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An Evolutionary Algorithmic Investigation of US Corporate Payout Policy Determination

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Abstract This Chapter examines cash dividends and share repurchases in the United States during the period 1990 to 2008. In the extant literature a variety of classical statistical methodologies have been adopted, foremost among these is the method of panel regression modelling. Instead, in this Chapter, we have informed our model specifications and our coefficient estimates using a genetic program. Our model captures effects from a wide range of pertinent proxy variables related to the agency cost-based life cycle theory, the signalling theory and the catering theory of corporate payout policy determination. In line with the extant literature, our findings indicate the predominant importance of the agency-cost based life cycle theory. The adopted evolutionary algorithm approach also provides important new insights concerning the influence of firm size, the concentration of firm ownership and cash flow uncertainty with respect to corporate payout policy determination in the United States.

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1 Introduction

In this Chapter we examine United States corporate payout policy determination using a genetic programming methodology, during the period 1990 to 2008. The term corporate payout policy relates to the disbursing of cash, by a corporation, to shareholders by way of cash dividends and/or share repurchases. Clearly, alongside investment and capital structure optimisation this is a chief responsibility of an organisation's financial officer.

The adopted Genetic Programming [1] methodology is also known as a symbolic regression methodology. It identifies the functional form as well as the optimal coefficients which optimises a program-performance criterion. As a result, this class of model estimation methodology is complementary to the random effects panel regression methodology, typically adopted in the conventional mainstream literature regarding corporate payout policy determination [2]. In addition, it is worthwhile emphasizing that while genetic programming techniques have been adopted to specify trading rules in foreign exchange markets [3, 4] and more broadly in financial modelling [5], there is no contribution to the extant literature which avails of Genetic Programming techniques to evaluate the determination of corporate payout policy.

By way of a foundation, to the topic of corporate payout policy determination, the Miller-Modigliani irrelevance proposition [6] indicates that, within a stylised setting, once corporate investment policy is optimal (*i.e.* once the Fisherian Net Present Value rule is satisfied), corporate payout policy has no implication for the value of the firm. In this setting, corporate payout policy merely involves different methods of distributing free cash flows - by way of cash dividends or share repurchases - and hence has no implication for the value arising from investment decisions. Notwithstanding, DeAngelo, and DeAngelo [7] conclude that the distribution/retention decision with regard to free cash flows, even assuming the stylised setting outlined in the Miller-Modigliani proposition [6], has 'first-order value consequences'. In brief, this follows from the fact that the feasible set of distribution/retention decisions, in the Miller-Modigliani stylised setting, is exactly the optimal set, *i.e.* full payout. Evidently, this precludes a payout policy decision. To mitigate for this oversight, DeAngelo and DeAngelo [7] advocate an extension of the classic Fisherian Net Present Value 'rule' with regard to capital budgeting decisions, to include the distribution of the full present value of free cash flows during the life of the firm. Essentially, it is now evident that there is considerable scope for value creation and destruction, by means of corporate payout policy. As a result, the determination of corporate payout policy merits careful attention.

In relaxing the configuration of assumptions underpinning the Miller-Modigliani proposition extended to include the assumption of full payout, several theories, which are mutually inclusive in principle, arise concerning the determination of the timing and form of optimal corporate payout policy. The open question appears to hinge on the relative importance of these the-

ories with regard to explaining the determination of corporate payout policy. In particular, these theories comprise: *first*, the so-called agency cost-based life cycle theory (see [8, 9, 7, 10] which implies that the decision to distribute or retain free cash flows, a trade-off between the prospect of credit constraints and excessive financial slack, varies according to the evolution of the phases of the firm's life cycle *i.e.* as typified by a firm's size, profitability, the nature of its capital structure and the growth opportunities of the firm. The reconciling of Jensen's agency cost-based theory [11, 12] with the life-cycle theory appears particularly beneficial. Indeed, the agency requirement of persuasion, on the part of the principal, for the agent to distribute free cash flows may be requisite such that the corporation disgorges cash. *Second*, the so-called signaling theory [13, 14, 15] which emphasises the importance of utilising corporate payout policy, to circumvent the information asymmetry which may arise between the management of the firm, who enjoy insider information, and the firm's investors. *Third*, the catering theory [16, 17] of corporate payout policy determination, which highlights the importance of corporate payout policy to satisfy the preferences of various, possibly time-varying, heterogenous payout clienteles. While there has been considerable evidence gathered to the contrary, with respect to the general increase in the level of dividends and a general tendency to increase dividends [18, 10], it cannot be rejected that this latter theory may contribute, albeit, perhaps, in a secondary manner, to the understanding in the extant literature of corporate payout policy determination.

Our findings may be summarised adopting three main sets of key points. First, we show the best evolved symbolic regression models with respect to the root mean square error criterion, these optimal specifications are evidently different to the conventional random effects panel regression model specifications. According to this approach, the theory which best explicates cash dividend payouts and share repurchases is the life-cycle theory of corporate payout policy determination, and it appears that a hybrid hypothesis with respect to both the agency cost-based theory and the life-cyle theory is of particular interest. Second, adopting the Pearson correlation coefficient, scatter plots and regressor containment we show the nature of the relation between individual regressors and identified optimal model specifications and expression-trees of the best-of-run individuals. Specifically, in line with the findings in the extant literature as well as the various theories of corporate payout, we document a positive relation between both the size of the firm and the earnings to assets ratio and cash dividend payouts and share repurchases. In the same vein, we document a compelling negative relation between the concentration of firm ownership and corporate payout and a somewhat weaker relation between cash flow uncertainty and corporate payout. These confirmations of earlier published findings are important in light of the relatively flexible model specification adopted in this Chapter. Third, we adopt a specification which comprises all the explanatory proxy variables in a single model specification. Consistent with theory, this auxiliary extended model

convincingly out-performs the individual models with regard to the root mean squared error criterion. Once again the aforementioned relations, with regard to the direction of effects, are evident in the data. Taken together, our findings support the agency cost-based life-cycle theory of corporate payout policy determination despite the adoption of a distinctive model specification modelling methodology.

