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CASE REPORT

Explaining impact of predictors in rankings: an illustrative case of states rankings

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ABSTRACT
This study presents an approach that can be used to identify important predictors used incalculating performance rankings and gauge their sensitivities. Random Forests is a powerful machine learning tool well known for their predictive powers. It is especially suited to broach the small-n, large-p problem usually found in rankings procedures. However, random forests are unable to shed any insight intohow the examined predictors affect individual entries in the ranked set. A procedure calledLocal Interpretable Model-Agnostic Explanations (LIME) enables decision-makers to discernthe most important individual variables and their relative contributions to the outcome ofeach element in the ranked set. To explain this procedure, we use the 2016 edition of theALEC-Laffer State Rankings data. With the method proposed in this study, a state's policymakerswould have specific knowledge on how to improve their state's ranking. This method is ofgeneral applicability to any policy domain.

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Ranking; random forests; local interpretable model-agnostic explanations; state economics

1. Introduction

Comparative or relative performance among the states of the United States is routinely gauged via various indicators. These indicators could be conventional ones such as gross state product per capita or employment growth or they could be composite indicators assembled algorithmically from elementary variables – such as the Freedom Index for the 50 States, the American Human Development Index, or Economic Freedom in North American Index[1]. The resulting ordering provided by these measures reduce the multiple analytic dimensions involved. This data aggregation, data reduction method facilitates comparisons and benchmarking, simplifying complex policy and economic debates and decision-making.

Once published, state rankings often compel self-reflection and scrutiny of the resulting standing – especially if it is an unfavorable one. Almost inevitably, rankings constitute invitations to look more closely at the cause or causes, or, more precisely, to scrutinize the constituent variables that underlie them (Saltelli, 2007). The rankings invite attention from the media and policymakers and, increasingly, from the general public, leading invariably to finger-pointing, or celebration[2].

The constituent components of any constructed index underscoring a proffered ranking naturally become the focal points of subsequent policy debates. In fact, calling attention to these variables with the intent of compelling action may often be the deliberate focus of the index creators. The Tax Foundation for example, publishes an oft-cited ranking of the states. Perhaps understandably, the Tax Foundation directs readers to a state's tax structure as the most vital feature determining a state's relative competitiveness[3]. Indeed, the self-serving nature of many of these indexes features prominently amidst the considerable criticism levied at them. Although the subjectivity in variable selection and domain relevance constitute key concern of critics, multiple aspects of the methodology underscoring the construction of composite indicators have been criticized. (Arndt & Oman, 2006; Artz, Duncan, Hall, & Orazem, 2016; Fisher, 2013; Gelman, 2009; Gladwell, 2011; Knack, 2006;, Kolko, Neumark, & Cuellar-Mejia, 2013; Kurtz & Schrank, 2007; Motoyama & Hui, 2013; Paruolo, Saisana, & Saltelli, 2012; Sitglitz, Sen, & Fitoussi, 2009). Our focus in this study is on a key feature of rankings: despite their popularity, rankings are largely unhelpful in conveying practical policy insights. This is because most rankings equally weigh each explanatory variable or subcategory that goes into the overall rank determination. This is helpful for state-by-state comparisons. It is not as helpful for practical applications, such as individual-state policy guidance. Rankings publishers provide little to no explanation as to what drives the rankings. No explanation is provided on how each variable impact an individual state's position in the proffered ranking, and what each state is doing – or not doing – right or wrong.

Rankings' inability to offer states any finer guidance or explanation beyond the constituent index variables can be especially frustrating for policymakers. Intentionally or not, the implicit assumption

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set forth by rankings publishers is that policymakers should repair all the predictor variables set forth. Rankings proffer no model structure, predictor importance, underlying relationships, predictor complexity, or covariates with the outcomes. Such characterizations are limited to models having precise parametric forms such as linear or logistic regression (Kuhn & Johnson, 2013).

More often than not, the rankings frenzy precipitates what some commentators have called "rank-seeking" behavior, whereby those impacted by their unfavorable position in the index do not take steps to improve to underlying "causes" (Hoyland, Moene, & Willumsen, 2012). Rather, their focus is on manipulating variables with the intention of improving their relative status vis-à-vis other states, especially those considered in direct competition for business investment and jobs.

