Trade credit forecasting: empirical analysis using a ratio targeting approach

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Abstract

This study employs a panel data model that uses trade credit's own recent history to predict trade credit levels. Companies set a predetermined target for trade payables and re-balance trade credit towards the desired level. A predictive model of trade credit is developed to predict the levels of trade payables and receivables. Previous forecasting techniques do not incorporate the targeting aspect and long period historical data. A target ratio should be set for trade payables and trade receivables to total assets. For instance, total assets in year two contain an amount which was part of total assets in year one. Trade credit is debt finance which is maintained at a certain ratio to total assets. In this paper, we make use of panel data from 230 non-financial South African listed firms from 2001 to 2013. Firms use trade credit targeting to pursue growth opportunities and their size affects their access to capital. Trade credit’s recent history can be used to predict target trade credit levels. The paper makes an original contribution by developing a model to predict the level of trade credit.

Keywords: trade credit, forecasting, historical data, South Africa

Introduction

All businesses can experience short-term cash management problems. Trade payables and receivables represent the timing of cash inflows and outflows and accurate prediction of future levels assists cash management. The need for and shortage of cash during times of liquidity constraints largely arise from the lack of integration between cash inflows and outflows and challenges in forecasting the levels (Kallberg, White, & Ziemba, 1982). Trade credit is a key financing and investment variable as firms use both trade payables and trade receivables to accomplish marketing and financing objectives. According to Summers and Wilson (2000, p. 37) *“trade credit is an important source of short-term finance for business and represents a substantial component of both corporate liabilities and assets”.* It performs a critical role in financing businesses, especially in developing countries (Fisman, 2001; Sun & Hu, 2013) and can increase during periods of financial crisis (Sheng et al., 2013). The essence of working capital management is to adjust a company’s mix of assets and liabilities to reduce the cost of cash surpluses and deficits over a predetermined planning period (Kallberg et al., 1982).

Cash management is critical to the smooth running and survival of enterprises and has been widely studied in the fields of finance, economics, management science and operations research (Kallberg et al., 1982). The financial planning puzzle typically involves the re-engineering of funds to attain specified goals and objectives (Mulvey & Vladimirou, 1992). In allocating capital resources, the available alternatives must be analysed from diverse perspectives. Financial modelling consists of capital budgeting, new borrowing or debt repayments, stock issue or repurchase, and dividends pertaining to the long term planning horizon. Financial modelling of trade receivables and trade payables as well as cash requirements usually pertains to a short term planning horizon of up to a year. Stone (1976) used a portfolio management model to determine the level of trade receivables in a company. Growth in the amount of trade receivables in a company increases both net working capital and the cost of holding and managing trade receivables. If holding trade receivables to a target level predetermined by the company provides greater benefits than disadvantages; the firm's value will grow. Adjusting the level of trade receivables affects the value of the company (Stone, 1976). Computer programming and mathematical programming methods have been used in corporate planning. The decision on what level of trade credit to use is both a marketing (Chern, Chan, Teng, & Goyal, 2014) and a financial one (Danielson & Scott, 2004). Previous studies on trade credit forecasting techniques such as Chern et al. (2014), Gill, Biger, and Mathur (2010) and Stone (1976) do not incorporate the targeting aspect and long period historical data. Cash flow and bad debts depend on accurate forecasting of trade credit levels and trade credit losses. Firms have a target level of trade payables (Kwenda & Holden, 2014b). If they can accurately predict the target level of trade payables to total assets they can accurately predict cash flow, bad debts and trade credit losses. Trade credit forecasting enables management to predict the firm's working capital needs at any given time. Having sufficient working capital on hand to meet financial obligations could prevent business failure.

In this paper, we propose a specific model to determine the level of trade payables or receivables using historical data. We investigate the pattern of trade credit in a specific context where the target level of trade credit is predetermined and there is need to adjust from current levels of trade credit to the target level. The adjustment process requires planning and we propose a model to forecast the level of trade credit. A question that arises immediately is whether firms predetermine their target level of trade credit so that they can plan and minimise the time involved in adjusting from current trade credit levels to the desired levels. The target level of trade credit needs to be determined beforehand so that the levels can be adjusted in the following trading period. The main purpose of this paper is to predict trade credit levels so that a firm can adjust towards the desired level of accounts payable and accounts receivable.