The Chapter is organized as follows. In the second section, we present the sample of data examined, we outline the proxy variables adopted and their hypothesised relations with respect to the theories of corporate payout policy determination assessed. In the third section, we describe the adopted genetic programming methodology and in the fourth section we examine our findings. We offer some concluding remarks in the final section.

2 Literature Review

Published findings with respect to United States corporate payout policy can be summarised by adopting five key points. *First*, as documented by Fama and French [8], due to equally important factors: changing firm characteristics - low profitability, high growth opportunities and relatively intangible fixed assets - as well as a declining propensity to pay, the fraction of US industrial firms paying cash dividends has dropped considerably from 66.5% in 1978 to 20.8% in 1999. *Second*, following a Securities and Exchange Commisions Ruling in 1982 legalising open market repurchases by corporate management, this tax favoured and flexible method, relative to cash dividends, of disbursing cash to shareholders has become of first order importance. Indeed, Skinner [19] indicates that share repurchases are now the preferred method for distributing cash to investors in the United States. *Third* the total value (nominal and real) of cash dividends and share repurchases has risen almost incessantly for several decades. In fact, Weston and Siu [20] show that the US corporate sector's cash dividend payout ratio has increased from 40% in 1971 to around 60% in 1990 and to 81% in 2001. Once share repurchases are included this payout ratio reaches 116 % in 2001.

As a *fourth* key point, DeAngelo, DeAngelo and Skinner [21] show that there has been increasing levels of concentration of dividends and earnings since the 1980s - nowadays a mere 25 firms account for over 50% of industrial earnings and dividends in the United States. In addition it is indicated that while there has been a decline in the number of industrial payers since 1978, the number of financial and utility payers has increased, as has the total value of their payout. These findings show how a declining tendency to disburse cash dividends, an increasing tendency of cash dividend payers to repurchase shares and a rising total value of real payout are internally consistent. Fifth, DeAngelo, DeAngelo and Stulz [10] show that a firm at an early phase of its financial life-cycle with a corresponding low level of retained earnings

to total contributed capital in its equity capitalization will tend not to pay dividends or will pay very little by way of a dividend. In the same vein, mature firms are inclined to pay dividends and to pay relatively more. In addition, DeAngelo, DeAngelo and Stulz emphasise the agency costs which may arise if more mature firms were not to increasingly disburse cash to shareholders with the decline of their investment opportunity sets in line with the maturation of their financial life-cycles. With this backdrop in mind with regard to corporate payout policy in the United States we turn to the determination of corporate payout policy in the United States.

2.1 Sample Data and Proxy Explanatory Valriables

Our data is sourced in the *Worldscope* database as detailed in Table 1. The sample extends from 1990 through to 2008 inclusive. The data is tailored such that it excludes firms in the financial and utilities industries, as well as American Depositary Receipts and foreign firms. The sample also excludes firms whose dividends are greater than their total sales, firms whose dividend, net income or sales figures are omitted and firms with negative book value of equity, market to book ratio, sales, dividends or share repurchases. In addition, we search the databases for active as well as dead and suspended listings in order to avoid survivor bias. Otherwise, the sample comprises of every firm headquartered in United States and listed on New York Stock Exchange (NYSE), for which there is available our set of proxy explanatory variables. These filters yield 1665 industrial (and transport) firms. Within this group, 960 firms disclose their cash dividend policy in 1990 of which 588 are cash dividend payers. This figure is 1059 in 2008 with a negligible increase in cash dividend payers to 596. Turning to repurchase observations, there are 958 firms which disclose their share repurchases policy in 1990 with 399 firms are observed to conduct share repurchases. This figure grows to 1039 firms disclosing their policy in 2008 with 670 firms conducting share repurchases. The total sample includes 14,507 firm-year observations on cash dividends of which 7,846 are cash dividend payers and 6,661 are firms that do not pay cash dividends. There are 14,405 firm-year observations on share repurchases of which 7,571 firm-year observations are for repurchasers and 6,834 for non-repurchasers. Our study examines the United States (primarily NYSE) circumstances, separately investigating *cash dividend paying* and *share repurchasing* firms, using a real US Dollar numeraire (1990 prices) in each instance.

Our principal payout variables are cash dividends (DIV) and share repurchases (SR). Share repurchases correspond to actual gross amounts. We arrange our principal proxy explanatory variables into groups according to their advocated theoretical linkages with respect to explicating the agency

Table 1 Description of the variables used in the random effects panel regression models.

Regressands	Description
Cash Dividends (DIV)	The logarithm of the total real value of common cash dividends distributed by the firm, in United States dollar 1990 prices. The logistic random effects panel regression models are specified to include a dummy variable =1 if cash dividends are paid, otherwise zero.
Share Repurchases (SR)	The logarithm of the total real value of open market share repurchases undertaken by the firm, in United States dollar 1990 prices. The logistic random effects panel regression models are specified to include a dummy variable =1, if share repurchases occur, otherwise zero.