Many mainstream econometric tools can be brought to bear on the problem of identifying the most significant predictor underscoring a ranking – in principle. But at least two vital considerations limit the usefulness of the conventional toolbox when working with state data. First, the variables typically selected to construct economic performance index do not convey independent signals but rather commonly display mutual interdependencies. In other words, economic variables seemingly account for the variance in state economic performance although not all convey information independent of each other; or, as Kruskal put it, "if the independent variates were stochastically independent, or at least, noncorrelated, one might have a natural linear decomposition of the variance of the dependent variable. That independence among the independent variables is, however, rare" (Kruskal, 1984).

Second, with only 50 data points, the exercise of ranking the states of the United States is by its nature a "small-n, large-p" type of problem. The small-n, large-p problem coupled with strong collinearity among predictors could make the variance of frequentist methods such as factor analysis, principal component analysis or stepwise regression unusually high. This may result in distorted p-values and misleading t-statistics leading researchers to claim support for either results of no practical significance, or, and to the contrary, dismiss significant claims (Lin, Lucas, & Shmueli, 2013).

Predictive models such as neural networks or random forests – inter alia – provide considerable advantages over conventional models (e.g. discriminant analysis, principal components) at this dimension reduction task (Bi, 2012; Sorzano, Vargas, & Montano, 2014). Predictive models have built-in or intrinsic measurements of predictor importance. This dimension-reduction feature can identify an index's most important variables. In addition, the partial plot capabilities of the algorithms are indicators of index responsiveness or sensitivity to its constituent variables.

However, beyond identifying the most important predictors for the set of all states, neural nets and random forests are unable to shed any insight into how the examined variables affect individual states. A fitted random forests model cannot inform the modeler as to the nature of the individualized relationship between the identified most important predictors and the outcome variable. Providing detailed characterizations to a particular state policymaker such as "increasing predictor X results in a de-crease in the realized rank," have been impossible. Local interpretable model-agnostic explanations (LIME) identify state-specific variables. A LIME result enables decision-makers to discern the most important individual variables and their relative contribution to the realized outcome of each of the 50 states. Thus, LIME models are capable of piercing the rankings black box and thus convey a more effective benefit to policy planning.

In this study, we illustrate random forests' ability to identify the most important predictors and the LIME

Table 1. Variable Definitions used in ALEC-Laffer rankings.

Variable	Definition
Top Marginal Personal Income Tax Rate	The marginal tax rate is the percentage taken from your next dollar of taxable income above a pre-defined income threshold. The marginal tax rate includes federal, state and local income taxes, as well as federal payroll and self-employment taxes.
Top Marginal Corporate Income Tax Rate	The amount of state tax – as a percent – paid by Corporations on the additional dollar of income earned; includes local taxes if any.
Personal Income Tax Progressivity	This measures the difference between the average tax liability per $1000 at incomes of $50,0000 and $150,000. The average tax rate is the total tax paid as a percentage of total income earned.
Property Tax Burden	Tax revenues from property taxes per $1,000 of personal income.
Sales Tax Burden	Tax revenues from sales taxes per $1,000 of personal income.
Remaining Tax Burden	Tax revenues from all taxes per $1,000 of personal income. It excludes personal income, corporate income, property, sales and severance taxes.
Estate/Inheritance Tax Levied?	Yes or No.
Recently Legislated Tax Changes	Relative change in tax burden over the 2014–2015 legislative session.
Debt Service as a Share of Tax Revenue	Interest paid on debt as a percentage of total tax revenue.
Public Employees per 10,000 of Population	Full-time equivalent public employees per 1,000 population.
State Liability System Survey	Quality of state legal system. A ranking of tort systems by state.
State Minimum Wage	State minimum wage, if applicable. Otherwise the federal rate is used.
Average Workers' Compensation Costs	Worker's Compensation Index Rate per $100 of payroll.
Right to Work State?	Yes or No. Whether a state requires union memberships for its employees.
Number of Tax Expenditure Limits	Whether the state has a (i) a state expenditure limit; (ii) mandatory voter approval of tax increases; and (iii) a supermajority requirement for tax increases.

variables for purposes of operationalizing state economic performance rankings. We use the 2016 ALEC-Laffer Economic Outlook and Performance of the states in the USA as our working data set. Constituent variables and variable definitions are presented in Table 1. We also demonstrate the policy usefulness of the procedures' partial plots and the local explanations. The methodology, references and sources of data underscoring the proposed method are provided in this paper; the associated R-code is available upon request.

