Predicting Firm Creation in Rural Texas:

A Multi-Model Machine Learning Approach to a Complex Policy Problem

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Abstract

What factors predict firm creation in rural America? Policymakers asking this question face two obstacles. First, research on firm creation centers on high-tech, urban firms. Second, entrepreneurship research stretches across disciplines, often using econometric methods to identify the effect of a specific variable, rather than comparing the predictive importance of multiple variables. In this paper, we apply three machine learning methods (subset selection, lasso, random forest, and extreme gradient boosting) in addition to linear regression to a novel dataset to examine what social and economic factors are predictive of firm growth in rural Texas counties from 2008-2018. Results suggest that some factors commonly discussed as promoting entrepreneurship (e.g., access to broadband and patents) may not be as predictive as socioeconomic ones (age distribution, ethnic diversity, social capital, and migration patterns). We also find that the strength of specific industries (oil, wind, and healthcare) predicts firm growth, as does the number of local banks. Most factors predictive of firm growth in rural counties are distinct from those in urban counties, supporting the argument that rural entrepreneurship is a distinct phenomenon worthy of distinct focus. We also discuss how this multi-model approach can offer initial, focusing guidance to policymakers seeking to address other complex policy problems.

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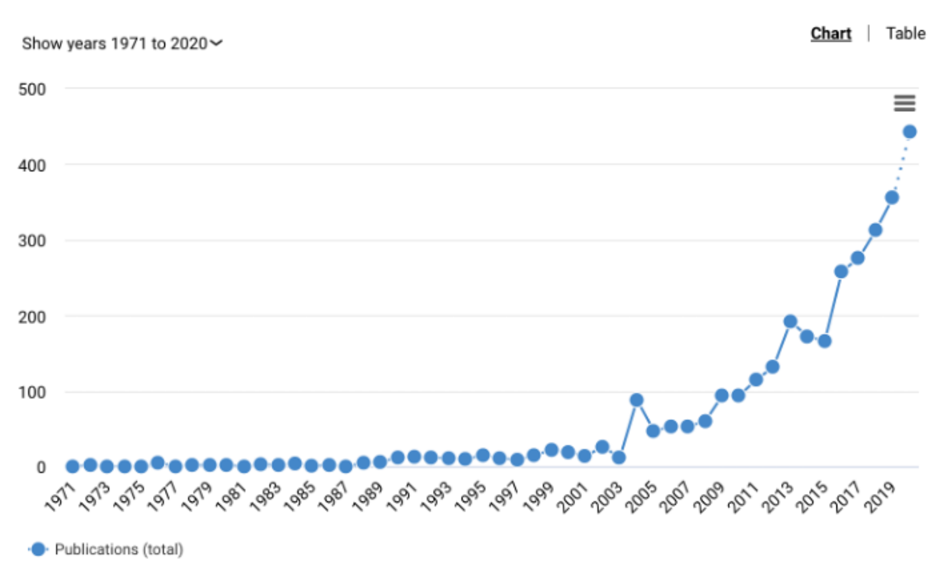
Introduction

Firm Creation in Rural America

What factors predict firm creation in rural America? Higher rates of entrepreneurship and self-employment can help communities jumpstart and sustain economic growth, create jobs, and mitigate trade shocks more effectively than attracting large firms [1]. For rural areas in particular, promoting entrepreneurship may be one of the few effective economic development strategies [2]. In these areas as elsewhere, spurring entrepreneurial activity can launch a larger feedback loop, reinforcing the regional conditions that make for further firm creation feasible [3]. But we know comparatively little about firm creation in rural areas. In fact, "More research is needed on what types of entrepreneurs are effective in promoting growth and on what types of infrastructure and technical-assistance support (including business planning and other forms of education) are most effective in helping develop and grow local businesses" [1]. This is particularly true in the U.S., as most of the work on entrepreneurial "rates" work is based in Europe or the developing world: One recent review found that rural entrepreneurship is "an essentially European concern" [4]. This is only just beginning to shift, with U.S. scholars calling for greater focus on more "ordinary" startup firms [5] and others putting forward typologies of state-level development interventions [6].

Historically, questions about entrepreneurship in rural areas have existed as a subset of conversations about rural development, and primarily with its impact on rural growth [7]. As interest in rural entrepreneurship has grown (Fig 1), scholars have begun to look to existing literature on entrepreneurship more broadly for clues about what factors might predict firm creation in rural areas specifically. In Table 1, we gather the most well-cited scholarship on entrepreneurial rates, collected from a range of disciplines and theoretical perspectives, divided into natural, market, cultural, demographic, and regulatory determinants of firm creation.