Regressors	Description
Firm Ownership (OWN)	The percentage of common stock held by the ten largest shareholders.
Cash Holding (CASH)	The sum of cash and short term investments as a percentage of the total assets of the firm.
Leverage Rate (LR)	The sum of short-term and long-term debt as a percentage of total assets.
R & D Exp. (RnD)	Research and development expenses percentage of the total assets of the firm.
Retained Earnings (RETE)	The retained earnings as a percentage of the market value of firm equity.
Asset Growth (DAA)	The relative (percentage) change in the real value of total assets.
Market to Book Value (MBF)	The market to book value of the firm.
Market Value (SIZE)	Percentile ranking (annual) of a firm with respect to the criterion of market value.
Capital Expenses (CapEx)	It represent the funds used to acquire fixed assets other than those associated with acquisitions percentage of total assets
Stock Return (DPP)	The annual percentage change in stock price measured at the end of the previous year.
Earnings Ratio (EA)	The firm earnings before interest but after tax as a percentage of total assets.
Catering Theory Proxy Variable (CCD)	A dummy variable (annual), which indicates whether the cash dividend payer (share repurchaser) has a higher median MBF than the cash dividend (share repurchaser) non payer. If true, dummy = 1 otherwise it's zero. A further requirement for a year specific non-zero dummy variable is a minimum of five observations for both payers and non-payers.
Earning Reporting Frequency (ERF)	The frequency (1 to 4 times) at which earnings are reported per annum. 4 = Annual and 1 = Quarterly Reporting.
Cash-Flow Uncertainty (VOL24)	The standard deviation of stock returns over the most recent two year period
Operating Profitability Volatility (INCV)	The standard deviation of the operating rate of return (*i.e.*, operating income as a percentage of total assets) during the most recent three year period, including the current fiscal year.
Income Risk (SDS)	The standard deviation of the net income during the most recent five year period divided by the most recent year-specific total sales.
Year (YEAR)	Year of Observation.
Constant (CONST)	The intercept of the regression equation.

cost-based theory, the catering theory, the life-cycle theory and the signaling theory of corporate payout policy.

We assess the empirical importance of the agency cost-based theory adopting 3 proxy explanatory variables. First, following Dittmar and Mahrt-Smith [22] and Pinkowitz *et al.* [23] we adopt cash and short term investments (CASH) as a measurement of prospective agency costs. The greater these prospective costs, the greater the expected corporate payout. In a similar vein, following Chay and Suh [24] and LaPorta *et al.* [12] the more concentrated the ownership of the firm (OWN), the smaller the scope for prospective agency costs. Finally, in regard to agency costs, following Black [25], Jensen [11] and von Eije and Megginson [2], we adopt a leverage ratio (LR) *i.e* the book value of debt divided by the book value of assets, to approximate for the scope for prospective agency costs. The greater the leverage of a firm the smaller the scope for prospective agency costs and the smaller the expected payoff. Alternatively, higher leverage may proxy for a firm's maturity which would imply a possible positive relation between firm payout and the leverage ratio (LR).

With regard to catering theory, we follow Baker and Wurgler [16, 17] and specify a dummy variable (CCD) that takes the value 1 if the natural logarithm of the median market to book value of a paying firm is greater than that of the median non-paying firm, otherwise zero. The focus, with regard to catering theory, is whether there is a payout (dividend or share repurchase) premium effect and, if so, how this effect varies over time.

Turning now to the life-cycle theory of corporate payout policy, we adopt 4 proxy explanatory variables. First, following, DeAngelo *et al.* [10] we include a proxy explanatory variable for the phase of the life cycle of the firm, the ratio of retained earnings to total equity (RETE) and, in the vein of, Fama and French [8] as well as Grullon and Michaelly [26] we adopt the market value of the firm to reflect firm size (SIZE), another complementary indication of the phase of the life cycle of the firm. The greater the maturity of the individual firm whether reflected in retained earnings to total equity (RETE) or firm size (SIZE), the greater its expected payout. Fourth, in respect to the development of the firm's set of investment opportunities, we include in our specifications the change in total assets (DAA) following Fama and French [26] and Denis and Osobov (2008). Finally, also following Fama and French (2001) and Denis and Osobov (2008), we adopt the market to book ratio (MBF) to reflect the set of the firm's investment opportunities. The larger the investment opportunity set, the smaller the expected payout.

To assess the empirical importance of the signaling theory of corporate payout policy we turn to our set of 5 proxy explanatory variables. We initially follow Wood [27] and von Eije and Megginson [18] and specify an Earnings Reporting Frequency (ERF) variable, corresponding to the frequency at which earnings are reported, by a firm, per annum. The greater the frequency, the smaller the expected payout and the lower the incentive to payout. Following Lintner [28], Miller and Rock [15] and von Eije and Megginson [2],

we also specify an explanatory variable corresponding to the Earnings Ratio
(EA). It is computed as the earnings before interest but after tax divided
by the book value of total assets. The greater the earnings ratio, the greater
the expected payout. Another variable examined, primarily in respect to the
signaling theory, is income uncertainty. Anticipated income uncertainty is
expected to negatively impact cash dividend payouts due to the expected
information content of a subsequent cash dividend decline deteriorating firm
value as well as the tendency for external financing to be relatively costly.
This latter proxy explanatory variable is operationalised in three ways: (1)
income risk (SDS) is computed following von Eije and Megginson [2] as the
standard deviation of income during the last 5-years scaled by total sales,
(2) operating profitability volatility (INCV) is computed following Chay and
Suh [24] as the three-year standard deviation of the operating rate of re-
turn and (3) cash-flow uncertainty (VOL24) is computed following Chay and
Suh [24] and Lintner [28] as the standard deviation of stock returns during the
most recent 3-year period. The greater the income uncertainty, the smaller
the expected payout.

In addition we adopt several further control variables. Following von Eije
and Megginson [2] we include a lagged return (DPP). There is expected to be
a negative relation between this explanatory variable and subsequent payout.
Following Fama and French [8] as well as Denis and Osobov [18], we also
include in our specifications a year variable (Year), with a view to assessing
secular trends over time.

3 Methodology

3.1 Genetic Programming

Genetic Programming (GP) [29, 30, 31, 32] is an automatic programming
technique that employs an Evolutionary Algorithm (EA) to search the space
of candidate solutions, traditionally represented using expression-tree struc-
tures, for the one that optimises some sort of program-performance criterion.
The highly expressive representation capabilities of programming languages
allows GP to evolve arithmetic expressions that can take the form of regres-
sion models. This class of GP application has been termed "Symbolic Regres-
sion", and is potentially concerned with the discovery of both the functional
form and the optimal coefficients of a regression model. In contrast to other
statistical methods for data-driven modelling, GP-based symbolic regression
does not presuppose a functional form, i.e. polynomial, exponential, logarith-
mic, etc., thus the resulting model can be an arbitrary arithmetic expression
of regressors [1]. GP-based regression has been successfully applied to a wide
range of financial modelling tasks [5].