2. Background and related work

The ALEC-Laffer State Economic Outlook and Performance Rankings gauge relative performance across the states (Laffer, Moore, & Williams, 2016).[4] This annual publication is a well-known contributor to the state-rankings arena and other economic and public policy circles. Methodologically, ALEC-Laffer is a "ranking of rankings" – whereby the 50 states of the United States are initially ranked across 15 select economic variables. In turn, the final ranking is an equally weighted average of the resulting variable rankings. The final tally constitutes the published Economic Outlook Rankings. The published ranking displays the proffered list of states in 2016 – in decreasing order; that is to say, the state with the best economic outlook is ranked first. However, there is no readily observable coherent rationale provided nor is there any economic theory articulated to justify the explanatory variables selected for the ALEC-Laffer rankings. Implicitly (and sometimes explicitly), rankings authors contend that all variables are contributors and therefore policymakers intent on improving their rankings should tend to all variables. The ALEC-Laffer report authors describe the chosen predictors as having "a proven impact on the migration of capital – both investment and human – into and out of states" (Laffer et al., 2016). The predictors stand out for at least two reasons. First, they are seemingly reflections of state government policy decisions; and, second, they are variables that impact individual wealth and income and associated work incentives.

Despite the lack of any explicit theoretical rationale by rankings publishers it is possible to find justification for the chosen predictors amidst existing economic theory. Economic theory offers broad insights into state economic performance variable selection – perhaps too broadly; many suitable variables could be proffered from a judicious reading of the extant literature. A considerable variety of theories and associated empirical work attempt to explain factors underscoring the realized difference in the relative economic performance of states. A sampling of recent work in this area include differences in tax policy (Gale, Krupin, & Rubin, 2015; McBride, 2012; Segura III, 2016), tax structure (Lee & Gordon, 2005); on the composition of clusters (Delgado, Porter, & Stern, 2012), on historical industry structure (Higgins, Levy, and Young, 2006), and knowledge and technology (Florida, 2002; Glaeser, 2011; Moretti, 2012). Indeed, many factors acknowledged in the literature are not among the ALEC-Laffer portfolio of predictor variables. We return to the relevance of these omissions in our concluding comments.

2.1. Variable importance of the determinants of economic performance for all states

Variable importance is a difficult task across the board but especially vexing in the performance indicator literature. The difficulty lies in the fact that selected economic explanatory variables reflect overlapping concepts thereby jointly contributing to the variability of the dependent variable. Endogeneity considerations, whereby economic performance is determined simultaneously with the predictor variables complicate conventional frequentist models. Moreover, various steps in the construction of an index or metric can be subjective. The resulting process of constructing a performance indicator tends to artfully reflect their author's remit, or – as the case might be, their ideological leanings, theoretical preconceptions, their political identity or agenda. The variables selected or purposely omitted, variable construction, variable treatment, the aggregation procedure, the time-period encompassed, and the weights utilized provide considerable leeway to an index builder to shape or assist a narrative (Nardo, Saisana, Saltelli, & Tarantola, 2005; Sitglitz et al., 2009). Subjectivity aside, the interactions among attributes also contribute to difficulties in isolating the impact or individual contribution of an attribute to the dependent variable. Such information on variable sensitivity is important in subsequent cost-benefit analysis of possible competing remedies.

In this study, the fifteen economic variables used in the construction of the ALEC – Laffer rankings are parsed to illustrate how they explain the observed variance in the resulting state economic rankings. The method proposed here is generalizable to any ranking and not particular to the ALEC-Laffer ranking. The variables and variable definitions are reproduced in the Appendix to this paper. Each of the variables are policy instruments – presumably in control of a state's elected officials and administrators.

