Contents lists available at SciVerse ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

A variable impact neural network analysis of dividend policies and share prices of transportation and related companies

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ARTICLE INFO

Article history:
Received 1 March 2010
Accepted 18 April 2012
Available online 1 May 2012

JEL classification:
C45
F23
G10

Keywords:
Dividend yield
Retention
Market-to-book value
Neural networks
Transportation

ABSTRACT

The purpose of this research is to investigate dividend policy, including its impact on share prices of transportation providers and related service companies, by comparing generalized regression neural networks with conventional regressions. Our results using regressions reveal that for Europe and for the US and Canada the market-to-book-value, as a surrogate for growth opportunities, fulfils expectations of pressures on dividends leading to a negative association with dividend yields in accordance with the pecking order theory. Neural network analysis indicates a clear role for growth opportunities for the US and Canada pointing to an underlying confidence on the part of transportation companies in their own internal policies. Finally, risk is rewarded especially in Europe.

1. Introduction

What do shareholders of transportation companies get for their money? How do dividends impinge on their share prices? Do dividends play a stronger role than retained profits in valuing these companies? These are important questions for the transportation industry, and need to be addressed. If share prices in this sector appreciate, then investors find that their returns comprise capital gains as well as

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1042-4431/$ – see front matter
http://dx.doi.org/10.1016/j.intfin.2012.04.008

dividends. Of course, if prices fall, capital losses ensue instead. But capital gains or losses are likely to be more volatile than dividends. Indeed, performance of global transportation firms is closely linked to variations in world trade (Goulielmos and Psifia, 2006) and global macro factors (Kavussanos and Marcoulis, 2000, 2005; Grammenos and Arkoulis, 2002).

In view of such exposure to fluctuations in global trade, and differences in national economic cycles, good planning and appropriate strategic long-term decision-making are important (Bendall and Stent, 2003). Of course, dividends are paid out of earnings, leaving a residual for the retentions which become available for strategic reinvestment, and so whether dividends are more important than retentions is a key issue that may also affect the future of the transportation industry. In accounting terms retentions produce a change in accounting book values, and indeed it is upon the network assets of the enterprise that the companies can generate their returns. In using these network assets, there is evidence to suggest that the risk in terms of freight volatilities can be reduced by operating small-sized vessels (Kavussanos, 2003). But do share prices of transportation providers and related service firms duly reflect dividends, retentions, market and book values per share? If so, which elements are more significant in such valuations? These are some of the empirical issues, which this paper attempts to investigate.

Given the international nature of the transportation industry, it is sensible to take cognisance of variations amongst capital markets across the globe. Regarding the relative importance of dividends, retained profits, market and book values, do European transportation providers and related service firms differ from those in North America, the Far East and Australia? In the determination of share prices of these companies, if a clear role can be established for dividends, then the next step is clearly to evaluate the factors that drive dividend yields. In this paper, from a review of some of the literature on dividend policy, several factors will be proposed that are likely to be of potential importance to dividend yield determination. It emerges from our literature review that potentially significant contenders for such an investigation are growth prospects, asset backing, business and financial risks, size/stability, profitability, capital expenditure needs, and cash flow generation.

The aims of this research are to identify relevant variables, and to test the predictive abilities of the models used for determining both share prices and dividend yields of transportation companies which term we use to refer to transportation providers and related service companies. As far as share prices are concerned our focus is on whether dividends are more important than retentions. As far as dividend yields are concerned, we are more interested in identifying relevant variables, and assessing which of these are more important than others. Furthermore, we suspect that there may be some regional differences, and if so then investors should be aware of them. Also, we consider how far our results accord with various economic theories pertaining to dividend behaviour, such as pecking order, agency cost and trade-off theories.

We find that the book value per share is the most important determinant of the share price. The variable impact analysis of share price demonstrates that dividends are more important than retentions in each region and overall. Furthermore, the main drivers of dividend yields are different in the three regions: market-to-book-value in the US and Canada (negatively associated); risk in Europe (positively associated); and cash flow as a percentage of sales (negatively associated) in Rest of the World.

Within the literature, dividends play a more important role than retentions in explaining share prices, as evidenced in a UK study by Rees (1997), in the spirit of the Ohlson model (Ohlson, 1995) on the value relevance of accounting information. However, Gwilym et al. (2005) demonstrate that for the UK this is not true after the effects of transaction costs and risk have been taken into account. Barker (1999), from survey evidence, finds that analysts tend to use dividend yields in the utilities and financial sectors. Benartzi et al. (1997) investigate the information content of dividend policy pertaining to future earnings, following the classic investigation by Lintner (1956). They do not find an association between a current dividend increase and future earnings' growth. Grullon et al. (2005) find that dividend changes bear no information-content regarding future changes in earnings, after account is taken of non-linearities in earnings' behaviour. Riahi-Belkaoui and Picur (2001) argue that the use of the PE ratio or dividend yield will depend on the investment opportunity set open to the firm. Benito and Young (2003) found that UK firms with greater growth opportunities (higher Tobin's

Q, which is similar to the market-to-book value measure) were more pressurised to omit dividends. Omran and Pointon (2004) found a negative relationship between the Q-ratio and the dividend payout ratio. However, D'Souza and Saxena (1999) cannot find a significant association between dividends and investment opportunities (Q).

In an agency-framework Lie (2005) finds that leverage is negatively associated with the dividend payout ratio – but there are dissenting voices, e.g. Tong and Green (2005) and Adedeji (1998). Benito and Young (2003) find that firms with lower profits are more likely to omit dividends. Fama and French (2002) tend to support pecking order theory but with some evidence for trade-off theory, in that they find a positive relationship between profitability and the dividend payout ratio. If retentions, as the first priority, are used to fund capital expenditure then there should be a negative relationship between the capital expenditure rate and dividend yields.

Benito and Young (2003) state that there is a negative relationship between 'cash-flow'[1] as a proportion of the replacement cost of capital stock and UK dividends. A study of German firms, by Andres et al. (2008), indicates that their dividends are more related to cash flows than to earnings.

Some researchers have found a negative relationship between market-to-book values and dividend yield (Eagan et al., 1999; Lie, 2005; Riahi-Belkaoui and Picur, 2001; Gwilym et al., 2005). Benito and Young (2003) find that UK firms with greater growth opportunities are more pressurised to omit dividends. We might sensibly expect risk to be is negatively related to the dividend yield, because a higher risk makes dividends less sustainable. Indeed, D'Souza and Saxena (1999) find a negative relationship between market risk and dividend payments. Furthermore, Lie (2005, p. 10) finds negative relationships between dividend increases and (i) prior beta, i.e. 'equity beta estimated using daily returns during the fiscal year prior to the event year', (ii) operating income (ratio of operating income to total assets) volatility change and (iii) prior operating income volatility, i.e. 'standard deviation of the ratio of operating income to total assets for the previous 5 years'. Size might also be a factor in dividend yields on the basis that smaller firms are relatively riskier leading as mentioned above to a higher discount rate for the income and a consequently a higher number for the yield.

The rest of this paper unfolds as follows: Section 2 sets the scene for the empirical analysis covering hypotheses and models designed for multiple regression analysis and generalized regression neural networks analysis; Section 3 describes the sources and collection of the data; in Section 4 the results and analysis are discussed, assessing both the role of dividends in share price determination, and the determinants of dividend yields and finally Section 5 comprises the conclusion.

2. Methodology

A number of significant hypotheses emerge from the above review of the literature:

H_1. Market-to-book value is negatively related to dividend yield (in accordance with pecking order).