Fig 1. Scholarly Papers Including the Phrase *Rural Entrepreneurship*. Source: Dimensions.ai, accessed 18th November 2020.



Drawing from the broad theoretical categories in Table 1, Table 2 outlines the results of classic and recent empirical work on firm creation, which have identified the following variables to be associated with firm creation: market characteristics (the availability of financial capital, labor and suppliers; the absence of an oil and gas industry), demographic characteristics (ethnic diversity, population density, age distribution, immigration); regulatory policies (democracy, control of corruption, labor market freedom, low interest rates, property rights, R&D expenditures and incentives programs [negatively correlated]), cultural characteristics (risk-taking, gender-egalitarianism, performance reward, and the social status accorded to risk-taking entrepreneurs), and even the amount of recent bridge construction [18].

There are two obstacles to applying this research to rural entrepreneurship, however. The first obstacle is that the list of factors that contribute to firm creation is expansive but theoretically disconnected; researchers with multiple lenses on entrepreneurship have yet to pull together a theoretically-coherent picture of the socio-economic factors that lead to firm growth [4,19]. This theoretical complexity, according to one recent review, is reflected in the existence of at least six distinct, disconnected theoretical approaches to rural entrepreneurship [20]. That theoretical disconnection has hampered progress in understanding the causes and effects of rural entrepreneurship.

The second obstacle to applying research on entrepreneurial determinants to rural areas is that rural entrepreneurship may be a different phenomenon from entrepreneurship concentrated in larger cities, and the rural context a unique context in which innovation can occur. Much of what we know so far about entrepreneurship is too focused on high-growth, big-city entrepreneurs to be relevant in rural areas, in which entrepreneurship and innovation is focused on agriculture, tourism, decentralized service provision, and manufacturing. [21]. Just as rural counties in the United States experienced a significant divergence in economic indicators from urban counties in the wake of the Great Recession [22], so might there might be material differences in the ways that rural and urban entrepreneurs respond to those changes.

Table 1: Previously Theorized Determinants of Firm Creation by Category.

Natural	Market	Cultural	Demographic	Regulatory	Source
Natural cost advantag es	Agglomeration of: Customers and Suppliers, Labor market and Technology spillovers	Entrepreneurial culture	Demographics	-	[8]
-	-	Social norms-culture, Cognitive dimensions, Belief systems	-	Political structure, Procedures-regulations, Contracts, Property rights	[9]
-	Market Conditions, Creation and Diffusion of Knowledge, Access to Finance	Entrepreneurial Culture	Entrepreneurial Capabilities	Regulatory Framework	[10]
-	Technological change, Per capita income, Savings, Demand, Unemployment rates, Wage rates, Failure rates	Protestant ethic, Existing innovative firms	-	Political change, Tax rates, Low interest rates	[11]
-	Density of established organizations, Technology transfer to new companies, Venture capital (VC) availability	Norms of gender-equity, value and reward of performance, and endorsement of status privileges	Quality of STEM education	National investment in R&D, Governmental support and policies for entrepreneurship	[12]

-	Technology Absorption, Globalization, Competition, Financing	Cultural Support	Human Capital	-	[13]
-	Financing for Entrepreneurs, Commercial and Professional Infrastructure, Internal Market Dynamics, Internal Market Openness	Cultural and Social Norms	Basic School and Post-School Entrepreneurial Education and Training	Government Support and Policies, Taxes and Bureaucracy Government Programs, R&D Transfer, Physical and Services, Infrastructure	[14]
Sensitivity to weather	Size of firms, growth orientation, subsidy dependence, agglomerative effects, transportation and information costs, cognitive proximity to new technologies	Strength of weak ties	Labor productivity	-	[15]
-	Self-employment earnings,	Culture favoring entrepreneurship	Population density, ethnic diversity	State policy toward labor market freedom	[16]
-	Market Conditions, Access to Finance, Creation and Diffusion of Knowledge,	Entrepreneurial Culture	Entrepreneurial Capabilities	Regulatory Framework	[17]

Table 2. Variables associated with firm creation, across contexts.

