model performed well in terms of overall fit, achieving a McFadden pseudo-R^2 of approximately 0.19 and an AUC of nearly 0.90, indicating excellent discrimination between bankrupt and non-bankrupt firms.

For robustness, this report considered a probit specification. It corroborated the main findings: agreeing with the coefficient signs, significance levels and marginal effects. All, being nearly identical to those obtained under the logit model. Finally, joint likelihood-ratio tests further demonstrated that leverage and profitability collectively provide substantial explanatory power for bankruptcy risk.

Several limitations should be noted. While multicollinearity was not present between variables, the main dependent variable, `Bankrupt`, experiences high imbalance, with only 3.2% of firms being classified as such. This affected sensitivity and predictive precision. Moreover, Liquidity measures exhibit extreme skewness and potential measurement error, and the cross-sectional nature of the data prevents analysis of deterioration patterns. Nevertheless, the overall conclusions remain strong and consistent with literature established financial distress theory.

To conclude, this report's analysis has shown that leverage and profitability are the primary firm-level characteristics associated with bankruptcy risk. These findings illustrate the usefulness of nonlinear econometric models in studying binary economic outcomes and the role of capital structure and operational performance in determining financial vulnerability.

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