H_2. Asset-backing is positively related to dividend yield (since when assets are sufficient a generous dividend does not threaten to put undue pressure on retentions).

H_3. Total debt to equity is negatively related to dividend yield (in accordance with agency theory).

H_4. Size is positively related to dividend yield (in view of the potential association with risk).

H_5. Return on equity is positively related to dividend yield (in accordance with trade-off).

H_6. Capital expenditure rate is negatively related to dividend yield.

H_7. Cash flow as a percentage of sales is positively related to dividend yield.

H_8. Risk is negatively related to dividend yield (on the basis that risk potentially prompts retention).

[1] The Pacific Basin Shipping Company (www.pacificbasin.com) announced in December 2004, for example, that its interim dividend reflected, inter alia, the 'level of cash available'.

There are four main components to the methodology. *Firstly*, we undertake a multiple regression analysis of the share price of firm i in year t with SP_{it}, as the dependent variable:

$$\mathrm{SP}_{it} = a + b_1\mathrm{DPS}_{it} + b_2\mathrm{RPS}_{it} + b_3\mathrm{BVPS}_{it} + e_{it} \tag{1}$$

where, DPS_{it} is the dividends per share of firm i in year t; RPS_{it} is the retentions per share by firm i in year t; BVPS_{it} is the book value per share; a is the constant; $b_1 \ldots b_3$ are the respective regression coefficients for the independent variables and e_{it} is the residual for firm i in year t. We run the regression globally, and again for each of the three regions. Eq. (1) is the standard model, in the value relevance of accounting literature, for assessing the impact of dividends, retentions and book value on share price. In this paper we are interested in the impact of dividends on actual stock *prices*, not on *rates* of return. Whilst using SP as our economic variable, we should indicate that the corresponding regression results may be spurious because of the possibility that SP is I(1).

Secondly, we conduct a multiple regression analysis of the dividend yield of firm i in year t with DY_{it}, as the dependent variable:

$$\begin{aligned}\mathrm{DY}_{it} = {} & \alpha + \beta_1\mathrm{MTBV}_{it} + \beta_2\mathrm{ASSBKG}_{it} + \beta_3\mathrm{TDE}_{it} + \beta_4\mathrm{SIZE}_{it} + \beta_5\mathrm{ROE}_{it} + \beta_6\mathrm{CAPEXRATE}_{it} \\ & + \beta_7\mathrm{CF\%S}_{it} + \beta_8\mathrm{STDEV(EB/TS)}_{it} + \varepsilon_{it}\end{aligned} \tag{2}$$

where, MTBV_{it} is the market-to-book value; ASSBKG_{it} is the asset-backing defined as fixed assets/total assets; TDE_{it} is the total debt/equity; SIZE_{it} is the natural logarithm of market capitalization; ROE_{it} is the return on equity; $\mathrm{CAPEXRATE}_{it}$ is the capital expenditure rate defined as capital expenditure/total assets; $\mathrm{CF\%S}_{it}$ is the cash flow as a percentage of sales; $\mathrm{STDEV(EB/TS)}_{it}$ is the risk defined as standard deviation of the ratio of earnings before interest, tax and depreciation/total assets; α is the constant; $\beta_1 \ldots \beta_8$ are the respective regression coefficients for the independent variables and ε_{it} is the white noise error term. The ε_{it} are independent and normally distributed with mean zero and variance σ^2. We run the regression globally, and again for each of the three regions.

In the Fama and French (2002) single country study, dividends are scaled by assets, whereas we scale dividends by market value, to arrive at the dividend yield. This avoids inadequacies in financial reporting practices, and inconsistencies between accounting systems across the globe that would arise if assets were used as the scaling factor. The point is that different countries use different valuation approaches for accounting purposes. But by using stock market values for scaling, this problem is avoided in this paper. Also in the Fama and French (2002) study of dividends and debt, size is used as a proxy for volatility. In our paper we use separate variables for size and risk. Indeed we later show that for transportation firms, when size is a highly significant determinant of the dividend yield, the risk is not significant, and vice versa.

Thirdly, we run a generalized regression neural network (GRNN) of the determinants of the share price. We undertake this for training and testing samples individually and again for the overall sample, globally and for each region. It should be emphasised that the training data are the data used to build the models, whilst the testing data play no role in building the models, but serve to test the predictive capabilities of the model. When we refer in this paper to an overall sample, we mean that the whole data set is used in building the model. We also provide a variable impact analysis in order to assess the relative importance of each determinant namely DPS_{it}, RPS_{it} and BVPS_{it}.

A neural network is a system that takes numeric inputs, performs computations on these inputs, and creates outputs for one or more numeric values. The inspiration for neural networks comes from the structure of the human brain. A brain consists of a large number of cells, referred to as ‘neurons’ or ‘nodes’. A neuron receives impulses from other neurons through a number of ‘dendrites’. Depending on the impulses received, a neuron may send a signal to other neurons, through its signal ‘axon’, which connects to dendrites of other neurons. Neural networks provide an alternative to more traditional statistical methods, such as linear regression (by use of function approximations), discriminant analysis and logistic regression (in classification problems). An advantage of neural networks is that they are capable of modelling extremely complex functions. This stands in contrast to traditional linear techniques (see for example Masters, 1995). A particularly powerful advantage of GRNN which is apposite to the present study is that GRNN obviates the need for SP to be I(1).

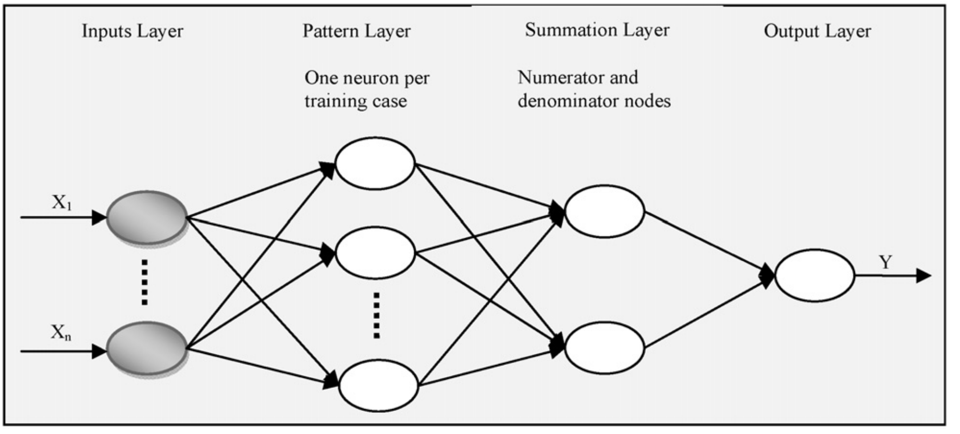

Fig. 1. Generalized regression neural network structure. This figure illustrates the structure of a GRNN for a number of independent numeric variables. The input layer contains a neuron for every independent variable in the model. The pattern layer contains one node for each training case. Each neuron in the pattern layer computes its distance from the presented case. The nodes in the summation layer sum its inputs, whilst the output node divides them to generate the prediction.
Source: Own figure.