We find that trade receivables to total assets is not influenced by firm size, whilst trade payables to total assets is influenced by the size of the firm. Firms use trade payables to pursue growth opportunities. They maintain a target ratio for trade receivables to total current assets and trade payables to total current liabilities. Targeting the ratios of trade receivables and trade payables enables the level of trade credit to be forecast. Our contribution to the working capital planning discourse is trade credit forecasting using the ratio targeting approach. This paper is related to the literature on financial modelling, forecasting, trade payables and trade receivables. Our work is also closely related to contemporary empirical studies by Gill et al. (2010), Kwenda and Holden (2014b) and Ozkan (2001). However, to the best of our knowledge, no previous study has empirically analysed the forecasting of trade credit using a ratio targeting approach. This is also true for South Africa. The rest of this paper is organised as follows. Section 2 reviews studies on trade credit in the accounting and management literature. Section 3 presents the methodology. In section 4, we use firm-level data to present the results. Section 5 concludes the paper and proposes avenues for further research.

Theoretical Framework and Literature Review

The average level of trade credit in use varies significantly from country to country (Seifert et al., 2013). Countries with less developed financial sectors are likely to rely more on trade credit than those with developed financial sectors. Kwenda and Holden's (2013) study of firms listed on the Johannesburg Stock Exchange (JSE) reveals that South African companies depend heavily on trade credit as a source of short term finance. The authors found that about 50% of current assets were financed by trade credit despite the level of financial sector development in South Africa.

There is a large body of literature on the determinants of trade credit terms between buyers and suppliers (Breza & Liberman, 2016) and the determinants of the use of trade credit (Giannetti et al., 2011; Hermes et al., 2015). Our work is closely related to many studies on both subjects, including Stone (1976) and Lewellen and Edmister (1973). Firms set a target leverage (debt to equity ratio) and move from actual to target level (Ozkan, 2001). Trade payables is part of a firm's credit finance, and by inference, firms must have a target level of trade payables, which is part of credit finance (Kwenda & Holden, 2014b). Nadiri (1969) developed a model which revealed that real trade payables levels may not always be the desired levels, and that firms take time to adjust from actual to target levels. When increasing trade receivables is no longer advantageous to the firm, shareholders will pressure companies to reduce trade credit granted. This will help to alleviate the opportunity cost and financial risk, and reduced profitability and liquidity. Managers will be encouraged to maintain an investment in trade receivables which maximises operational, financial, and commercial benefits (Martínez-Sola, García-Teruel, & Martínez-Solano, 2013). In other words, firm value increases with receivables up to a point and then starts decreasing beyond that point. There is an optimal debt level and by implication, firms must set a target level of trade receivables which minimises the cost of receivables and maximises the benefits. Kwenda and Holden (2014b) used a vital approach to analyse trade credit in corporate financing, and postulated that firms adjust towards their desired level of trade payables.

An increasing number of papers argue that trade credit is an influential and critically important source of external capital (Özlü & Yalçın, 2012). For this reason, we construct the basic framework for our study by forecasting the trade credit target levels in order to plan for the adjustment process from the real to the desired levels of accounts payable in order to minimise time and costs. Firms need time to adjust from actual trade credit levels to target levels. Discrepancies occur between real and desired levels of trade credit due to challenges in estimating with certainty the firm's level of sales, purchases and current assets such as inventories (Martínez-Sola et al., 2013). Not surprisingly, computer based corporate models have generated considerable interest among management scientists and corporate planners in recent years. The number of operating corporate models is growing rapidly and they represent virtually all types of industries. The size and complexity of corporate-level planning problems have tended to favour the development of descriptive simulation models to evaluate planning alternatives (Hamilton & Moses, 1973). A financial model is a representation of the activities of a business in terms of quantitative relationships among variables that can help an analyst to understand the financial consequences of past activities or assumed future activities (Kosy & Wise, 1984). The equations comprising such models form a knowledge base which can be used to generate explanations (Kosy & Wise, 1984).