The outcome of the important variable selection procedure is displayed graphically in Figure 1. The top variables in importance are considered most significant in explaining realized performance for all the states. This information conveys crucial information in understanding the *relative* performance of the states; that is to say, it explains that the difference in outcomes between Connecticut and Florida is attributable to the comparative position taken by each state in the various variables presented, with primacy attached to whether a state's citizens are subject to an estate tax. Whether a state is among those considered "right to work" states appears a close second in its explanatory relevance. The importance of the remaining variables in this relative importance task figures in the rank ordering in Figure 1.

An estate or inheritance tax is a tax on the transfer of the estate of a deceased person. Advocates of estate taxes argue that they alleviate the tax burden on working taxpayers. Proponents argue, inter alia, that an estate tax has disincentive effects on lifetime labor supply and saving of individuals. Identifying as a "right-to-work" state accounts for a significant portion of the variation in the proffered ranks. In right-to-work states, employees in unionized workplaces are banned from negotiating contracts that require all members who benefit from the union contract to contribute to the costs of union representation. Whether a state levies and estate or inheritance tax similarly contributes significantly to explaining relative rank position as well. The variable corporate tax rates refer to the impact of marginal tax rates on corporations. The variable "progressivity" refers to a state's Personal Income Tax Progressivity. The term progressive refers to the way the personal income tax rate increases from low to high – resulting in average (or effective) rates lower than marginal (or incremental) rates. Its relevance is significant in that progressivity mutes the harsher effects of income-inequality but may stifle economic growth, if overdone.

The predictor importance representation is informative, to be sure. It offers a broad-based roadmap for policy makers. However, the ranked variables are identical for all states; it is an average calculation. It is not possible to draw any implications as to which variable may have more resonance in a particular state over another. And importantly, there is no indication of the relative impact in one state of ascribing resources to a particular predictor variable; that is to say, no way of gauging the "bang-for-the-buck" of allocating resources to one predictor over another.

3. Model

We now discuss the models and procedures used in the study. Our approach is based on Random Forests and Local Interpretable Model-Agnostic Explanations (LIME).

3.1. Fitting a random forests model

There are numerous quantitative approaches available – both frequentist and Bayesian – to determine predictor importance (Bi, 2012). Analysis of variance, principal components analysis, factor analysis, discriminant analysis, multivariate regression, conjoint analysis, preference mapping, various machine learning algorithms, and logistic regression inter alia, are used to relate attributes to dependent variables (Bi, 2012; LeBreton, Ployhart, & Ladd, 2004). All these procedures are generally capable of ascribing predictor influence based on the variability of the response variable.

Random Forests (RF) algorithms can identify and rank predictor variables based on their explaining

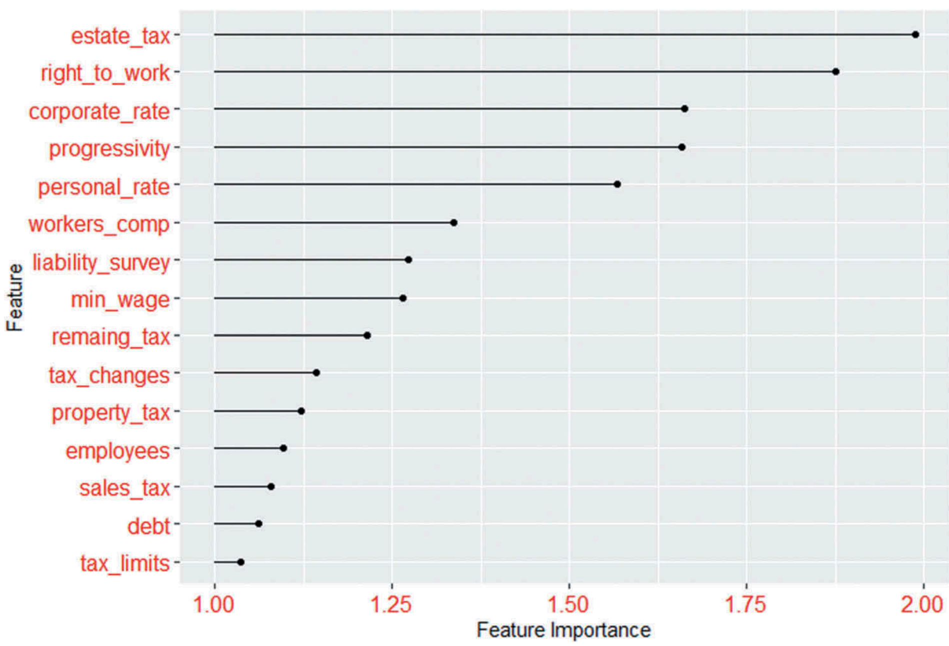

Figure 1. Predictor Importance used in ALEC Lafer State Rankings.