Generalized regression neural networks have four layers, as depicted in Fig. 1. Firstly, the input layer contains a neuron for every independent variable in the model. Secondly, in the pattern layer there is a node for each training case. Distances from the presented value from the training data to the target value are computed following a radial basis/kernel, and normally a Gaussian function in the smoothing factor is applied with mean squared error minimization being achieved through the conjugate gradient descent optimization method. The GRNN automatically applies the mean squared error during training in the utilization of these smoothing factors. Thirdly, in the summation layer, summations are made of inputs from the pattern layer at numerator and denominator nodes. Fourthly, and finally, the output layer takes the computed numerator value and divides by the respective denominator value to obtain the prediction (see for example, Master, 1995; Specht, 1991). These generalized regression neural networks are robust to outliers, and should be well suited to our international transportation data which comprises a wide range of diverse companies. Whilst probabilistic neural networks, for example, are used for classification purposes of categorical data, GRNNs are used for a regression analysis of a continuous dependent variable(s). To measure and compare the overall accuracy of both conventional regression and GRNN models we use quasi-quadratic root mean square error (RMSE) and linear mean absolute error (MAE) as measures of model accuracy. Specht (1991) introduces such a 'memory-based network' that can be used for regression problems, and which is particularly well suited to situations in which the underlying relationships may be non-linear. He demonstrated that the algorithm exhibits smooth links between observed values. Tomandl and Schober (2001), building on the work by Specht, show that their algorithms are robust to parameter-sensitivity, that the vectors do not have to be equal, and they provide a discussion inter alia of the slopes of the regression surfaces. In particular, Leung et al. (2000) apply GRNNs to the problem of forecasting foreign exchange rates, making comparisons both with random walks and multi-layered feed-forward networks, and demonstrate superiority in predictions.

Fourthly, in order to evaluate the significance of dividend yield, we run a GRNN of its determinants, for training and testing samples individually and again for the overall sample, globally and for each region. Furthermore, we conduct a variable impact analysis to assess the relative importance of each determinant (MTBV_{it}, ASSBKG_{it}, TDE_{it}, SIZE_{it}, ROE_{it}, $\mathrm{CAPEXRATE}_{it}$, $\mathrm{CF\%S}_{it}$, and $\mathrm{STDEV(EB/TS)}_{it}$). Eagan et al. (1999) used a neural network to provide a preliminary data analysis of dividends of US corporations, but did not find any strong non-linear relationships. In this paper, we do not use a neural network model for data-mining purposes, and neither do we attempt to identify non-linear relationships, instead we only allow for their possibilities. Thus, our approach is to use GRNNs, as

Table 1
Descriptive statistics for different regions and countries based on size ($ millions).

Region	Country	Mean	St. Dev	Minimum	Maximum	No. companies
Europe		1351.313	6001.161	2.481	50,652.300	57
	Denmark	7979.431	16,149.728	6.776	50,652.300	5
	France	902.435	1174.763	3.991	5310.431	8
	Germany	209.149	724.371	2.481	3433.362	4
	Italy	250.053	137.436	91.461	657.233	2
	Netherlands	687.457	713.221	42.876	3122.818	5
	Norway	279.042	426.311	5.771	2127.103	20
	Sweden	162.069	187.139	31.238	825.002	5
	UK	862.940	1021.895	28.844	3555.251	8
US and Canada		494.700	602.120	3.704	2492.643	20
	Canada	445.239	639.570	3.704	2492.643	5
	US	519.864	586.397	5.161	2177.054	15
Rest of the World		654.068	1434.918	5.254	11,442.751	62
	Australia	1169.485	1544.802	12.990	4918.361	3
	China	514.391	534.747	71.214	2319.687	12
	Hongkong	881.060	1325.247	5.254	9553.315	9
	India	321.364	273.692	29.805	1072.987	5
	Japan	690.324	1822.935	14.596	11,442.751	28
	New Zealand	238.947	216.768	21.865	626.479	5
Total						139

Size is measured by market capitalization. The sample consists of 139 transportation companies covering 16 countries from three regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand). The data are extracted from Datastream for 9 years from 1997 to 2005 inclusive.

well as multiple regressions, in order to assess the impact of variables pre-specified, but without the restrictive constraints of linearities.

3. Data-set

This study is based upon a global data-set of 139 transportation providers and related service companies. They include firms specialising in marine transportation and shipping, other transportation services, oil equipment and related services and travel and tourism. Within the shipping component are, inter alia, deep sea foreign transportation of freight, water transportation of freight, freight and cargo transportation arrangement, deep sea foreign transportation, general storage, ship-building and repairing, towing and tugboat services and transportation services and NEC industry. The data are extracted from Datastream, across 16 countries for 9 years from 1997 to 2005 inclusive as shown in Table 1. The sample is investigated as a whole set and again individually for the regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand).

We have provided in Table 1 descriptive statistics for different regions and countries based on size, namely market capitalization. Companies in the Rest of the World, which include a high profile of Japanese companies, are similar in size to those in the US and Canada. In Europe, which comprises a large representation from Norway, the companies are generally larger than in the other two regions.

4. Results and analysis

4.1. Model$_1$: share price

The estimation methods of Model$_1$ are: firstly a multiple regression, using share price as the dependent variable, further details of which are given in Section 2, and secondly GRNNs. The intention

Table 2
Multiple Regression Model$_1$: determinants of share price.

	US and Canada		Europe		Rest of World		All regions	
	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value
Constant	6.95604	0.0011	99.2491	0.0000	32.1264	0.0027	73.876	0.0000
DPS	2.70456	0.0538	0.15046	0.8255	18.0691	0.0000	0.19485	0.7375
RPS	2.09344	0.0000	−0.0501	0.8264	1.69366	0.0040	0.25798	0.1768
BVPS	0.55230	0.0000	0.3098	0.0013	0.33844	0.0000	0.48838	0.0000
Further analytical results								
F-ratio	49.30***		3.72**		104.80***		70.31***	
ANOVA *P*-value	0.0000		0.0117		0.0000		0.0000	
R^2 adj.	60.9064%		2.32678		48.4741		21.2848	
RMSE	10.13501		181.367		135.451		159.554	
MAE	7.61753		116.991		81.2094		99.6671	

** and *** denotes a statistically significant difference at 5 and 1% level, respectively.
The sample consists of 139 transportation companies covering 16 countries from three regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand). The data are extracted from Datastream for the years 1997–2005 inclusive. The table shows the results of estimating:

$$\mathrm{SP}_{it} = a + b_1\mathrm{DPS}_{it} + b_2\mathrm{RPS}_{it} + b_3\mathrm{BVPS}_{it} + e_{it}$$

The dependent variable is share price (SP). The independent variables are dividend per share (DPS), retention per share (RPS) and book value per share (BVPS). The table shows regression models for each of the three regions and for all regions combined with root mean square error (RMSE) and mean absolute error (MAE), as measures for model accuracy.

behind the first model, as shown in Table 2, is to determine whether the share price of transportation companies can be explained in terms of dividend per share (DPS), retentions per share (RPS) and book value per share (BVPS).

For transportation companies in the US and Canada, two independent variables are positive and significant at the 99% level of confidence (RPS and BVPS), and the other (DPS) at the 90% level of confidence. The variables explain 60.9% (R^2 adjusted) of the variation in share prices. The message of these findings for the US and Canada is consistent with what agency theory would lead us to expect for a relatively transparent and complete market where accounting numbers have a significant degree of economic credibility and where transaction costs are relatively low.

Turning to the first of the above findings – importance of dividend per share – a generous dividend reduces the free cash flow available to management and imposes more frequent recourse to the outside world for needed funds. Such recourse imposes discipline as managers have to substantiate their quest for resources. Furthermore dividends can be an attraction to institutional shareholders in so far as they need to rely on an income stream to meet regular commitments to clients such as pensioners and in so far as institutions are subject to lower tax rates than individuals. The presence of institutions is a further reassurance to investors since their expertise and large holdings will act as a discipline on managers.