GP adopts an Evolutionary Algorithm (EA), which is a class of stochastic search algorithms inspired by principles of natural genetics and survival of the fittest. The general recipe for solving a problem with an EA is as follows. Chose a representation space in which candidate solutions can be specified; design the fitness criteria for evaluating the quality of the solution, a parent selection and replacement policy, and a variation mechanism for generating offspring from a parent or a set of parents. The rest of this section details each of these processes in the case of GP.

In GP, programs are usually expressed using hierarchical representations taking the form of syntax-trees, as shown in Figure 1. It is common to evolve programs into a constrained, and often problem-specific user-defined language. The variables and constants in the program are leaves in the tree (collectively named as terminal set), whilst arithmetic operators are internal nodes (collectively named as function set). In the simplest case of symbolic regression, the function set consists of basic arithmetic operators, while the terminal set consists of random numerical constants and a set of explanatory variables termed regressors. Figure 1 illustrates an example expression-tree representing the arithmetic expression $x + (2 - y)$.

GP finds out how well a program works by executing it, and then testing its behaviour against a number of test cases; a process reminiscent of the process of black-box testing in a conventional software engineering practice. In the case of symbolic regression, the test cases consist of a set of input-output pairs, where a number of input variables represent the regressors and the output variable represents the regressand. Under this incarnation of program evaluation, GP becomes an error-driven model optimisation procedure, assigning program fitness that is based on some sort of error between the program output value and the actual regressand value; mean squared error being the most prominent form of error employed. Those programs that do well (i.e. high fitness individuals) are chosen to be varied and produce new programs for the new generation. The primary variation operators to perform transitions within the space of computer programs are crossover and mutation.

The most commonly used form of crossover is subtree crossover, depicted in Figure 1. Given two parents, subtree crossover randomly (and independently) selects a cross-over point (a node) in each parent tree. Then, it creates two offspring programs by replacing the subtree rooted at the crossover point in a copy of the first parent with a copy of the subtree rooted at the crossover point in the second parent, and vice-versa. Copies are used to avoid disrupting the original individuals. Crossover points are not typically selected with uniform probability. Function sets usually lead to expression-trees with an average branching factor of at least two, so the majority of the nodes in an expression-tree are leaf-nodes. Consequently, the uniform selection of crossover points leads to crossover operations frequently exchanging only very small amounts of genetic material (i.e., small subtrees); many crossovers may in fact reduce
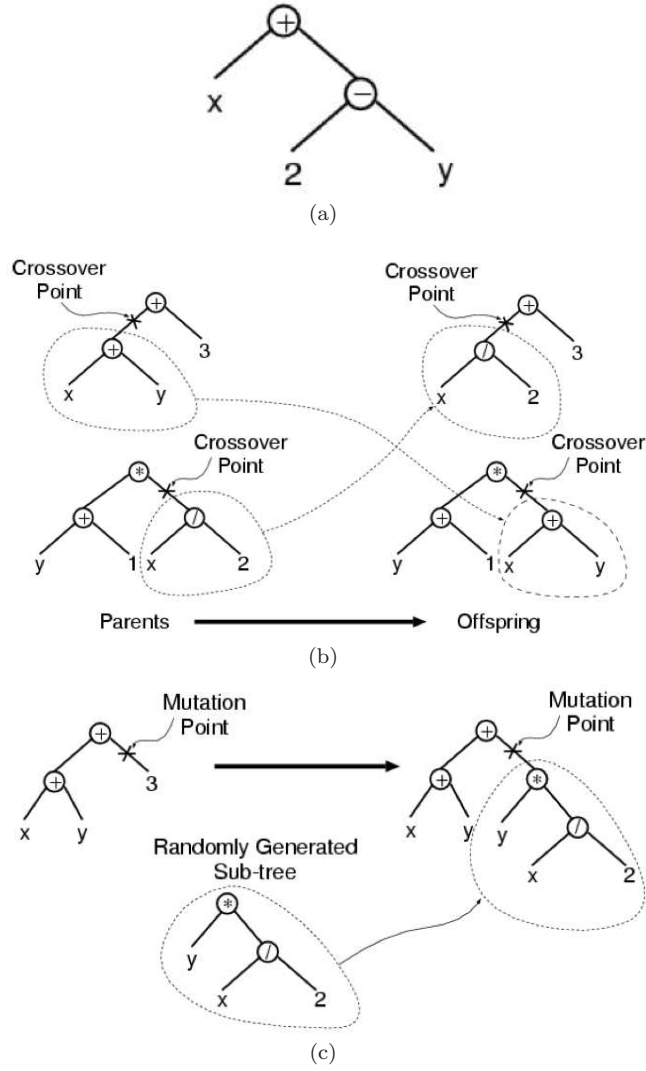
Fig. 1 Genetic programming representation and variation operators.

to simply swapping two leaves. To counteract this tendency, inner-nodes are randomly selected 90% of the time, while leaf-nodes 10% of the time.

The most commonly used form of mutation in GP is subtree mutation, which randomly selects a mutation point in a tree and substitutes the subtree rooted there with a randomly generated subtree. An example application of the mutation operator is depicted in Figure 1. Another common form of mutation is point mutation, which is roughly equivalent to the bit-flip muta-

tion used in genetic algorithms. In point mutation, a random node is selected and the primitive stored there is replaced with a different random primitive of the same rarity taken from the primitive set. When subtree mutation is applied, this involves the modification of exactly one subtree. Point mutation, on the other hand, is typically applied on a per-node basis. That is, each node is considered in turn and, with a certain probability, it is altered as explained above. This allows multiple nodes to be mutated independently in one application of point mutation.

Like in any evolutionary algorithm, the initial population of GP individuals is randomly generated. Two dominant methods are the *full* and *grow* methods, usually combined to form the *ramped half-and-half* expression-tree initialisation method [1]. In both the *full* and *grow* methods, the initial individuals are generated so that they do not exceed a user-specified maximum depth. The depth of a node is the number of edges that need to be traversed to reach the node starting from the tree's root node (the depth of the tree is the depth of its deepest leaf). The *full* method generates full tree-structures where all the leaves are at the same depth, whereas the *grow* method allows for the creation of trees of more varied sizes and shapes.