performance metric variability. RF is ideally suited for the type of data assembled here (Kuhn & Johnson, 2013). First the predictor variables are mixed-types: binary and numeric. Second, the number of explanatory variables is large compared to the number of observations – what is known in the literature as the "small-n, large-p" problem. Third, the predictors are collinear and some highly collinear. Non-independence can affect standard error estimates used to determine statistical significance. Fourth, the proffered performance variables may reflect an endogeneity that compromises coefficient estimates from parametric models.

Random Forests is non-parametric and requires no distributional assumptions and no explicit model; rather, it infers nonlinearities and interactions from the data. RF's ability to approximate arbitrary functional forms and thus its ability to identify the presence of complex nonlinear relationships accounts for its enhanced performance over conventional models in econometrics. The latter require an explicit specification of the relationship between explanatory and outcome variables.

3.2. *Local Interpretable Model-agnostic Explanations (LIME)*

Random Forests' inability to provide a clear algorithm linking predictors to response variability is a handicap that limits their interpretability and their usefulness for state policy decisions. Local Interpretable Model-Agnostic Explanations (LIME) is a technique that helps explain individual predictions (Ribeiro, Singh, & Guestrin, 2016). It is "model agnostic," applicable to any supervised regression or classification model. Behind the workings of LIME lies the assumption that every complex model is linear on a local scale and asserting that it is possible to fit a simple model around a single observation that will mimic how the global model behaves at that locality. The simple model can then be used to explain the predictions of the more complex model locally.

LIME modifies a single data sample by subjecting the feature values to a finite perturbation and reporting the resulting impact on the output. This provides local interpretability and it identifies feature changes with most impact on the prediction. The procedure assigns to each predictor its contribution to the total variance explained. This allows for a ready assessment of a predictor for the outcome of interest. In addition, the LIME results presented below are based on the averaging of the sequential sum-of-squares obtained from all the possible orderings of the predictors (Gromping, 2006). This procedure of identifying the relative contribution to a joint outcome is a Shapley Value consideration and an application of Shapley Value Regression (Lipovetsky & Conklin, 2001). A recent contribution to the literature provides a unified treatment of the various extant methods recently proposed to help users interpret the predictions of complex models (Lundberg & Lee, 2017).

4. An illustrative case

We applied the procedures proposed in this study on two states: Connecticut and Florida. We used the R package *random forest* to extract predictor importance and sensitivities, and the R package *iml* to obtain Local Interpretable Model-Agnostic Explanations (LIME) estimates.

Figure 2 presents the analytical workflow used in the study. Importantly, random forests marshal considerable power when used to derive predictive outcomes. Procedurally, this requires some form of cross-validation or out-of-sample testing to fit the model. Predictive accuracy measures drawn from training testing protocols provide a basis against which to appraise any