Turning to the second of the above results – importance of retentions – a sophisticated market would not be fooled by dividend payments with inadequate retention cover nor by a roundabout in which generous but inadequately covered dividends were paid to taxable investors only to be followed by an appeal to the market for funds. The third result – importance of book value per share – like the first is consistent with agency theory. High book value of assets reassures investors in so far as they see it as a proxy for tangible assets. Deployment of tangibles is less at managers' discretion than intangibles thus reducing the danger of discretionary redeployment of resources from, for example, safe projects to risky projects or into low-yielding projects which would provide managers with shirking opportunities. Furthermore tangible assets will provide access to cheaper debt with accompanying tax relief. In short the findings for dividends and book value are consistent with agency theory and these findings are economically consistent with the finding for retention.

For European transportation companies, the model performs badly overall (R^2 adjusted = 2.3%), although BVPS is significant at the 99% level of confidence. The negative coefficient for retentions under Europe is not significantly different from zero because of its high *P*-value of 0.8264, and can thus be ignored. It is particularly interesting that the influence on share price which carries over most strongly into Europe is book value per share. A less sophisticated, more nervous investor confronted by less transparent accounts in a riskier marketplace will find reassurance in a backing of tangible assets. This is in accordance with agency theory since as explained for the US and Canada BVPS will be perceived by investors as less susceptible to managerial discretion and which will attract more economic borrowing and leasing opportunities.

For transportation companies in Rest of the World the model performs moderately well (R^2 adjusted = 48.5%) and all three variables are significant (and positive) at the 99% level of confidence. Like the other results this is consistent with agency theory. For the Rest of the World, dividends play a more important role than retentions, for the coefficient for DPS is 18.1 compared with 1.7 for RPS. For US and Canada the coefficients are close (2.7 and 2.1, respectively). A less sophisticated, less transparent market can be expected to set higher store by dividends than retentions, retentions being less trusted and dividends carrying reassurance.

For all regions combined only BVPS is significant at the 99% level of confidence, with the model overall explaining 21.3% (R^2 adjusted), of variation in the share prices of international transportation companies.[2]

From the previous analysis, it is clear that the inclusion of European companies has caused this distortion and reflects the influence of the uncertainty that investors in European transportation were facing during this period of time. If the investor community does not expect dividends to be sustained, then the dividends would show up as being not significant in the regression models. This is in fact the case. Nevertheless, the *F*-ratios indicate that all models are performing well, since they are significant at a confidence level of at least 95% or above. We can also observe that the model for US and Canada generates a much lower root mean square error (RMSE) of 10.1 and mean absolute error (MAE) of 7.6 than for the other models. For the Rest of the World, dividends play a more important role than retentions since the coefficient for DPS is 18.1 compared with 1.7 for RPS. Interestingly, for US and Canada the coefficients are close (2.7 and 2.1). Encouraging as these results are we must acknowledge the possibility that, as mentioned in our methodology for Model_1, the regression outcomes may be spurious because of the possibility that SP is I(1).

We run diagnostic tests for the multiple regressions in Model_1. The regression residual is tested for autocorrelation using the Ljung–Box (*Q*) standardised residuals (for 36 lags) and the Breusch–Godfrey Lagrange Multiplier test (7 lags), as shown in Table 3. The tests indicate that autocorrelation is not present in the residuals. Furthermore, the presence of heteroskedasticity is checked using the squared (Q^2) standardised residuals (36 lags) and the ARCH test, which is a Lagrange multiplier (LM) test for ARCH (7 lags) in the residuals. Again the results show that there are no ARCH effects in the residuals. Furthermore, the augmented Dickey–Fuller tests demonstrate that for each variable the null hypothesis of a unit root is rejected in favour of stationarity (see Table 3).

The generalized regression neural networks approach to which we now turn does not require stationarity so that stationarity tests are not needed. This commends it as an attractive technique, and has led directly to one of the most informative findings of our work. As shown in Table 4, GRNN confirms the strongly suggestive result of the conventional multiple regression to the effect that for each and all regions BVPS stands out as the main and consistent explanatory variable.

We observe that in the US and Canada both DPS and RPS have a relatively consonant impact of 27.9% and 22.3% respectively on share price. As argued above, we would expect that investors in a sophisticated capital market would approach closer to indifference between dividend and capital gains than in less developed markets where the reassurance of dividends might carry greater weight. In Europe DPS has a much bigger impact on share price than RPS (31.9% versus 1.0%). For the Rest

[2] We re-ran the regression using additional variables for regional dummies, namely, DUM1US&CAN and DUM2EUROPE. The same conclusions were found as those without the dummies. The variables with their *P*-values were as follows: constant (0.0000), BVPS (0.0000) DPS (0.9132), RPS (0.1941), DUM1US&CAN (0.0031) and DUM2EUROPE (0.0710). These statistics also show significantly different results for regions, which agree with our previous analysis. The overall *P*-value for the model was 0.0000 with an *F*-ratio of 46.76, and an adjusted R^2 adjusted of 22.93%. Also, we re-ran a regression for Model_1 using dummies for years, and we found that the dummies were not significant. Furthermore, we applied a test of linear trend over time, which showed that time was not significant under any of our models.

Table 3
Diagnostic tests for $Model_1$.

(a) Equation (Dependent = SP; Skewness = 6.1650; and Kurtosis = 18.09840)

Test	$Q(7)$	$Q(21)$	$Q^2(7)$	$Q^2(21)$	BG LM	JB	ARCH
Statistic	0.0399	0.0189	0.0539	0.0314	0.8366	1264.90	0.00068
P-value	0.3078	0.5277	0.7929	0.9365	0.5863	0.0000	0.97555

(b) Stationarity tests

Variable	ADF statistic	*P*-value
SP	−20.3744	0.0000
DPS	−18.3823	0.0000
RPS	−15.3525	0.0000
BVPS	−20.9820	0.0000

This table shows the results of the stationarity tests for variables in $Model_1$. The results show that our data are stationary. Notation: *Q*, Ljung–Box standardised residuals for given lags; BGLM, Breusch–Godfrey Lagrange Multiplier test for 7 lags; JB, Jarque–Bera normality test; ARCH, Lagrange multiplier test for ARCH for 7 lags in the residuals; and ADF, augmented Dickey–Fuller test.

of the World DPS is more important than RPS (22.9% versus 9.9%). For all regions DPS was much more important than RPS (25.6% versus 11%). These results suggest that in the transportation sector the capital market is more developed in the US and Canada than that observed for other regions. However, a contributory factor may be that investors in other regions are more nervous of the growth potential associated with retentions thus placing less emphasis on retentions and more on dividends. The $GRNN_1$-$Model_1$ shows lower RMSE and MAE for US and Canada. To the extent that a lower error suggests a better model, as shown in Table 4, this finding is a step in establishing GRNN as useful practical model for transportation companies, particularly in that region.

Since the multiple regression analysis provides a low adjusted R^2 for European transportation companies it may have been expected that the alternative methodology, using GRNN, would have produced a poor prediction rate for Europe. Actually, the neural network approach ($GRNN_1$-$Model_1$) gives the lowest bad prediction rate (100% – 87.8% = 12.2%), as shown in Table 4. In terms of errors (RMSE and MAE) the multiple regression for Europe is the worst model, but using the GRNN the model for Europe is the second best after that for the US and Canada. This implies that GRNN has a role in safeguarding against cursory acceptance of the results of conventional multiple regression.