3.2 Evolving symbolic regression programs

Our GP algorithm is a standard elitist (the best is always preserved), generational (populations are arranged in generations, not steady-state), panmictic (no program mating restrictions) genetic algorithm with an expression-tree representation. The algorithm uses tournament selection with a tournament size of 7. Root mean squared error (RMSE) is employed as a fitness function. Evolution proceeds for 50 generations, and the population size is set to 1,000 individuals. Ramped-half-and-half tree creation with a maximum depth of 5 is used to perform a random sampling of rules during run initialisation. Throughout the evolution, expression-trees are allowed to grow up to a depth of 8. The evolutionary search employs a combination of crossover, subtree mutation and point mutation; a probability governing the application of each set to 0.5, 0.25 and 0.25 for each operator respectively. We employed a standard single-typed program representation; the function set is consisted of the four basic arithmetic operators (protected division), whereas the terminal set contains the regressors.

3.3 Model overfitting avoidance

In order to avoid model overfitting [4, 33], we employed a technique that combines the three datasets (training, validation, testing) machine learning

methodology, and the objective of minimising the structural complexity of the model [34]. The two sets methodology (training and test dataset) for learning a model using an iterative model-training technique does not prevent by itself overfitting the training set. A common approach is to add a third set – a validation set – which helps the learning algorithm to measure its generalisation ability. Another common practice that has been shown to prevent model overfitting in learning algorithms that employ symbolic model representations is to minimise the model structural complexity. The learning technique uses a validation set to select best-of-generation individuals that generalise well; individuals considered for candidate elitists are those that reside in the Pareto-frontier of a two-objective population ranking of program-size versus the root mean square error (RMSE) criterion.

The initial dataset is randomly segmented into two non-overlapping subsets for training and testing with proportions of 60% and 40% respectively. The training set is further randomly divided into two non-overlapping subsets: the fitness evaluation data-set, with 67% of the training data, and the validation data-set with the remaining 33%. The fitness measure consists of minimising the RMSE on the fitness evaluation data-set. At each generation, a two-objective sort is conducted in order to extract a set of non-dominated individuals (Pareto front) with regards to the lowest fitness evaluation data-set RMSE, and the smallest model complexity in terms of expression-tree size, as measured by the number of tree-nodes. The rationale behind this is to create a selection pressure towards simpler prediction models that have the potential to generalise better. These non-dominated individuals are then evaluated on the validation data-set, with the best-of-generation model designated as the one with the smallest validation RMSE. The use of a Pareto-frontier of canidate elitists reduces the number of individuals tested against the validation set in order to avoid selecting best-of-generation programs that are coincidentally performing well on the validation set. Additionally, such a method allows the learning algorithm to evaluate the generalisation ability of a wide range of accuracy/complexity tradeoffs.

During tournament selection based on the fitness evaluation data-set performance, we used the model complexity as a second point of comparison in cases of identical error rates, thus imposing a bias towards smaller programs though the use of lexicographic parsimony pressure. In every independent evolutionary run, initial dataset segmentation is randomly performed.

3.4 Experimental context

We employ an evolutionary machine learning method to induce models that best describe a regressand variable given a set of input regressor variables. Regressands are the Cash Dividends (DIV) and Share Repurchases (SR), whereas regressors are related to four different theories of corporate

payout policy determination, namely, *Agency theory*, *Life-cycle theory*, and *Information-asymmetry signalling theory* as well as *catering* theory, for which a dummy proxy variable is included. Our first aim is to discover accurate symbolic regression models, given different sets of regressor variables defined in each theory separately. Secondly, we are interested in determining whether the evolutionary method will be able to learn models that are in accordance to the conventional theories, by allowing the search algorithm to work on a regressor-space that incorporates all of the regressor variables that are defined in the three conventional theories. This experiment has been specially designed to take advantage from the inherent capability of the GP algorithm to perform feature selection, by allowing the error-minimising search to concentrate of those areas of the model space that contain individuals consisting of the most well-explanatory regressor variables. We performed 50 independent evolutionary runs for each different regressor-setup in order to account for the stochastic nature of the adaptive search algorithm.

4 Results

Table 2 illustrates the best evolved symbolic regression models using regressor variables from different theories of corporate payout. The first column indicates the regressand variable (either cash dividends, DIV or share repurchases, SR), whereas the second column indicates the regressors which we adopt in relation to each theory of corporate payout. Resulting models have been clustered according to the set of regressor variables defined in each different theory of corporate payout. These optimal solution models indicate a considerable complexity with regard to model specification relative to the variety of classical statistical models adopted in the mainstream literature, particularly the panel regression modelling methodology. Figure 1 presents a box-plot illustrating the distribution of best-of-run RMSE, indicating the best-fit models from 50 independent evolutionary runs under each different regressor-setup. Contrasting among the corporate payout theories, results suggest that both DIV and SR modelling are more accurately performed using regressor variables defined in Life-cycle theory; the best models attaining a root mean square error (RMSE) of 1.72 and 2.20 respectively. In addition, it is worthwhile observing that, in every instance, the theories of corporate payout substantially outperform in their explanations of cash dividend payouts relative to share repurchases.