Regional Determinants	Context	Source
Changes in technology, Protestant Ethic[1], interest rates, prior rates of entrepreneurship, risk-taking propensity, business failure rates, economic growth, immigration, age distribution of population	US firm creation at the national level, 1900s	[11]
Financial entrepreneurial capital (inverse U-shaped relationship)	US states	[23]
Abundant workers and presence of many small suppliers; to a lesser extent level of local customers and suppliers	US manufacturing startups across cities and industries	[8]
Ethnic diversity of the population, population density, state-level labor market freedom policy	Self-employment in US counties	[16]
Growth in nearby MSAs (-)	Self-employment in rural US counties	[24]
Incentives (-) and inter-sectoral job mobility	Post-recession start-up rates in US counties	[25]
Oil and gas sector expansion (-)	Self-employment in US counties	[26]
Norms of gender-egalitarianism, value and reward of performance, and endorsement of status privileges	Company founding across countries	[12]
Access to stock markets and the financial system, hiring and firing rules and controls, control of corruption, democracy, government size and capability, property rights, the presence of role models	Multiple	[9]
Innovation and new technologies, peer effects, the sociocultural environment, R&D transfers, and the availability of government subsidies	Entrepreneurial founding across countries, 2014	[27]

Note: A minus sign (-) indicates a negative correlation

[1] We consider this variable to be culturally biased and irrelevant for this analysis. Its insignificance as a determinant of firm creation is further evident from our results.

Machine Learning in Public Policy and Entrepreneurship Scholarship

As in other complex socioeconomic systems, the effects of all the variables identified in Table 2 are difficult to isolate because they are by their nature collinear and mutually reinforcing to varying extents. That complexity outstrips the ability of standard econometric tools to help us understand such a system beyond basic correlations. When the number of potential variables becomes large, or when their interactions are important but unknowable, predictive methods can fill the gap—not by establishing causal connections between one independent and dependent variable, but by surfacing the variables that merit the greatest research focus [28].

As with many disciplines, policy research has depended greatly on causal inference through econometric methods. As Kleinberg et al. argue, this makes sense, given that policymaking often requires consideration of a counterfactual; what will happen with and without a particular policy? [28] When the question at hand is "what impact will this action have on that outcome?" causal inference should be central. But not all policy questions are structured like this, and especially not at the beginning of the agenda-setting process. When the question at hand is "among the hundreds of possible policy responses, which should we consider further?" then the task at hand is to establish predictive accuracy first, then attempt to identify the relationships among the predictors [29].

The use of machine learning methods has greatly expanded in public policy scholarship over the last decade. In criminology, the first policy discipline in which machine learning began to be incorporated in 2013 to forecast reoffending [30], researchers have used it to predict local crime rates [31], partner violence [32], firearm violence and mass shootings [33], sexual recidivism [34], and land use policies [35]. Even in 2013, the outlines of the dangers of its application—to reinforce discriminatory institutions or provide new tools to authoritarian governments, e.g.—were clear, having been previewed in other disciplines [36,37]. Since then, the use of machine learning in public policy has ramified into other policy domains, including poverty-reduction, workforce development and health inspections [for a more complete list, see [28] and [38]].

Entrepreneurship and innovation scholars are working even more assertively in predictive direction, as well, with recent review focusing on the potential applications of "big data" and artificial intelligence to entrepreneurship research [39,40]. Gimenez-Nadal et al. [27] apply bootstrap and forward selection techniques to the Global Entrepreneurship Monitor data for the year 2014, finding that "innovation and new technologies, peer effects, the sociocultural environment, entrepreneurial education at University, R&D transfers, and the availability of government subsidies are among the most important predictors of entrepreneurial behavior." [41] use Italian firm data to predict how innovative firms will be, and then correlate that measure with subsequent firm survival. [42] uses stacked generalization and boosted trees to predict the size of venture financing rounds. [43] use multiple machine algorithms to predict venture success, and [44] to suggest successful revenue models.