Table 4
$GRNN_1$ (overall sample) $Model_1$: determinants of share price.

Model analysis	US and Canada	Europe	Rest of World	All regions
Diagnostic criteria				
Good prediction %	79.7872%	87.7907%	34.3373%	26.2338%
RMSE	5.023	49.85	116.54	140.56
MAE	3.208	17.57	62.15	79.19
Std. Dev. of abs. errors	3.865	46.65	98.58	116.13
Variables impact analysis				
DPS	27.8925%	31.9204%	22.8860%	25.5585%
RPS	22.2670%	1.0396%	9.8649%	11.0073%
BVPS	49.8405%	67.0400%	67.2491%	63.4341%
$\sum$	100.00%	100.00%	100.00%	100.00%

The sample consists of 139 transportation companies covering 16 countries from three regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand). The data are extracted from Datastream for the years 1997–2005 inclusive. The table shows the results of estimating the dependent variable namely share price (SP). The independent variables are dividend per share (DPS), retention per share (RPS) and book value per share (BVPS). The table shows our generalized regression neural network models ($GRNN_1$-$Model_1$) for each of the three regions and for all regions combined with root mean square error (RMSE) and mean absolute error (MAE), as measures for model accuracy.

Table 5
$GRNN_2$ (training/testing sub-samples) $Model_1$: determinants of share price.

Model analysis	US and Canada		Europe		Rest of World		All regions	
	Train.	Test.	Train.	Test.	Train.	Test.	Train.	Test.
Diagnostic criteria								
Good prediction %	93.056	36.364	92.857	29.487	39.916	28.723	81.771	21.134
RMSE	2.573	15.93	16.55	197.38	87.52	188.53	36.33	232.50
MAE	1.457	13.13	6.483	110.67	43.48	104.09	11.67	136.60
Std. Dev. of abs. errors	2.121	9.014	15.23	163.44	75.96	157.19	34.40	188.14
Variables impact analysis								
DPS	25.6909		29.6928		33.4571		31.8871	
RPS	22.8176		26.5715		1.0120		28.2423	
BVPS	51.4915		43.7357		65.5309		39.8705	
$\sum$	100.00		100.00		100.00		100.00	

The sample consists of 139 transportation companies covering 16 countries from three regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand). The data are extracted from Datastream for the years 1997–2005 inclusive. We divide our sample into data for 1997–2003 (training sub-set) and data for 2004–2005 (testing sub-set). The training data is used in building the neural network models, whilst the testing data is used for testing the predictive ability of the fitted model. In the testing case the data plays no role in building the models. The table shows the results of estimating the dependent variable namely share price (SP). The independent variables are dividend per share (DPS), retention per share (RPS) and book value per share (BVPS). The table shows our generalized regression neural network models ($GRNN_2$-$Model_1$) for each of the three regions and for all regions combined with root mean square error (RMSE) and mean absolute error (MAE), as measures for model accuracy. Train. denotes training sub-sample and Test. denotes testing sub-sample.

As well as taking the whole data-set for analytical purposes, we divide our sample into data for 1997–2003 and data for 2004–2005. The former sub-set of data is used in building the neural network models, whilst the latter is used for testing the predictive ability of the fitted model. In the testing case the data plays no role in building the models. Therefore, we have a data-set for training and a data-set for testing (see Table 5). Thus, turning our attention to the $GRNN_2$-$Model_1$ it can be observed that the predictive ability of the training sample in each region is better than the predictive ability of the respective testing sample, which is to be expected. For US and Canada again the predictive ability from both training and testing samples is better than that for the other regions. Similarly, their errors (RMSE and MAE) are much lower than for other regions across both training and testing samples.

As to the training sample (see Table 5), Europe has a similarly good prediction rate (92.9%) to that of US and Canada (93.1%). For the Rest of the World, the prediction rate of the training sample is poor (39.9%). Nevertheless for all regions combined the good prediction rate of the training sample is high (81.8%). In terms of minimum errors the model for US and Canada is excellent (2.6% RMSE; 1.5% MAE); and the errors for Europe are smaller than for the Rest of the World. The variable impact analysis reveals that BVPS is the prime determinant of share price across all different regions. For the Rest of the World RPS is much less important (only 1.0% impact). Individually for US and Canada, Europe and the Rest of the World, DPS is more important than RPS. However, combining all regions, DPS and RPS exhibit similar importance (28.2% DPS; 31.9% RPS).

It is possible that there might have been structural changes in the share price determination across all global regions in 2004 and 2005 combined. But these years are used for testing predictive ability and not for testing for structural changes.[3]

4.2. *$Model_2$: dividend yield*

As in the case of $Model_1$, the estimation methods for $Model_2$ are multiple regression and generalized regression neural networks. For $Model_2$, the multiple regression analysis uses the dividend yield as

[3] Structural change tests using recursive multiple regressions would have been an option, but here we are using neural networks instead which can accommodate changes in structural relationships either linear or non-linear.

Table 6
Multiple Regression $Model_2$: determinants of dividend yield.

	US and Canada		Europe		Rest of World		All regions	
	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value
Constant	0.20627	0.0079	0.00895	0.9517	0.04189	0.6164	0.09464	0.1797
MTBV	−0.0293	0.0630	−0.0007	0.0007	−0.0001	0.6106	−0.0005	0.0002
ASSBKG	0.04957	0.5845	−0.1873	0.0244	−0.0125	0.8226	−0.1073	0.0297
TDE	−0.0001	0.5338	−0.0001	0.3766	−0.0000	0.1091	−0.0000	0.1161
SIZE	−0.0194	0.0062	0.01372	0.1483	0.00260	0.5182	0.00266	0.4727
ROE	0.00016	0.7903	0.00086	0.1323	0.00035	0.3338	0.00078	0.0176
CAPEXRATE	−0.0485	0.5415	−0.0098	0.3090	−0.0078	0.2268	−0.0104	0.0704
CF%S	0.00267	0.0000	−0.0003	0.5797	−0.0009	0.0000	−0.0010	0.0000
STDEV(EB/TS)	0.17788	0.6258	1.59617	0.0000	0.03859	0.8786	1.17608	0.0000
Further analytical results								
F-ratio	6.78***		6.96***		99.43***		48.18***	
ANOVA *P*-value	0.0000		0.0000		0.0000		0.0000	
R^2 adj.	47.5626		13.4865		75.8291		38.2229	
RMSE	0.03789		0.23155		0.12079		0.18865	
MAE	0.02543		0.126096		0.05289		0.08949	

*** denotes a statistically significant difference 1% level.
The sample consists of 139 transportation companies covering 16 countries from three regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand). The data are extracted from Datastream for the years 1997–2005 inclusive. The table shows the results of estimating:

$$\mathrm{DY}_{it} = \alpha + \beta_1\mathrm{MTBV}_{it} + \beta_2\mathrm{ASSBKG}_{it} + \beta_3\mathrm{TDE}_{it} + \beta_4\mathrm{SIZE}_{it} + \beta_5\mathrm{ROE}_{it} + \beta_6\mathrm{CAPEXRATE}_{it} + \beta_7\mathrm{CF\%S}_{it} + \beta_8\mathrm{STDEV(EB/TS)}_{it} + \varepsilon_{it}$$

The dependent variable is dividend yield (DY). The independent variables are market-to-book-value (MTBV), asset-backing (ASSBKG) defined as fixed assets/total assets, total debt/equity (TDE), size defined as natural logarithm of market capitalization (SIZE), return on equity (ROE), capital expenditure rate (CAPEXRATE) defined as capital expenditure/total assets, cash flow as a percentage of sales (CF%S) and risk (STDEV(EB/TS)) defined as standard deviation of the ratio of earnings before interest and tax and depreciation/total assets. The table shows regression models for each of the three regions and for all regions combined with root mean square error (RMSE) and mean absolute error (MAE), as measures for model accuracy.

the dependent variable. As shown in Table 6, the Multiple Regression $Model_2$ sets out the factors that help to explain the dividend yield across global regions.