Changes in trade credit policy affect firm value and can be measured using economic value added (Michalski, 2007). Such changes create new payables and receivables levels. Trade credit policy therefore has an impact on firm value (Michalski, 2007). When goods are delivered and payment is not required immediately the supplier runs the risk that the buyer may default or fail to pay on time (Mramor & Valentincic, 2003). Companies that use a payment-pattern approach to forecasting do so within the framework of a lagged regression in which past receivable balances are regressed on a lagged function of past sales (Stone, 1976). Popular forecast techniques (average days outstanding, ratios, and percentage balance) are based on one-number summaries of credit sales in relation to receivables. Trade credit policy is evident in the average time for which trade receivables are outstanding. This variable is measured by determining the firm's days of sales outstanding (DSO) (Gill et al., 2010). The essence of forecast procedures based on average days outstanding is to solve the usual defining equation for average days outstanding for total receivables and then to use a pro forma value for average days outstanding to project receivables (Stone, 1976).

Ratio-based projection refers to any forecast procedure that assumes that receivables at a point in time are proportional to some measure of sales. The percent-of-balance method of forecasting receivables assumes that payments received in a given month are some constant proportion of the start-of-month receivables sales. The payment-pattern approach to forecasting cash flows and receivables expresses the quantities as a linear function of past credit sales (Stone, 1976). The most straightforward way to estimate payment proportions is to compute the average value realised from past data. The use of trade credit can lower the transaction costs of making payments; rather than paying bills now and again when goods are delivered, a buyer might opt to pay monthly (Petersen & Rajan, 1997). Another reason for using trade credit could be a matching approach whereby a firm finances short-term needs with short-term funds and long-term needs with long-term funds (Deloof & Jegers, 1999). The matching principle demands that short-term assets be financed with short-term liabilities and long-term assets should be financed with long-term liabilities (Guin, 2011). A company's current assets and current liabilities are short-term assets and short-term financing, respectively (Fosberg, 2012). However, if a firm is managing its liquidity position it will tend to maintain more current assets than current liabilities. In business, trade credit can be used to stimulate demand as customers may not have the cash and prefer credit and it also affords breathing space in managing the cash position and liquidity. Businesses often grant a permissible delay in payment to their customers in order to stimulate and increase sales. This has a positive influence on demand but a negative one on default risks and costs (Chern et al., 2014). Many suppliers extend a permissible delay in payments to retailers in order to stimulate demand. The retailer can either pay all accounts at the end of the credit period or incur interest charges on the unpaid and overdue balance (Cheng, Chang, & Ouyang, 2012).

Methodology

The data used in this study was collected from the annual balance sheets of 230 companies listed on the JSE from 2001 to 2013 and available on Bloomberg. Trade receivables to total assets, and trade payables to total assets are used to approximate trade credit and the computed ratios incorporate the targeting aspect. We build on the work of Kwenda and Holden (2014b) who established that JSE listed firms pursue a target of trade payables to total assets and that the mean target for all firms is the same. We argue that, in a similar way, firms also pursue a target trade receivables to total assets ratio. The ratio of trade receivables to total assets $\frac{Trade\ receivables}{Total\ assets}$ (TR/TA*)*, the ratio of trade payables to total assets $\frac{Trade\ payables}{Total\ Assets}$ (TP/TA), the ratio $\frac{Trade\ Receivables}{Total\ Current\ Assets}$ (TR/TCA) and $\frac{Trade\ payables}{Total\ Current\ Liabilities}$ (TP/TCL) are independent variables. We assume that the variables TR/TA and TP/TA change relatively slowly from period to period, and that it is possible that the information TR/TA (t) *and* TP/TA (t) contain with respect to trade credit (t) is already contained in trade credit (t-1), trade credit (t-2), etc., i.e., in trade credit's own recent history. We thus develop a model to utilise this in our forecasting. In this paper trade credit is estimated by using an average ratio of trade receivables to total assets and trade payables to total assets. The assumption is that there is a target level of trade receivables to total assets and trade payables to total assets balances which should be maintained. For instance, the total assets in month/year two already contain an amount which was part of total assets in month/year one.