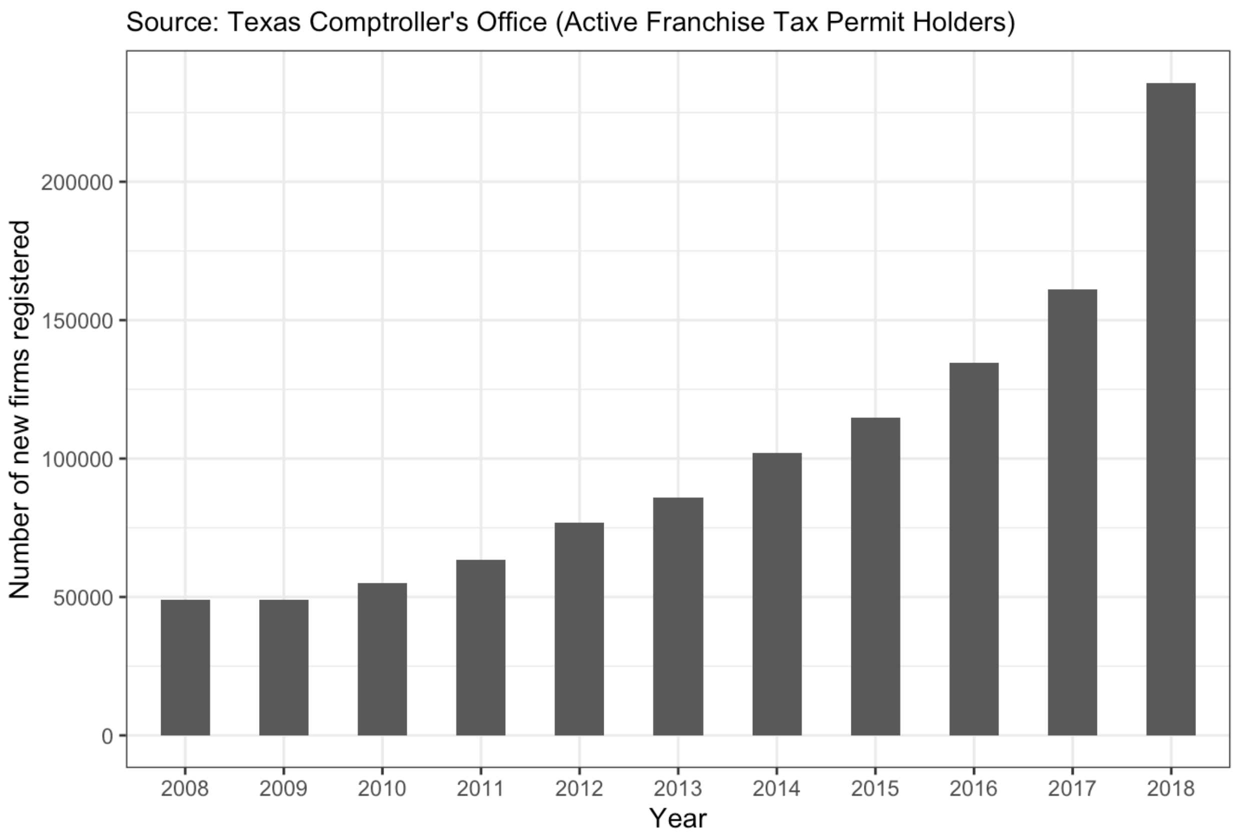
Entrepreneurship, like many economic questions, is also a question of policy, not just observation of how humans work in a policy vacuum. This paper looks not just at what factors lead to rural entrepreneurship, but grapples with the options available to policymakers whose goal is to increase firm creation to create jobs and build up economic resilience in their communities.

Data[2]

In the analyses below, we examine firm creation in all 254 counties in Texas across ten years, from 2008-2018, a period in which 1,255,963 new firms were created in the state. According to the U.S. Office of Management and Budget, 157 of those counties are rural, and the rest are urban or micropolitan. Together, these counties account for 8.4% of all U.S. counties and 8.7% of the total U.S. population, providing variation across a wide dimensional space but allowing us to control for state policy regime. Texas also has a unique publicly available dataset on firm creation: Texas Comptroller of Public Accounts' Active Franchise Tax Permit Holders data. Within this data, which stretches from 1843 to the present, each business in Texas is assigned a *Responsibility Beginning Date* from which we build our dependent variable of county-year firm creation, our dependent variable. Fig 2 shows the number of firms created in rural Texas from 2008-2018, our period of study; see Appendix A for descriptive statistics of all variables. This unique data frame limits our current study to Texas counties, and the availability of our independent variables listed below limit our study to 2008-2018. We return in the discussion to the question of generalizability from this data, in the context of the decision-making process of public policymakers.

[2] All data used in this analysis are available in a reproducible RStudio Project, available at https://drive.google.com/open?id=10XwGcg7xMY-mcS4l8AFxeyIqe1n2IwWm&authuser=mark.c.hand%40gmail.com&usp=drive_fs.