The model for US and Canada transportation companies yields three significant results namely market-to-book-value (MTBV), size and cash flow as a percentage of sales (CF%S). This model shows that 47.6% (R^2 adjusted) of variations in yields is explained by the independent variables. MTBV (−) is significant at the 90% level of confidence with the right sign in accordance with Hypothesis H_1. This accords with the theory of pecking order which highlights the preference for retention funded investments. In terms of our model higher market-to-book values, which are consistent with more investment opportunities, should be associated with greater retentions and lower dividends and a consequently strongly negative relationship between market-to-book value and dividend yield. CF%S (+) is significant at the 99% level of confidence with the right sign in accordance with Hypothesis H_7. The more sophisticated investors of North America are particularly likely to appreciate cash flow as a credible backing for dividends.

Size is negatively related to dividend yield at the 99% level of confidence, contrary to Hypothesis H_4. This result is consistent with smaller firms being relatively risky leading to a higher discount rate being applied to their income stream giving a lower market value and a consequently higher dividend yield.

The model for European transportation companies yields three significant results namely MTBV, asset backing (ASSBKG) and risk (STDEV[EB/TS]). Only the first of these significantly supports its Hypothesis H_1. This model shows that 13.5% (R^2 adjusted) of variations in yields is explained by the independent variables. As is the case for US and Canada, MTBV (−) is significant at the 99% level of confidence with the right sign in accordance with Hypothesis H_1, as shown in Table 6.

Contrary to Hypothesis H_2 greater asset backing coincides with lower dividend yield, and this result is significant at the 95% confidence level. ASSBKG limits risk in so far as assets can amount to a valuable put option to break up the company if its corporate plan fails. Secondly, in agency terms, tangible assets are less vulnerable to discretionary behaviour by management. These things would appear in the market as a lower discount being applied to assets, a higher present value for those assets and consequently lower dividend yield. Contrary to Hypothesis H_8 STDEV(EB/TS) is found to be positively related to dividend yield at the 99% level of confidence. This is consistent with a higher market discount being applied to the income stream of risky companies leading to lower present values and higher dividend yields.

However, overall the R^2 for Europe is low. This suggests that the European regression analysis is less useful as a whole model (whilst our neural networks are more capable as discussed later), although the above hypothesis testing for individual variables is still valid. This is consistent with our earlier discussion pertaining to our findings on share price determination in that European investors in the transportation sector appear to have been nervous about the sustainability of dividends.

For Rest of the World the model provides a high R^2 adjusted of 75.8%. The only significant variable affecting dividend yield is cash flow as a percentage of sales (−), which is significant at the 99% level of confidence, but the wrong sign for Hypothesis H_7 (cash flow). Given the high R^2 and since the *F*-ratio for the Rest of the World is very high (99.43), and the other variables are not significant, then the cash flow as a percentage of sales has a very strong influence in explaining the dividend yield for the Rest of the World, as shown in Table 6. Why should high cash flow as a percentage of sales lead to low dividend yield? Part of dividends' signalling value is to convey information about imminent and future cash flows. If these are visible and apparent the reason for the signal is removed and dividends no longer need to serve this purpose.

The model for all regions which combine all data yields six significant results namely market-to-book-value, asset backing, return on equity (ROE), capital expenditure (CAPEXRATE), cash flow as a percentage of sales and risk. Three out of them namely MTBV, ROE and CAPEXRATE significantly support their Hypotheses H_1, H_5 and H_6. This model shows that 48.2% (R^2 adjusted) of variations in yields is explained by the independent variables. At the 99% level of confidence, key determinants of the dividend yield are: MTBV (−), CF%S (−) and STDEV(EB/TS) (+); at the 95% level of confidence, the key determinants are ASSBKG (−) and ROE (+); and at the 90% level of confidence, CAPEXRATE (−), as shown in Table 6.

Within the three supportive results the finding for Hypotheses H_1 MTBV (growth) is significant and with the correct sign. This coincides with the individual findings for the US and Canada and for Europe. Also significant and with the correct sign are the findings for H_5 ROE (return on equity) and H_6 CAPEXRATE (capital expenditure). The case of ROE reflects the rationale that companies with lower profits are more likely to omit or reduce dividends. This shows as the positive relationship between profitability and the dividend payout ratio. The case of capital expenditure is consistent with a preference for retentions being the first port of call for capital expenditure and is reflected in a negative relationship between the capital expenditure rate and dividend yields.

Within the results that go against their hypotheses Hypothesis H_2 ASSBKG (asset backing), H_7 CF%S (cash flow) and H_8 STDEV[EB/TS] (risk) are also significant but with incorrect signs. Contrary to Hypothesis H_2 (ASSBKG) is found as for Europe to be negatively related to dividend yield. Contrary to Hypothesis H_8 (STDEV[EB/TS]) is found as for Europe to be positively related to dividend yield. Contrary to Hypothesis H_7 (CF%S) is found as for Rest of the World to be negatively related to dividend yield.

From Multiple Regression Model$_2$ we can also see that the *F*-ratios indicate that all models perform well, since they are significant at a confidence level of 99%.[4] We can also observe that once again the data for US and Canada generate much lower RMSE (0.04) and MAE (0.03) than for the other models, as

[4] We re-ran the global regression using additional variables for regional dummies as mentioned in the previous footnote. Similar conclusions were found, namely, that MTBV, CF%S and STDEV(EB/TS) were significant at the 99% confidence level. The dummy for US and Canada was not significant (*P*-value = 0.8495), but the dummy for Europe was significant at the 99% confidence level (*P*-value = 0.0071). This confirms our analysis in Table 6. The overall *P*-value for the model was 0.0000 with an *F*-ratio of 39.92, and an adjusted R^2 of 38.95%. Also, we re-ran a regression for Model$_2$ using dummies for years, and we found that the dummies were not significant. Furthermore, we applied a test of linear trend over time, which showed that time was not significant under any of our models.

Table 7
Diagnostic tests for $Model_2$.

(a) Equation (Dependent = DY; Skewness = 7.4932; and Kurtosis = 96.8786)

Test	Q(7)	Q(21)	$Q^2(7)$	$Q^2(21)$	BG LM	JB	ARCH
Statistic	1.5446	13.0030	0.1210	1.1932	0.0000	230,086.7	1.5502
P-value	0.9810	0.9090	1.0000	1.0000	1.0000	0.0000	0.2146

(b) Stationarity tests

Variable	ADF statistic	*P*-value
DY	−35.6887	0.0000
MTBV	−18.0045	0.0000
ASSBKG	−25.9986	0.0000
TDE	−20.0953	0.0000
SIZE	−11.5111	0.0000
ROE	−3.7358	0.0047
CAPEXRATE	−27.7887	0.0000
CF%S	−21.2540	0.0000
STDEV(EB/TS)	−26.9662	0.0000

This table shows the results of the stationarity tests for variables in $Model_2$. The results show that our data are stationary. Notation: Q, Ljung–Box standardised residuals for given lags; BGLM, Breusch–Godfrey Lagrange Multiplier test for 7 lags; JB, Jarque–Bera normality test; ARCH, Lagrange multiplier test for ARCH for 7 lags in the residuals; and ADF, augmented Dickey–Fuller test.

shown in Table 6. For $Model_2$, the regression residual is tested for autocorrelation using the Ljung–Box (*Q*) standardised residuals (for 36 lags) and the Breusch–Godfrey Lagrange Multiplier test (7 lags), as shown in Table 7. The tests indicate that autocorrelation is not present in the residuals. As to the possible presence of heteroskedasticity, we run tests using the squared (Q^2) standardised residuals (36 lags) and the ARCH test, which is a Lagrange multiplier (LM) test for ARCH (7 lags) in the residuals, and the results showed that there are no ARCH effects in the residuals. For each variable, the null hypothesis of a unit root is rejected in favour of stationarity, as per the augmented Dickey–Fuller tests, as shown in Table 7.