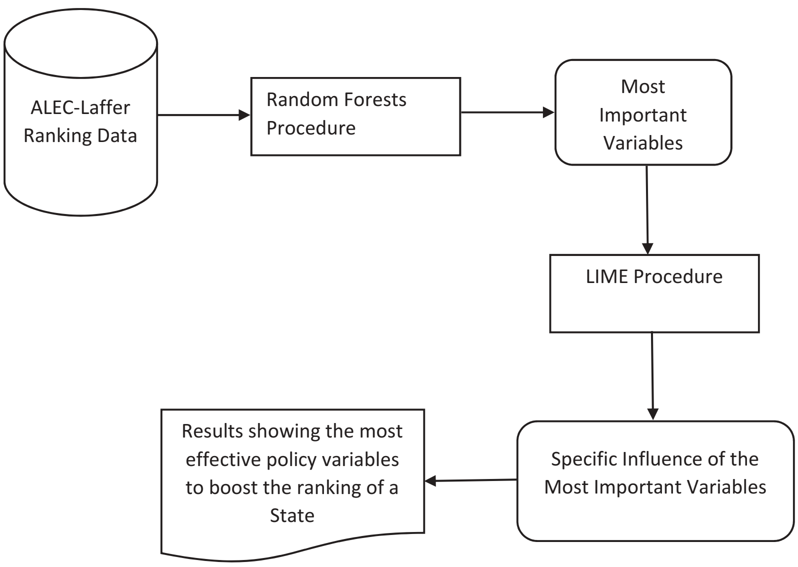

Figure 2. The procedure used in the study.

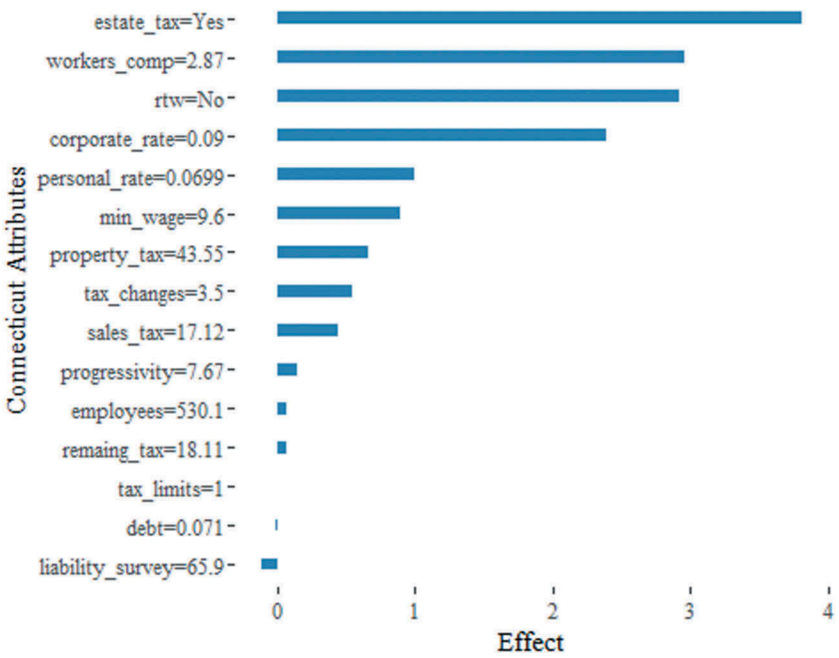

Figure 3. Contribution to Rank Position for Connecticut.

incremental gains over a benchmark model used by the particular algorithm deployed, if any. Our primary task in this paper is to illustrate the potential insights into model interpretability conveyed by the LIME procedure – and we thus largely eschew prediction. Accordingly, the input into the second node uses the full data set without any prior training-cum-testing. It proceeds with the random forest algorithm as the prediction tool benchmarked against an ordinary least squares model trained and tested with the full data set. Gauged predictive accuracy improves from a RMSE of 3.75 for the OLS model to a 3.3 for the random forest algorithm.

The output of the third node highlights the average or model-wide estimates of the most important variables. Thus, for instance, in identifying estate-tax status as an important predictor the procedure provides the average impacts on relative position in the rankings of all states. This particular variable's importance or its outcome sensitivity may not necessarily apply to individual states. This latter point is precisely the contribution of the LIME-procedure. Accordingly, the fourth node proceeds to identify the "local" influences and its marginal contribution to the broader outcome variables by examining its impact via localized perturbations. In the last node – the resulting outcome provides an inside view into the here-to-fore random-forest "black box."

Figure 3 shows the specific influence of the identified most important predictors on the State of Connecticut's position in the rankings. The graph displays two variables: the Effect or influence of the particular variable on the x-axis of the variables listed on the y-axis. All of the variables in the data set are listed. The magnitude of the Effect is conveyed as a barchart.