Fig 2. New Firms Registered in Rural Texas from 2008-2018.



Our list of independent variables is built from a range of data sources, including the US Census's County Business Patterns, the US Geographical Survey wind turbine database, the University of California Berkeley Lab's Tracking the Sun database, and the Texas Railroad Commission by way of Texas2036, an Austin-based think tank. In line with a report prepared for the Appalachian Regional Commission [45], we construct multiple variables from the US Census's American Community Survey. We use lending data from the Community Reinvestment Act, bank availability data from the Federal Deposit Insurance Corporation, patent data from the US Patent Office, broadband access data from the National Telecommunications and Information Administration, and several variables from the Robert Wood Johnson Foundation's County Health Rankings. Many of these variables are unavailable before 2008, so we restrict our time series to 11 years from 2008-2018. In Table 3 we list those variables and their sources.

As predictor variables, we use the datasets above to build measures that account for just over 40 percent of the variables used by previous researchers as listed in Table 2, either directly or by close proxy. The remaining variables are not available at a county-level resolution or are constructed from proprietary datasets, which we avoid to improve transparency and reproducibility of our analysis. We then add several variables not included in previous models, including wind capacity and solar installations, two other growing sources of energy production and employment in rural Texas. As additional economic indicators we include unemployment rate, income inequality, and industry diversity. In addition to migration variables, we create and add a variable for ethnic diversity. We also include a measure of counties' ability to regain job growth after the Great Recession (called resilience by Boettner et al.), along with a number of variables for specific industries associated with resilience [45].

Most of the variables used in the analysis below are available at the county-year level for each of those years. Where the data for a certain variable are not available for every year, but multiple values were available over the period (for example the percentage of population who were in- or out-migrants), we impute values so as not to lose these observations during analysis. For those variables where only one value is available (for example social capital index), we attribute that value as a stable characteristic of the county. Lastly, to be able to compare the magnitude of coefficients across variables and the predictive accuracy across models, we standardize all variables.

Table 3. Description of Variables and Sources.

Variable Type	Variable ID	Description	Source	Timeframe
Dependent Variable	newfirms	Number of new firms established per county per year	Texas Comptroller's Active Franchise Tax Permit Holders	2008-2018
Demographic Variables	population	Total population	American Community Survey	2008-2018
	population_density	Population per land area of the county	American Community Survey	2008-2018
	percent_age_25_44	Percent of population aged 25-44 years (%)	American Community Survey	2008-2018
	percent_age_65	Percent of population aged 65 and above (%)	American Community Survey	2008-2018
	percent_residence_born	Percent of population who were born in the state of residence (%)	American Community Survey	2008-2018
	percent_edu_college	Percent of population age 25+ with bachelor's degree or higher (%)	American Community Survey	2008-2018
	ethnic_diversity	Ethnic diversity of minorities (except white)	American Community Survey	2008-2018
	percent_mobility_in_mig	Percent of population who are in-migrants (%)	American Community Survey	2009-2015
	percent_mobility_out_mig	Percent of population who are out-migrants (%)	American Community Survey	2009-2015
	protestant_ethic	Ratio of Protestant to Catholic residents	The Association of Religion Data Archives	2010

Economic Variables	unemployment_rate	Unemployment Rate	Bureau of Labor Statistics	2008-2018
	percent_self_ employment	Ration of (nonfarm) proprietors to total employed	Bureau of Economic Analysis	2008-2018
	total_emp	Total employment in all occupation categories	Bureau of Economic Analysis	2008-2018
	banks	Number of banks per county	Federal Deposit Insurance Corporation	2008-2018
	deposits_thousand	Total deposits held in local banks, $1000s	Federal Deposit Insurance Corporation	2008-2018
	fed_fund_rate	Effective Federal Funds Rate	Federal Reserve Economic Data	2008-2018
	income_inequality	Gini index of income inequality	American Community Survey	2008-2018
	percent_poverty	Percent of population in poverty (%)	American Community Survey	2008-2018
	county_gdp	Current-dollar GDP (thousands of current dollars)	Bureau of Economic Analysis	2008-2018
	failedfirms	The number of firms that closed in the prior year.	Texas Comptroller's Office	2008-2018
	newfirms_prevyear	Number of new firms established in the previous year (lagged DV)	Texas Comptroller's Office (Active Franchise Tax Permit Holders)	2009-2018
	business_density	Number of establishments per 1,000 age 20-64 population	County Business Patterns	2008-2018
	patents	Number of patents issued in each county	U.S. Patent Office	2008-2018