Before leaving our discussion of the conventional regression, it is worth noting that the prominent support afforded to Hypothesis H_1 by the significance of market-to-book-value is consistent with the theory of pecking order which highlights the preference for retention funded investments. Accordingly higher market to book values, which are consistent with more investment opportunities, should be associated with greater retentions and lower dividends. Thus, pecking order behaviour suggests a strongly negative relationship between market-to-book-value and dividend yield, which is the case for transportation companies in the US and Canada, Europe and all regions combined. The discussion of the GRNN which follows also stresses the importance of market-to-book-values in the US and Canada.

We now turn to the generalized regression neural networks approach which does not require stationarity tests. As is the case for $Model_1$ this commends it as an attractive technique. $GRNN_1$-$Model_2$, which utilizes the whole data-set, reveals interesting results for the regional comparisons, as shown in Table 8. In terms of variable impact, the main determinants of dividend yield vary across regions: market-to-book-value (37.0%) for the US and Canada; risk (29.8%) for Europe; and cash flow (83.9%) for the Rest of the World. For all regions combined, the main determinants of dividend yield are risk (36.6%) and cash flow (36.0%). The diagnostics reveal excellent prediction rates: virtually 100% for the US and Canada, and 98.7% for Europe. Europe has the lowest MAE of the neural network models for individual regions and all regions combined. In fact in our analysis the RMSE and MAE are very low across all regions.

For US and Canada the importance of market-to-book values is strongly confirmed as we might expect in transparent sophisticated markets where growth is relatively credible and where a preference for finance by retention will lead to low dividends. This finding accords with the strong indications from our conventional regressions. In Europe the most important factor in dividend yield determination is risk. This again accords with our earlier findings. In Rest of the World cash flow is the main

Table 8
$GRNN_1$ (overall sample) $Model_2$: determinants of dividend yield.

Model analysis	US and Canada	Europe	Rest of World	All regions
Diagnostic criteria				
Good prediction %	100.00	98.6971	71.8254	86.5794
RMSE	0.0007357	0.0009050	0.02325	0.02508
MAE	0.0002801	0.0001011	0.009073	0.007415
Std. Dev. of abs. errors	0.0006802	0.0008993	0.02140	0.02396
Variables impact analysis				
MTBV	37.0407	7.6942	0.3513	1.9131
ASSBKG	0.0207	13.7526	3.5072	0.1777
TDE	11.3337	8.9113	2.4831	4.6317
SIZE	13.6439	12.0018	5.2368	10.2069
ROE	11.8651	11.4896	3.4177	6.0667
CAPEXRATE	17.7083	6.9807	1.0597	4.3659
CF%S	8.3693	9.3313	83.9442	35.9980
STDEV(EB/TS)	0.0182	29.8385	0.0000	36.6402
$\sum$	100.00	100.00	100.00	100.00

The sample consists of 139 transportation companies covering 16 countries from three regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand). The data are extracted from Datastream for the years 1997–2005 inclusive. The table shows the results of estimating the dependent variable namely dividend yield (DY). The independent variables are market-to-book-value (MTBV), asset-backing (ASSBKG) defined as fixed assets/total assets, total debt/equity (TDE), size defined as natural logarithm of market capitalization (SIZE), return on equity (ROE), capital expenditure rate (CAPEXRATE) defined as capital expenditure/total assets, cash flow as a percentage of sales (CF%S) and risk (STDEV(EB/TS)) defined as standard deviation of the ratio of earnings before interest and tax and depreciation/total assets. The table shows our generalized regression neural network models ($GRNN_1$-$Model_2$) for each of the three regions and for all regions combined with root mean square error (RMSE) and mean absolute error (MAE), as measures for model accuracy.

agenda item for dividend yields which is again consonant with its high significance in our conventional regression models. For the model of all regions combined, risk and cash flow together account for more than 72% of variable impact on dividend yield again matching the high significance of these variables in our earlier findings.

$GRNN_2$-$Model_2$ divides the data-set using 2004 and 2005 data for testing purposes only, as shown in Table 9. Once again, the predictive ability for both training and testing samples is better for the US and Canada than for the other regions. The prediction rates of the training sample approach 100% for the US and Canada, 98.8% for Europe, and 89.4% for Rest of the World. For the testing samples the good prediction rates are 35.7% (US and Canada), 29.9% (Europe) and 28.0% (Rest of the World). The errors (RMSE and MAE) are low across all samples and exceptionally so in the training samples for the US and Canada and for Europe. The variable impact analysis reveals cash flow as a percentage of sales as the main determinant of dividend yield (52.8%) for the US and Canada, and again (86.1%) for Rest of the World. For Europe, the main single determinant is risk (19.8%). Combining all regions, cash flow as a percentage of sales has the main impact (57.4%) and the next factor is risk (24%).

By comparing the results of $GRNN_2$-$Model_2$ with $GRNN_1$-$Model_2$, we see that there is a structural change in the determinants of dividend yield in the US and Canada. For the whole sample period, from 1997 to 2005, market-to-book-value and cash flow as a percentage of sales account for 37.0% and 8.4%, respectively; whereas for 1997–2003 they account for 16.2% and 52.8%, respectively.

Finally, we turn to diagnostic comparisons across all models and regions, as shown in Table 10. For $Model_1$, which addresses determinants of share price, the US and Canada provide the lowest errors (RMSE and MAE) across all our models (Regression, $GRNN_1$, $GRNN_2$-Training, and $GRNN_2$-Testing). For $Model_2$, which addresses determinants of dividend yield, the US and Canada also provide the lowest regression errors (RMSE and MAE), the lowest $GRNN_1$ RMSE, whilst Europe has the lowest MAE for $GRNN_1$.

However, when the sample period is split into training (1997–2003) and testing (2004–2005), Europe provides the lowest RMSE for $GRNN_2$ (training) and the same MAE as that for US and Canada for $GRNN_2$ (training). For testing purposes (using 2004–2005) the US and Canada provide the lowest RMSE and MAE for $GRNN_2$ (testing).

Table 9
$GRNN_2$ (training/testing sub-samples) $Model_2$: determinants of dividend yield.