In order to quantify the relationship between the use of each regressor variable and the model-output (for the optimal models presented in Table 2), we calculated their Pearson correlation coefficient (PCC) via monitoring the model-output in a series of model invocations with model-inputs represented by particular realisations of regressor variables. To complement our investigation of the regressor *vs.* model-output relationship we present the scatter
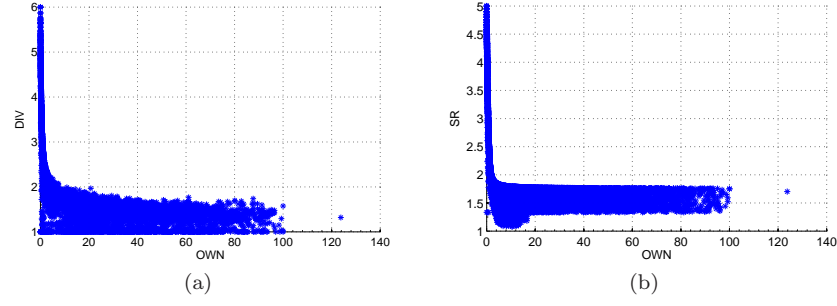
Fig. 2 (a) Model output for DIV vs. OWN; (b) Model output for SR vs. OWN.

wf
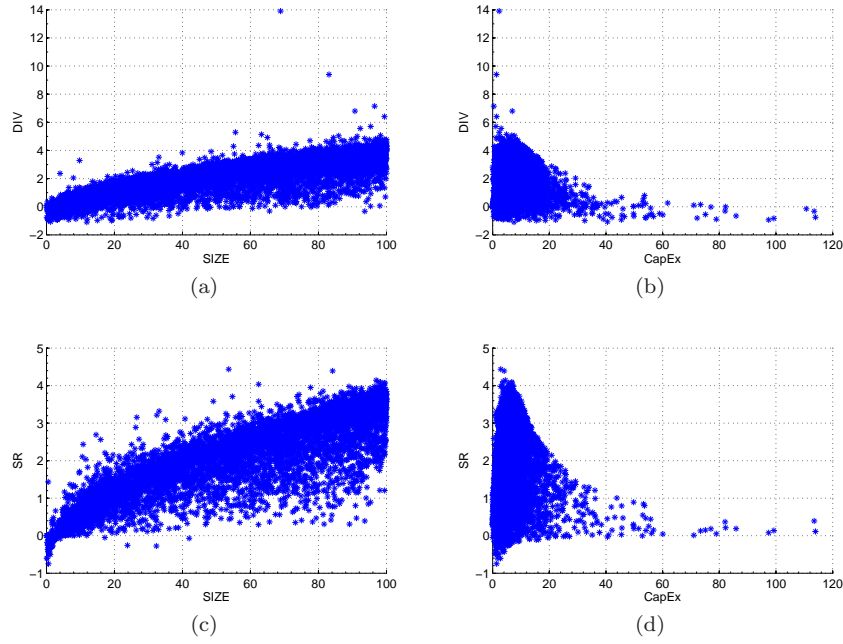
Fig. 3 (a) Model output for DIV vs. SIZE; (b) Model output for DIV vs. CapEx; (c) Model output for SR vs. SIZE; (d) Model output for SR vs. CapEx.

plots of the values that were used to calculate these correlations, for the strongest relationships discovered.

In addition, we present statistics from the average proportion of regressors contained (APU) in the expression-trees of best-of-run individuals, which gives an indication of the relative importance of particular regressors given
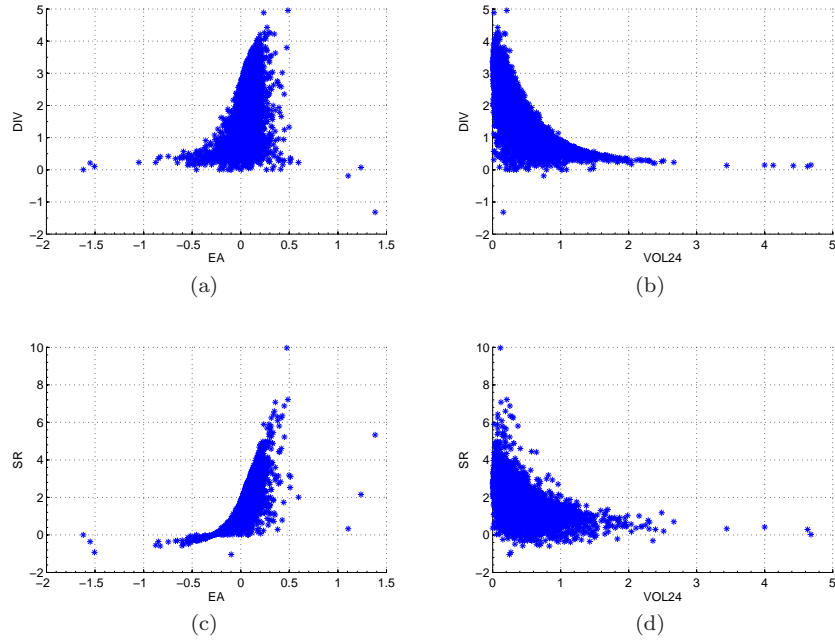
Fig. 4 (a) Model output for DIV vs. EA; (b) Model output for DIV vs. VOL24; (c) Model output for SR vs. EA; (d) Model output for SR vs. VOL24.

that the survival and propagation of their embodying model thoughout the evolutionary run signals the evolutionary viability and thus merit of that model. Regressor containment is quantified via the proportion of a particular regressor variable in an expression-tree relative to the rest of the regressors included in that expression-tree.

Table 3 collectively presents the Pearson correlation coefficient (PCC) between the regressors of a particular theory and the model-output representing cash dividends (DIV) or share repurchases (SR). In the case of Agency theory, the evolved expressions modelling both cash dividends (DIV) and share repurchases (SR) encapsulate a medium negative correlation between model-output and the regressor concerning the level of concentration of firm ownership (OWN). The level of concentration of ownership (OWN) is a relatively important regressor as evidenced by its pronounced average containment in best-of-run expression-trees. Figure 2 presents the corresponding scatter-plots of the values used to calculate the Pearson correlation coefficient (PCC). In the case of Life-cycle theory, the relative value of the firm (SIZE) has a strong positive correlation in both cash dividends (DIV) and share repurchases (SR) modelling. In both cases this particular regressor has a relatively dominant proportion of 18% and 22% in the best-of-run expression trees for DIV and