	percent_insured	Percent of population with health insurance	American Community Survey	2008-2018
	percent_broadband	Percent of population with access to broadband internet	Federal Communications Commission	2016-2017
Energy Industry Variables	total_oil	Total gas production (barrels)	Railroad Commission of Texas (curated by Texas 2036)	2008-2018
	total_gas_boe	Total gas production (barrel of oil equivalents), including casinghead gas production	Railroad Commission of Texas (curated by Texas 2036)	2008-2018
	solar_installations	Total solar power installed Capacity (in MW)	University of California Berkeley Lab (Tracking The Sun database)	2008-2018
	wind_capacity	Total number of wind turbine installations	U.S. Geological Survey (Wind Turbine Database)	2008-2018
	play	Which of the five major oil and gas plays a county is part of	Texas Railroad Commission	2020
Other Industry Variables	percent_industry_farming	Percent of employment in farming - NAICS 11 (%)	County Business Patterns	2008-2018
	percent_industry_extraction	Percent of employment in extraction - NAICS 21 (%)	County Business Patterns	2008-2018
	percent_industry_recreational	Percent of employment in arts, entertainment, and recreation - NAICS 71 (%)	County Business Patterns	2008-2018
	percent_industry_oil_gas	Percent of employment in oil and gas extraction (%)	County Business Patterns	2008-2018

	percent_industry_ edu_prime_secondary	Percent of employment in Elementary and Secondary Schools - NAICS 6111 (%)	County Business Patterns	2008-2018
	percent_industry_ manufacturing	Percent of employment in manufacturing - NAICS 31 (%)	County Business Patterns	2008-2018
	percent_industry_ edu_com_college	Percent of employment in Community college - NAICS 611210 (%)	County Business Patterns	2008-2018
	percent_industry_ healthcare	Percent of employment in offices of physicians, dentists, and other health practitioners - NAICS 6211-3 (%)	County Business Patterns	2008-2018
	percent_industry_ coal	Percent of employment in coal mining - NAICS 2121 (%)	County Business Patterns	2008-2018
	percent_child_ elder_care	Percent of employment in child day and elderly care services - NAICS 62441, 61412 (%)	County Business Patterns	2008-2018
County-Level Variables	land_area	Land area in square miles	ARC 2018 (Cited from U.S. Census Bureau)	2000
	distance_250k	Distance (miles) to a county with more than 250,000 population	ARC 2018 (Author's calculation)	2005
	natural_amenity	Natural amenities	ARC 2018 (Cited from U.S. Dept. of Ag)	2005
	per_point_diff_2020	Difference between two major party presidential candidates	MIT Election Lab	2020
	social_capital	Social Capital Index	Northeast Regional Center for Rural Dev.	2014

Methods

In modeling studies results may be sensitive to the data and the modeling technique selected. In econometrics this issue is partly addressed by conducting sensitivity analyses by modifying parameter specifications while typically keeping the core algorithm unchanged. While the strength of machine learning methods is in being able to implement non-parametric non-linear algorithms to achieve higher predictive accuracies, there is often less visibility into the inner workings of the algorithms. Therefore, it is possible that the results are sensitive to the specified machine learning algorithm. This issue is widely recognized, and in many fields, it is now standard practice to implement a number of different models on the same dataset to compare their predictive accuracies [46–49]. Random forest models can, for example, be used to predict rare events such as the onset of civil wars with much higher accuracy than classical logistical regressions models [50]. This is just one example, of course; in other comparisons linear or logistics models might perform better than more flexible algorithms. *Ex ante*, it is impossible to know what sort of model performs best on a set of data.

The complex algorithms that machine learning models employ in pursuit of greater predictive accuracy often trade-off interpretability. When the modeling objective is to optimize the algorithms to achieve the highest predictive accuracy, models that achieve the lowest prediction errors can be selected, regardless of their interpretive value. However, while investigating complex social science problems such as we do in this paper, interpretability is as important as predictive accuracy. While predictive accuracies give an understanding of the relative performance of different models, different models offer different types of interpretive capabilities, and there is no straightforward way to compare the interpretation of variables from different models. This is important, because two or more models may perform almost equally well, but because of their use of different algorithms, they may display completely different relationships between the dependent and independent variables [29]. In any case, multiple methods might actually be necessary to investigate complex causal relationships [51]. We therefore argue in favor of and propose a framework for comparing the importance of variables across multiple machine learning models. This allows for an exploration of variables that appear consistently across different models, and those that are sensitive to model-specific algorithms.