Model analysis	US and Canada		Europe		Rest of World		All regions	
	Train.	Test.	Train.	Test.	Train.	Test.	Train.	Test.
Diagnostic criteria								
Good prediction %	100.00	35.7143	98.7500	29.8507	89.4118	28.0488	71.4286	26.9939
RMSE	0.00003	0.05046	0.00002	0.1999	0.01006	0.1986	0.04250	0.3565
MAE	0.00000	0.02779	0.00000	0.08866	0.00412	0.0738	0.01568	0.1082
Std. Dev. of abs. errors	0.00003	0.04212	0.00002	0.1792	0.00917	0.1844	0.03950	0.3396
Variables impact analysis								
MTBV	16.1800		9.1129		0.2341		1.7945	
ASSBKG	2.8486		14.9576		2.1951		4.5945	
TDE	3.5877		10.5542		1.5597		3.2760	
SIZE	7.1966		12.6688		4.1272		5.4846	
ROE	8.8076		12.6685		2.5103		0.4578	
CAPEXRATE	4.4540		8.4586		0.5939		2.8489	
CF%S	52.7748		11.8053		86.0799		57.4268	
STDEV(EB/TS)	4.1507		19.7741		2.6998		24.1170	
$\sum$	100.00		100.00		100.00		100.00	

The sample consists of 139 transportation companies covering 16 countries from three regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand). The data are extracted from Datastream for the years 1997–2005 inclusive. We divide our sample into data for 1997–2003 (training sub-set) and data for 2004–2005 (testing sub-set). The training data is used in building the neural network models, whilst the testing data is used for testing the predictive ability of the fitted model. In the testing case the data plays no role in building the models. The table shows the results of estimating the dependent variable namely dividend yield (DY). The independent variables are market-to-book-value (MTBV), asset-backing (ASSBKG) defined as fixed assets/total assets, total debt/equity (TDE), size defined as natural logarithm of market capitalization (SIZE), return on equity (ROE), capital expenditure rate (CAPEXRATE) defined as capital expenditure/total assets, cash flow as a percentage of sales (CF%S) and risk (STDEV(EB/TS)) defined as standard deviation of the ratio of earnings before interest and tax and depreciation/total assets. The table shows our generalized regression neural network models ($GRNN_2$-$Model_2$) for each of the three regions and for all regions combined with root mean square error (RMSE) and mean absolute error (MAE), as measures for model accuracy. Train. denotes training sub-sample and Test. denotes testing sub-sample.

Table 10
Diagnostic analysis with comparisons between models.

	US and Canada		Europe		Rest of World		All regions	
	$Model_1$	$Model_2$	$Model_1$	$Model_2$	$Model_1$	$Model_2$	$Model_1$	$Model_2$
RMSE								
Multiple regression	10.135	0.03789	181.367	0.23155	135.451	0.12079	159.554	0.18865
$GRNN_1$	5.0230	0.00074	49.85	0.00091	116.54	0.02325	140.56	0.02508
$GRNN_2$								
Training sub-sample	2.573	0.00003	16.55	0.00002	87.52	0.01006	36.330	0.04250
Testing sub-sample	15.93	0.05046	197.38	0.1999	188.53	0.1986	232.50	0.35650
MAE								
Multiple regression	7.61753	0.02543	116.991	0.12610	81.2094	0.05289	99.6671	0.08949
$GRNN_1$	3.2080	0.00028	17.570	0.00010	62.15	0.00907	79.190	0.00742
$GRNN_2$								
Training sub-sample	1.4570	0.00000	6.4830	0.00000	43.480	0.00412	11.670	0.01568
Testing sub-sample	13.130	0.02779	110.67	0.08866	104.09	0.07380	136.60	0.10820

The sample consists of 139 transportation companies covering 16 countries from three regions: North America (Canada and the US), Europe (Denmark, France, Germany, Italy, Netherlands, Norway, Sweden and the UK) and Rest of the World (Australia, China, Hong Kong, India, Japan, and New Zealand). The data are extracted from Datastream for the years 1997–2005 inclusive. Share price is the dependent variable in $Model_1$, whilst dividend yield is the dependent variable in $Model_2$. The multiple regressions are based on the whole period from 1997 to 2005 inclusive, as is the case for generalized regression neural network ($GRNN_1$) where the whole data-set is used as training data. $GRNN_2$ uses data from 1997 to 2003 inclusive as the training sub-set, and uses data from 2004 to 2005 inclusive as the testing sub-set. The training data is used in building the neural network models, whilst the testing data is used for testing the predictive ability of the fitted model. In the testing case the data plays no role in building the models. The table compares error rates namely root mean square error (RMSE) and mean absolute error (MAE) for each of the models and for each of the three regions and for all regions combined, as measures for model accuracy.

Our purpose has been to investigate dividend policy using models which focus on share price and dividend yield respectively. We make use of GRNN and conventional multiple regression as mutually supportive techniques. We have been able to generate a range of significant results. Some of these support our hypotheses and some challenge them but in both cases it has been possible to link our findings to significant aspects of the theoretical debate and the decisions which confront investors and corporate financial management in the industry. Our results for the US and Canada are broadly consistent with a relatively transparent and complete market where accounting numbers have a significant degree of economic credibility and where transaction costs are relatively low. Other markets around the world appear to penalise retentions and reflect a more pessimistic attitude towards the future of transportation providers and related service companies. Part of the originality of our research has been to distinguish our findings across the globe and to cast light on this distinctiveness.

5. Conclusion

For the US and Canada, the book value per share is the main determinant of the share price for transportation companies. Broad indifference between dividends and capital gains embodied in future growth expressed as retained earnings is also identified for US and Canada. This is consistent with a sophisticated transparent capital market in which dividend clienteles are satisfied. For Europe, there is greater uncertainty in terms of dividend sustainability. Indeed, for all regions, there is some instability especially for 2004–2005 as we find in our testing sample. However dividends appear in Europe to have kept some of their traditional informative value at least in comparison with retentions. The multiple regression analysis provides a low adjusted R^2 for Europe whilst neural network reveals the highest good prediction rate. This illustrates how GRNN can guard against cursory acceptance of the results of conventional multiple regression. The neural networks variable impact analysis of share price demonstrates that dividends are more important than retentions and that book value per share is the main driver under each of the regions and all regions combined. When dividend yield becomes the dependent variable, the conventional regression output for the US and Canada shows that the market-to-book-value is negatively associated with dividend yield. In addition greater cash flow as a percentage of sales and smaller market capitalizations are strongly associated with higher dividend yields. For Europe market-to-book-value is strongly negatively associated with the dividend yield, supporting the pecking order theory. However, higher risk is associated with higher dividend yields whilst lower asset backing is associated with higher dividend yield. Many firms outside Europe, the US and Canada are maintaining dividends whilst their cash flows may not support such a policy. However, it could be interpreted as a signal of their confidence in the prospects for this industry.

The diagnostics reveal that the GRNNs perform very well in terms of minimizing errors and are superior in this respect to the conventional regressions. In terms of dividend yield neural networks variable impact the main drivers are (i) market-to-book-value in the US and Canada, which is consistent with the pecking order theory; (ii) risk, which is consistent with higher dividend yields duly compensating investors in the case of Europe; and (iii) cash flow in Rest of the World, which is consistent with concern about financial mobility. For the global model for all regions, risk and cash flow as a percentage of sales are the most important variables and together account for more than two-thirds of the total impact on the dividend yield. It is clear that, through the dividend yield, investors in transportation companies have indeed been rewarded for risk on a global basis. The results of our various models for the US and Canada are consonant with a relatively transparent, well informed market peopled by relatively sophisticated investors. In terms of both share price and dividend yield, Europe has been found to be different from the two other regions. It follows that future research might be directed at investigating attributes specific to European transportation companies, and also investigating trans-country differences in the profiles of investors and companies, inside and outside Europe, whether due to fiscal, cultural, institutional or industrial factors.

Acknowledgement

The authors would like to thank the anonymous referee(s) and editor(s) for helpful comments, which have been most useful in revising the manuscript.

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