All variables on the positive side of the x-axis have an impact on Connecticut's relative position. And because Connecticut is in an unenviable position in the rankings, a policy focus on the top variables in importance are likely to improve its position. It should be clear that the rankings are on an inverse scale; this means that the variables on the positive side of the scale impact a state's performance negatively. Conversely and symmetrically, increases in the variables on the negative side of the x-axis enhance or increase a state's relative position, a state's economic performance. In Connecticut's case, it ranks favorably when it comes to its system of justice reflected by the variable State Liability Survey, and thus improves its position in the rankings.

Of the identified predictors, Connecticut's estate tax, and not a right-to-work status (rtw), and its corporate (marginal tax) rate levels seem to be the most influential predictors explaining its relative ranking. By contrast, the same variables contribute favorably to the state of Florida's ranking. In terms of its estate-tax status, its right-to-work status, and similarly, its marginal tax rate levels Florida ranks among the best (highest) in the rankings. Thus, the graph displays these variables as the most salient variables via a barchart emerging towards the negative portion of the x-axis. On the other hand, Florida ranks poorly in terms of the quality of its judiciary – a result that can be observed in Figure 4 where the predictor labeled State Liability System Survey protrudes towards the positive side of the x-axis reflecting its detrimental effect on Florida's position in the rankings.

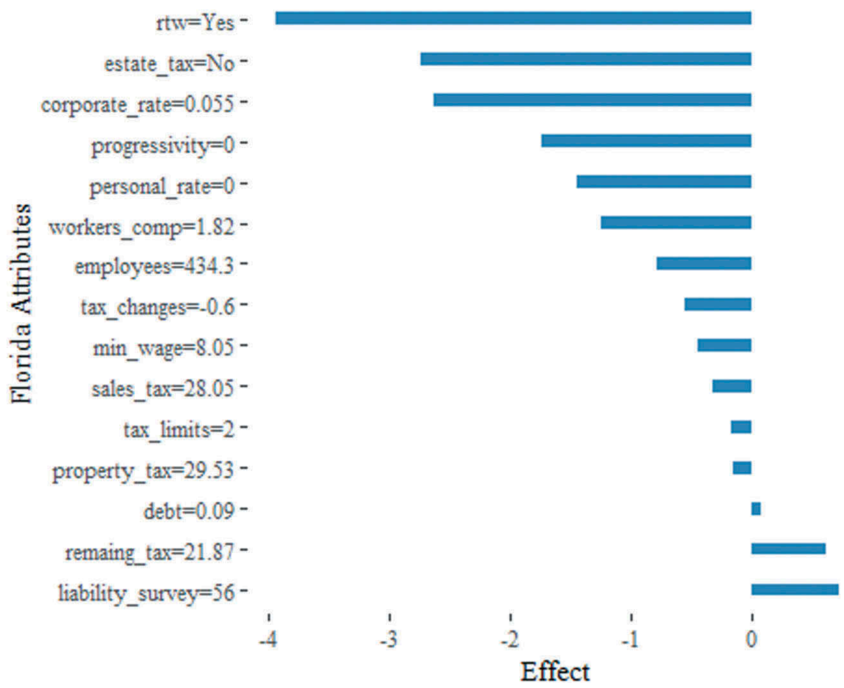

Figure 4. Contribution to Rank Position for Florida.

Contrary to the aggregate view of predictor importance extracted from the initial procedure using random forests, the features resulted from the LIME procedure (shown in the figures) offer policy-makers a more refined influence map and importance of each of the policy variables examined. Connecticut ranks poorly in the Alec-Laffer Economic Rankings; Florida among the best-performing. This means that the same policies that work in Florida to rise in the ranked list may not work in Connecticut. Connecticut policymakers responding to a poor showing in the rankings could turn to the LIME projections (given in Figure 3) for better results. The LIME projections constitute a veritable punch-list of activities that may have discernible impact of economic performance and on the rankings.

5. Discussion

LIME results, offer a glimpse beyond the averages and provide policymakers intent on redressing a poor economic showing with a distinct roadmap. This is actionable information for individual state policy programs. To conserve space, we illustrated the LIME variable results for the states of Connecticut and Florida to show their individual relevance and relative influence on the realized rankings. Connecticut and Florida are selected based on their seemingly opposite positioning on each of the most important predictor variables.