Table 2 Best evolved symbolic regression models

Regressand	Regressors	Model
Agency Theory		
Cash Dividends	OWN, CASH, LR	$\dfrac{\left(LR+\frac{2*LR}{LR+OWN+(OWN*CASH)}\right)+(OWN+4*LR)}{\frac{(OWN+LR)*2*LR}{\frac{LR}{OWN}+OWN+LR}+OWN+LR}$
Share Repurchases	OWN, CASH, LR	$\dfrac{2*OWN+5*CASH}{OWN+CASH+\frac{2*(CASH+OWN)}{\frac{CASH}{OWN}+2*OWN}}$
Life Cycle Theory		
Cash Dividends	RnD, RETE, DAA, MBF, SIZE, CapEx, DPP	$\dfrac{SIZE-CapEx-RnD-DAA-CapEx*DPP}{2*CapEx*DPP^2+RnD+DAA+CapEx+\frac{SIZE+RnD+DAA*SIZE}{RnD+CapEx}}$
Share Repurchases	RnD, RETE, DAA, MBF, SIZE, CapEx, DPP	$\dfrac{DPP-SIZE-4*CapEx+(DPP-SIZE)*(DAA+DPP)+SIZE*CapEx}{\frac{CapEx+SIZE}{2*MBF}+2*CapEx^2+SIZE}$
Information-Asymmetry Signaling Theory		
Cash Dividends	EA, ERF, VOL24, INCV, SDS	$\dfrac{EA+ERF+VOL24+(VOL24*SDS)+\frac{2*ERF-VOL24}{(ERF-EA)*(ERF+VOL24)}}{ERF-EA+2*VOL24^2+\frac{SDS}{ERF}*(INCV+ERF)}$
Share Repurchases	EA, ERF, VOL24, INCV, SDS	$\dfrac{EA*ERF+6*EA+2*ERF}{EA^2-2*EA+2*SDS+VOL24+(ERF+SDS)*ERF+2*SDS^2*INCV}$
Regressors from all theories		
Cash Dividends	OWN, CASH, LR CCD, RnD, RETE, DAA, MBF, SIZE, CapEx, DPP, EA, ERF, VOL24, INCV SDS	$\dfrac{SIZE-(CASH-VOL24)*(VOL24-ERF)+\frac{RnD+CASH}{OWN+VOL24}}{INCV+CapEx+CASH+\frac{SIZE+LR}{CapEx+CASH}}$
Share Repurchases	OWN, CASH, LR CCD, RnD, RETE, DAA, MBF, SIZE, CapEx, DPP, EA, ERF, VOL24, INCV SDS	$\dfrac{3*SIZE-CapEx-LR-SIZE*DAA+EA+\frac{SIZE*CCD}{OWN+VOL24}}{\frac{VOL24}{\frac{EA^2}{\frac{SIZE*VOL24}{CapEX+INCV}}}+VOL24*CASH*SDS*ERF+CapEx+SIZE-EA+ERF}$

SR models respectively. A weak negative correlation is also found between capital expenditure (CapEx) and model output for both cash dividends (DIV) and share repurchases (SR). Figure 3 presents the corresponding scatter-plots of the values used to calculate the Pearson correlation coefficient (PCC). Finally, in the case of Information-asymmetry signalling theory, strong positive correlations were found between model output and regressor EA, while strong negative correlations were found between model output and regressor VOL24. This finding is consistent in both DIV and SR modelling. Figure 4 presents the corresponding scatter-plots of the values used to calculate the Pearson correlation coefficent (PCC).

Very interesting results were also obtained in the second series of experiments which collectively used all proxy explanatory regressor variables defined in the three potentially mutually inclusive theories of corporate payout policy determination. The box-plot depicted in Figure 5 suggests that models based on all regressors outperform those based on individual theories; best models attaining a RMSE of 1.65 and 2.12 for DIV and SR modelling respectively. Once again it is evident that these theories exhibit superior ex-

Table 3 Pearson correlation coefficients (PCC) between the values of regressors used in the best evolved model and the output value of the model. Table also presents the average proportion of regressors containment (APU) in best-of-run individuals. Averages from 50 independent evolutionary runs (std. deviation in parentheses).

Regressor	Agency		Life Cycle		Info. Asym. Signal.		All	
	PCC	APU	PCC	APU	PCC	APU	PCC	APU
Cash Dividends								
OWN	-0.54	0.33 (0.05)	-	-	-	-	-0.45	0.12 (0.06)
CASH	-0.14	0.23 (0.16)	-	-	-	-	-0.17	0.09 (0.04)
LR	0.13	0.43 (0.15)	-	-	-	-	-0.06	0.12 (0.06)
CCD	-	-	-	-	-	-	0.001	0.10 (0.05)
RnD	-	-	-0.03	0.14 (0.08)	-	-	0.02	0.06 (0.02)
RETE	-	-	0.07	0.05 (0.01)	-	-	n/a	0.0 (0.0)
DAA	-	-	-0.15	0.15 (0.07)	-	-	0.01	0.08 (0.03)
MBF	-	-	0.03	0.09 (0.04)	-	-	0.02	0.11 (0.05)
SIZE	-	-	0.78	0.18 (0.07)	-	-	0.79	0.14 (0.07)
CapEx	-	-	-0.16	0.37 (0.10)	-	-	-0.08	0.10 (0.05)
DPP	-	-	0.03	0.17 (0.07)	-	-	0.13	0.06 (0.01)
EA	-	-	-	-	0.34	0.12 (0.07)	0.20	0.12 (0.08)
ERF	-	-	-	-	-0.04	0.13 (0.03)	0.03	0.12 (0.06)
VOL24	-	-	-	-	-0.75	0.17 (0.07)	-0.39	0.12 (0.07)
INCV	-	-	-	-	-0.12	0.15 (0.12)	-0.17	0.11 (0.05)
SDS	-	-	-	-	-0.10	0.14 (0.06)	-0.07	0.09 (0.06)
Shared Repurchases								
OWN	-0.43	0.43 (0.05)	-	-	-	-	-0.40	0.11 (0.07)
CASH	-0.01	0.40 (0.09)	-	-	-	-	0.02	0.07 (0.02)
LR	-0.03	0.15 (0.07)	-	-	-	-	-0.19	0.11 (0.05)
CCD	-	-	-	-	-	-	0.03	0.09 (0.04)
RnD	-	-	-0.01	0.12 (0.07)	-	-	0.04	0.04 (0.006)
RETE	-	-	0.01	0.13 (0.03)	-	-	n/a	0.0 (0.0)
DAA	-	-	-0.04	0.17 (0.09)	-	-	-0.03	0.07 (0.02)
MBF	-	-	0.04	0.20 (0.10)	-	-	0.03	0.07 (0.01)
SIZE	-	-	0.82	0.22 (0.07)	-	-	0.77	0.17 (0.09)
CapEx	-	-	-0.10	0.36 (0.15)	-	-	-0.08	0.08 (0.02)
DPP	-	-	0.05	0.11 (0.07)	-	-	0.14	0.07 (0.02)
EA	-	-	-	-	0.67	0.37 (0.10)	0.32	0.15 (0.07)
ERF	-	-	-	-	-0.06	0.17 (0.07)	-0.004	0.12 (0.06)
VOL24	-	-	-	-	-0.58	0.15 (0.10)	-0.29	0.09 (0.04)
INCV	-	-	-	-	-0.08	0.15 (0.10)	-0.10	0.12 (0.06)
SDS	-	-	-	-	-0.09	0.19 (0.08)	-0.04	0.07 (0.04)