A model with fixed or random effects for company and for time effect is created with the Hausman test used to choose the type of effect. A residual analysis is carried out to verify the assumptions of the regression model such as homoscedasticity, absence of serial correlation and normality of errors, trade receivables/total assets and trade payables/total assets. The ratio targeting for trade receivables and trade receivables is modelled according to the regression equations below:

$$\frac{TP}{TA_{it}} = \frac{TP}{TA}(t-1)\beta + \frac{TR}{TA} + \frac{TR}{TCA} + \frac{TP}{TCL} + growth + size + n_i + \alpha_i + \mu_{it} \text{ (i)}$$

And

$$\frac{TR}{TA_{it}} = \frac{TR}{TA}(t-1)\beta + \frac{TP}{TA} + \frac{TR}{TCA} + \frac{TP}{TCL} + growth + size + n_i + \alpha_i + \mu_{it} \text{ (ii)}$$

We propose two unique measures of trade credit which are based on targeting receivables and payables to total assets. Such targeting is a short-term decision. Given that firms receive trade credit from suppliers and give trade credit to their customers, we investigate both trade credit receiving and extension. We therefore created the model above with both *trade payables/total assets* and *trade receivables/total assets.* Size distinguishes capital constrained firms as it affects a firm's ability to access finance (Kwenda & Holden, 2014a). Small firms rely more on trade credit than larger firms and they confirm the substitution hypothesis of trade credit (Sheng, Bortoluzzo & Santos, 2013). Developing countries do not have well-developed formal financial systems such as financial institutions and stock markets and under such circumstances trade credit is crucial alternative financing (Yano & Shiraishi, 2014). External capital differs amongst business types due to size and financial conditions (Ozlu & Yalcin, 2012). Small firms have limited access to bank credit during tight periods and it is also observed that capital constrained firms with limited access to bank finance substitute trade credit for bank loans during difficult times.

Firm size is measured as the natural log of total assets (Long, Malitz, & Ravid, 1993). A positive connection exists between extending trade credit and firm size (Deloof & Jegers, 1996). Size is approximated as *size = ln (bs_tot_asset)*. Firms use trade credit to pursue growth opportunities; therefore, the variable is approximated as: *growth = (bs_tot_asset- l.bs_tot_asset)/bs_tot_asset*. n_i measures the unobservable individual effects. These may include the nature of a company's products and management's attitude towards risk. α_i controls for both observable and unobservable time effects in the model which can influence the firm's trade credit policy but are beyond its control.

The extension of trade credit creates receivables whilst receiving trade credit creates payables. Trade credit extended is approximated as the ratio of trade receivables to total assets whilst trade credit received is approximated as a ratio of trade payables to total assets. The ratio of trade payables to total assets gives the percentage of current liabilities financed by trade credit. In the same way, the ratio of trade receivables to total assets gives the percentage of current assets that is financed by trade credit.

Fixed Effects

Fixed effects (FE) regression models are widely used to analyse panel data with repeated measures on both predictor and outcome variables (Allison, 2005). This method is especially useful in the context of causal inference (Gangl, 2010) and can provide unbiased estimates (Brüderl & Ludwig, 2015).

Fixed effects are used to analyse the effect of variables that vary over time. They explore the relationship between independent and outcome variables within a country and firms (Mugova & Sachs, 2017). The rationale is that something within the individual firm may have an effect or bias on the independent and dependent variables and this must be controlled. There is a relationship between firms' error term and the independent variables of trade receivables and trade payables. Therefore, an FE model is necessary to deal with issues of endogeneity. The FE model deals with the effect of time-invariant characteristics so that we can assess the net effect of the independent variables on the outcome variable (trade credit). Time-invariant characteristics are peculiar to the individual firm and should not be correlated with other individual characteristics, as each entity is different. Therefore, the entity's error term and the constant should not be correlated with the others (Torres-Reyna, 2007). The presence of serial correlation in linear panel-data models results in bias and standard errors and causes the results to be less reliable. Thus, serial correlation in the idiosyncratic error term in a panel-data model should be computed (Allison, 2005).