Applying the procedures explained in this article, three key drivers underscoring the 2016 ALEC-Laffer economic performance ranking based are identified. These variables are (i) whether a state identifies as a "right-to-work" state; (ii) whether a state levies a tax on the transfer of the estate of a deceased person: and, (iii) and the amount of state tax – as a percent – paid by Corporations on the additional dollar of income earned. These variables exert considerable influence on the realized outcomes – jointly, for all states.

There are three caveats. Other non-frequentist and machine learning algorithms are also capable of identifying key drivers; and it is not necessarily clear that they should be identical to the ones singled out via Random Forests (Hue, Nair, Chen, & Sudjianto, 2018). An alternative recommendation may emerge upon further examination under alternative individual machine learning procedures or an ensemble approach or any other perturbation method (Zeiler & Fergus, 2014). Second, and notwithstanding the clear advantages offered by knowledge of LIME variables, it should be clear that no variable selection algorithm can appraise the importance of variables that are not included in the initial predictor set. It is entirely plausible that the original choice of 15 prospective explanatory variables omitted some that would relegate the drivers identified above to secondary status. Last, despite the knowledge of key predictors and their sensitivities, and the specificity provided policymakers by the LIME process it is still unclear whether an identified key-variable is merely a proxy for a wider pro-business policy. Under such circumstances, merely altering or reversing the specific key-variable may be insufficient. Nevertheless, the principle remains: it is possible to select key drivers for individual states if one accounts fully for the heterogeneity of the performance variables. Important contributions for policy can be drawn from close scrutiny of key-drivers and the particulars of LIME-extracted intelligence.

6. Conclusion

Kruskal identified two general motives for identifying relative importance of predictor variables. A technological motive was characterized by the desire to change things economically and effectively, calling attention to "what should we attend to first in trying to reduce cancer deaths, improve education, maintain our system of highways, increase productivity growth, etc." (Kruskal, 1984). In this study, a random forests procedure is used to dissemble a popular state-rankings metric in search of the most influential policy variables – the factors that should be "tended-to first". Largely due to the significant multi-collinearity of the predictive variables, and the small-sample multiple-variable character of the problem at hand, random forests outperforms conventional multiple regression methodology at this task.

But even identifying the most important variables from among a larger basket of explanatory variables can be frustratingly vague for policy-makers intent on addressing their rankings placement. Until recently, knowledge of the particular sensitivity or local importance of the key predictors identified via machine learning tools was not available. Advances in local approximations methodology known as Local Interpretable Model-Agnostic Explanations (LIME) are able to provide individual state decision-makes with individual factors, attributes that should be tended-to first.

This enhancement, known as model-interpretability, comes at a time when disciplines ranging from criminal justice, to finance, and including health outcomes, genetics, taxation, *inter alia* are looking for a reckoning, a deeper understanding of the reasons and causes underscoring predicted outcomes, or both. Much of the firepower undergirding model-interpretability, was developed largely independent of the many users and user-contexts across which it has been recently and successfully deployed. According to commentators this detachment of the tool from its origins may have led to "value-laden" challenges (Veale, Van Kleek, & Binns, 2018). Whether these concerns are relevant to the economic policy tool proffered here remains open for discussion; in our opinion such scrutiny will only enhance its appeal.

Notes

1. The Freedom in the 50 States ranking [https://www.freedominthe50states.org/]; The Human Development Index [https://www.measureofamerica.org/maps/]; Economic Freedom in North American Ranking [https://www.fraserinstitute.org/studies/economic-freedom-of-north-america-2017].
2. See, e.g., U.S. News & World Report's 2016 Best Places to Live rankings [http://realestate.usnews.com/places/rankings-best-places-to-live], and Forbes' Best Places to Retire in 2016 [http://www.forbes.com/sites/williampbarrett/2016/04/04/the-best-places-to-retire-in-2016/#669dc952703e].
3. See, e.g. [https://taxfoundation.org/publications/state-business-tax-climate-index/].
4. They can be found online: https://www.alec.org/publication/rich-states-poor-states/.

Disclosure statement

No potential conflict of interest was reported by the authors.

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