planatory power with respect to cash dividend payouts rather than share repurchases. The most substantial finding was that in order to induce models that are more accurate than the ones based on subsets of regressors, the evolutionary algorithm synthesised expression-trees, which used regressor variables that showed the strongest correlations in previous modelling based on distinct theories. Throughout an implicit feature selection process, GP was able to identify the most information-rich regressors, which have been

proven efficient in different theories of corporate payout, and combine them
in an useful, novel way. Once again, in this all-encompassing extended speci-
fication, the level of concentration of ownership (OWN), the relative market
value of the firm (SIZE), the scaled adjusted earnings variable (EA) and the
cash flow uncertainty variable (VOL24) exhibit pronounced effects consistent
with the indicated theories of corporate payout. In particular, these regressor
variables exhibit the following effects: the level of concentration of firm own-
ership, OWN (medium negative correlation), the relative firm value, SIZE
(strong positive correlation), and the scaled adjusted earnings, EA (medium
positive correlation), VOL24 (medium negative correlation). Detailed statis-
tics are depicted is Table 3.
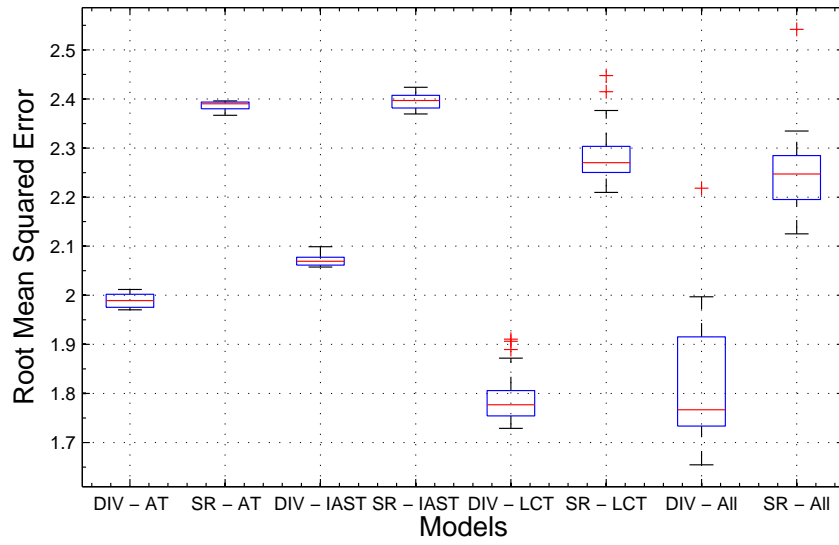
Fig. 5 Distribution of Root Mean Squared Errors from best-of-run individuals for different
experimental setups. Total cash dividends and Share repurchases have been abbreviated to
DIV and SR respectively. Agency Theory has been abbreviated to AT. Life Cycle Theory
has been abbreviated to LCT. Information-Asymmetry Signalling Theory has been abbre-
viated to IAST. "ALL" represents the experiments that took into account all regressors.

5 Summary and Concluding Remarks

In this Chapter, we have examined the determination of corporate payout policy in the United States during the period 1990 to 2008, using a novel genetic programming methodology to inform our model specifications. Furthermore, our best evolved symbolic modelling specification is unprecedented with regard to the broad range of pertinent proxy explanatory variables included simultaneously in our ultimate, as well as our candidate, model specifications.

Taken together, in line with the mainstream literature, our findings corroboratively provide a preponderance of support for the agency cost-based life-cycle theory of corporate payout policy determination. In addition, proxy variables relating to this latter hybrid hypothesis, with regard to corporate payout policy determination, show strong, theoretically consistent, effects on corporate payout. Specifically, across our modelling specifications, we document a pronounced positive relation between both the relative market value of the firm and the adjusted earnings to assets ratio and measures of corporate payout, cash dividend payouts and share repurchases. In the same vein, we document a compelling negative relation between the level of concentration of firm ownership and cash dividend and share repurchase corporate payouts. In addition, we document a somewhat weaker relation between cash flow uncertainty and these forms of corporate payout. These findings are, on the whole, corroborative with respect to the extant literature. They are important in light of the relatively flexible, genetic programming style, model specification inference methodology, adopted in this Chapter.

Future work in this important area might extend the adopted genetic programming methodology to include constants in the grammar. In addition, it may be helpful to conduct a random effects panel regression model utilising these data to allow a direct comparison of findings across these methodologies as well as including a contrast of the underlying theoretical frameworks from which these methodologies are derived. We opt to leave this avenue of research for future work.

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