Random Effects

Random effects is appropriate if there is no basis to assume that differences across companies have some influence on the outcome variable (Torres-Reyna, 2007). Random means that there is fluctuation over units in the same population. A conclusion can be drawn for the population, rather than about the particular units (Snijders, 2005) The logic behind the random effects model is that the differences across companies are assumed to be random and uncorrelated with predictor variables in the model. Random effects assume that the individual-specific effect is a random variable that is uncorrelated with the independent variables of preceding, current and following time periods of the same individual firm. The random effects model is the practical generalized least squares (GLS) estimator (Schmidheiny & Basel, 2011).

Hausman test

The Hausman specification test (Hausman, 1978) compares a random effects model to its fixed counterpart (Park, 2011). It is useful in panel data when comparing the estimates of the fixed and random effects models (Sheytanova, 2015). Hausman (1978) provided a test for the exogeneity of the second instrument when none of the instruments are weak (Hahn et al., 2011). To decide between fixed or random effects, one can run a Hausman test where the null hypothesis is that the preferred model is random effects versus the alternative of FE (Torres-Reyna, 2007). If the orthogonality assumption is violated, the random effects estimator is biased and inconsistent while the FE estimator is not affected by this failure (Hausman, 1978). The accuracy of the Hausman test is an important issue in panel data analysis (Sheytanova, 2015).

Data Analysis

Hausman test

The selection between fixed or random effects is effected by running a Hausman test. The Hausman test has a null hypothesis which states that the preferred model is random effects versus the alternative FE model. The essence of the test is check whether the unique errors (u_i) are correlated with the independent variables, while the null hypothesis is that they are not correlated (Torres-Reyna, 2007). The Hausman test was computed to choose between the FE and random effects models. The result of p=0.000 led to the rejection of the null hypothesis and the FE model was chosen. The Hausman test results are presented in Table 1 below:

Table 1: Hausman test results: Equation 1

	Coefficient			
	Fixed	Random	Difference	SE
lagDP1	.1201227	.37398	-.2538573	.0010467

DP2	.0411267	.0470263	-.0058997	.
tradecreditin	.0291254	.0267655	.00236	.
tradecreditout	.3632031	.3564435	.0067596	.
size	-.0088994	-.0036399	-.0052595	.0009523
Growth	.0000154	.0000165	-1.07e-06	.
	Prob>chi2=0000			

Trade Payables/Total Liabilities =*tradecreditin*
Trade Receivables/Total Current Assets=*tradecreditout*

Following the results of the Hausman test, we proceeded to perform the FE regression analysis. The FE regression results for equation one are presented in Table 2 below.

Table 2: Fixed Effect Regression results (Equation 1)

Independent variables	Baseline Model			Model I		
	Baseline Model	SE	p value	β (SE)	SE	p value
lagDP2				-.001	.0037	0.769
DP1				1.28	.1159	0.000***
tradecreditin				.103	.0291	0.000***
tradecreditout				-.249	.0610	0.000***
size	-.3964	.031	0.000***	-.022	.0067	0.000***
Growth	-.0004	.00005	0.000***	-.0005	.0000	0.000***
Constant	2 295	.1708	0.000***	.0993	.0437	0.023*
Observation	2,605			2,521		
Groups	230			230		
R (Overall)	0.0342			0.5531		

*** $p \le .001$; ** $p \le 0.01$; * $p \le .05$;

P=0.000 for DP1, tradecreditin, tradecreditout, size and growth, leading to the conclusion that the model is statistically valid at 95% level of confidence. That is, the model can be used to predict the level of trade credit.

Regression equation (ii) could not meet the assumptions of the Hausman test; therefore, a generalized least squares was used. Generalized Least Squared (GLS) is a method of averaging least squares estimators for the linear regression model with mode with homoscedastic errors in the presence of many regressors (Liu, Okui & Yoshimura, 2016). It minimises the mean squared error (MSE). In the presence of heteroscedasticity, generalized least squares provides better prediction than least squares estimators because GLS estimators have smaller variances (Liu, Okui & Yoshimura, 2016).

Table 3: GLS regression Homoskedastic results (Equation ii)

Independent variables	Model I		
	β (SE)	SE	p value
lagDP2	.0076	.0037	0.042*
DP1	.5929	.0662	0.000***
tradecreditin	.29764	.02161	0.000***
tradecreditout	-.15035	.0439	0.001***
size	-.0035	.0024	0.144
Growth	-.00059	.00001	0.000***
Constant	-.0097	.01950	0.616
Observation	2,521		
Groups	230		

*** $p \leq .001$; ** $p \leq 0.01$; * $p \leq .05$;

The panels are homoskedastic and there is no auto correlation. A heteroscedasticity test was done and there was no heteroscedasticity. In Table 3 above at 95% confidence level, p=0.000 for tradecreditin, p=0.001 for tradecreditout and p=0.000 for growth, meaning that the model has explanatory power on the dependent variable trade receivables to total assets. The size of the firm does not have a significant influence on the determination of trade receivables.

Equation (i)

Wooldridge test for autocorrelation in panel data

H0: no first-order autocorrelation

F(1, 227) = 411.380

Prob > F = 0.0000

Equation (ii)

Wooldridge test for autocorrelation in panel data

H0: no first-order autocorrelation

F(1, 227) = 222.718
Prob > F = 0.0000

The test for serial correlation in random or FE one-way models was developed by Wooldridge (2002) (Drukker, 2003). Serial correlation in linear panel-data models and equations biases the standard errors and causes the results to be less reliable; thus, there is a need to identify serial correlation in the idiosyncratic error term in a panel-data model (Drukker, 2003). The Wooldridge (2002) test is very important. It requires relatively few assumptions and is easy to compute. The idiosyncratic error term μ_{it} is assumed to be uncorrelated with the explanatory variables of all past, current and future time periods of the same individual firm (Schmidheiny & Basel, 2011)

Discussion

The model can be used to predict the trade credit level in the next trading period given that current trade credit and previous trade credit levels are known. The predictive model uses a series of changes in trade credit, trade receivables to total assets and trade payables to total assets from one period to the next. The level of trade credit is not constant, but is always changing due to variations in business activity and working capital requirements. Working capital requirements and the deliberate trade credit policy adopted by firms influence the percentage that should be financed through trade receivables and trade payables. Firms use both trade receivables and payables to finance working capital, ensuring that the target level is always maintained. Prediction of the target will reduce the time and cost of adjusting trade credit from the current level to the desired level.

The data-set used enabled us to simultaneously analyse the levels of trade credit as a percentage of total assets and to forecast the level of trade credit. The analysis is critical because it illustrates the strategic use and relevance of trade credit as a source of external capital. The FE model controls for all time-invariant differences between individual firms; thus, the estimated coefficients of the FE model cannot be biased due to omitted time-invariant characteristics. The ratio of trade receivables to total assets, trade payables to total current liabilities, growth and firm size are all significant in determining trade payables to total assets in the equation (1) results. An increase in trade receivables will result in a corresponding increase in the ratio of trade payables as a percentage of total assets. Firms maintain the ratio within their target and if the ratio is off target payables or receivables will be increased or reduced. The lagged dependent variable trade payables/total assets, is also a significant predictor of trade payables, implying that previous trade credit levels can be used to predict future levels of trade credit.

The ratio of trade payables to total assets, trade receivables to total current assets, trade payables to total current liabilities, growth and firm size are all significant in determining trade receivables to total assets in the equation (2) results. An increase in trade payables will result in a corresponding increase in the ratio of trade receivables as a percentage of total assets. The size of the firm does not have a significant influence in determining trade receivables. The level of trade receivables is influenced by the risk of default, and the level of business activity and sales, unlike trade payables which is a form of borrowing and is affected by the size of the organisation. Large firms use considerably more trade payables than smaller firms due to their superior negotiating power over smaller firms.

Firms set a target ratio of trade receivables to total current assets, maintaining a certain level of receivables amongst other current assets such as stock and cash in order to manage working capital efficiently. Trade receivables are maintained at a certain level due to credit risk and the time it takes to convert them to cash. Firms also adopt a target ratio of trade payables to total current liabilities. Trade payables are debt and represent the trade credit employed to finance growth. Trade receivables and trade payables are also maintained at a target level to total assets. The target level changes with sales growth, firm growth and the volume of trade from one period to another. These ratios can be used to predict trade credit levels. Trade credit inwards, trade credit outwards, and the size and growth of the firm can be used to predict future working capital requirements. Large firms employ more trade credit than smaller firms. These firms usually have more negotiating power than their smaller trading partners. Trade payables influences the level of trade receivables because payables are used to finance growth so that the firm achieves an increase in sales. Firms pursuing growth will use more trade credit than those that are not growing.

Conclusion

This paper presents causal evidence that trade credit levels can be forecast using a ratio targeting model following Kwenda and Holden (2014b) who found that firms maintain a target level of trade payables to total assets. They also maintain a target level of trade receivables to total assets. Trade credit is used in pursuit of growth opportunities and firm size influences the level of trade payables. The ratio of trade receivables to total assets is not influenced by firm size. Firms maintain a target ratio for trade receivables to total current assets and trade payables to total current liabilities. Through targeting these ratios, the level of trade credit can be predicted. Firms may not always be at target level, but they increase or decrease trade credit in an effort to reach the target. The results also show that the level of trade payables influences the level of trade receivables and vice versa. There is give and take in terms of trade credit from suppliers and trade credit extended to customers. Forecasting trade credit assists in financial planning and in determining overall working capital requirements. Determining trade credit levels assists in estimating the cash and stock levels required. This research adds to the financial planning puzzle by using ratio targeting to forecast the trade credit level. Stone (1976) emphasised the importance of adjusting trade receivable levels to reduce the costs and maximise the benefits of holding receivables in order to increase the value of the firm.

Trade credit is a regular component of market transactions and constitutes a major source of short-term financing (Seifert et al., 2013). It represents a substantial part of corporate resources (Canto-Cuevas et al., 2016). It could thus play a significant role in solving financing problems and increasing firms' activities and performance. For this reason, we developed a model that can be used to predict trade credit levels on a monthly or annual basis. We assumed that trade credit in the current period already contains an amount which was part of total assets and total liabilities in the preceding trading period. Several methods have been used in the literature such as the payment-pattern approach to forecasting, the percent-of-balance method, and forecast techniques based on average days outstanding, ratios and percentage balance.

Firms use trade credit to pursue growth opportunities which requires that the level of trade payables and trade receivables be adjusted to finance growth. Firm growth is important to determine the level of trade credit in a firm. Firm size impacts a company's ability to access funds from financial institutions and trading partners. Size is a key determinant in forecasting trade payables and trade receivables. The findings confirm that firms use trade credit, targeting the percentage to total assets. Trade credit inwards (trade payables) has an important effect in forecasting trade credit outwards (trade receivables). The level of trade credit in the previous trading cycle is important to determine the trade credit for the following trade period.

Further research should develop expanded models which include a "macro factor" such as the rate of GDP growth or price inflation since they were not considered as they do not vary across individual firms. The level of a country's financial sector development should also be considered as it is likely to improve a firm's access to capital markets and consequently alter the target level of trade credit financing. It would also be important to consider how the debtor's collection period and the bad debts ratio affect the prediction of trade receivables and trade payables. The rate of collection is also influenced by the firm's trade credit policies and the debt collection methods employed, which should also be considered in future studies. This paper added another approach to forecast trade credit levels based on the targeting of both trade receivables and trade payables to current assets and current liabilities as well as to a firm's total assets.

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