Model Selection

Linear regression is the simplest and most popular modeling technique that finds the line of best fit by minimizing the sum of squared residual errors. The strength of linear regression lies in the easy interpretability of resulting coefficients. Among the many widely known limitations of linear regressions, an important one is its focus on minimizing in-sample error, which can lead to problems of "over-fitting" and poor performance while predicting out-of-sample data. For improving the predictive capability of a model, it is important to reduce the out-of-sample error, even at the expense of trading off in-sample error. Machine learning techniques offer an empirical way to manage this trade-off and improve out-of-sample predictive performance [52]. Specifically, in this paper we use 10-fold cross validation technique to obtain the out-of-sample prediction errors (also called Test Mean Standard Error or Test MSE) for comparing the performance of different models.

In this paper, we use linear regression, linear regression with forward and backward subset selection, lasso regression, random forest, and XG Boost models to investigate the socio-economic determinants of new firm starts in Texas counties. We have selected these techniques for their ability to model a continuous response variable, as well as their ability to provide interpretable outputs, albeit in different forms. Other models such as K-nearest neighbor (KNN) regression and Principal Component Regression can also be applied but offer less interpretable results. A number of textbooks such as [53] provide a detailed introduction to a range of machine learning techniques that may be applied over the interpretability vs. complexity tradeoff spectrum.

Forward and backward subset selection models work by iteratively adding (or removing) variables from a series of models, one-at-a-time, at each step considering which variable offers the greatest additional improvement (or reduction) in model fit. From this series of models, at each step the one with the least Bayes Information Criterion (BIC) statistic is selected as the best performing model, thus yielding a "greedy" (i.e., suboptimal) but computationally efficient approach. Lasso regression belongs to a class of "shrinkage" or "regularization" models that apply a tunable penalty term while minimizing the residual sum of squares, resulting in a sparse model wherein less important coefficients could be set to zero. Random forest is a class of tree-based models that aggregates repeated, decorrelated decision trees build from random subsets of predictors at each step. Finally, extreme gradient boosting, or XG Boost, is a technique that uses the processes of gradient boosting and regularization to improve the prediction rate by adjusting the weights and penalties for errors made by previous weaker models.

The random forest, lasso regression, and XG boost models were tuned to optimize the hyperparameters to minimize the out-of-sample errors, as is standard in the literature [54–56]. The random forest model was tuned to select the optimal mtry value (where mtry is the number of variables randomly sampled at each split). In the lasso regression model, cross validation was used to select the lambda value which minimizes the mean cross-validated error. In the XG boost model, and in line with prior research, a grid search with 5-fold cross validation was performed to tune five hyperparameters - the maximum depth of a tree (max_depth), subsample ratio of the training instance (subsample), subsample ratio of columns when constructing each tree (colsample_bytree), lambda, and alpha values [57–60].

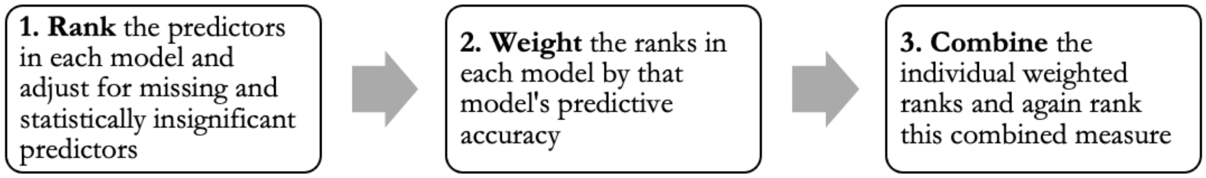
In terms of outputs, linear regressions provide the magnitude and direction of the coefficients associated with each predictor, along with p-values indicating their level of significance. Subset selection and lasso regression models result in a selected subset of predictors along with their magnitude and direction of impact. Random forest models generate variable importance plots, which is a summary of the extent to which each predictor contributes to the reduction in mean squared error and gini index, which are both indicators of their relative level of importance.

We chose these techniques for their ability to model a continuous response variable, as well as their ability to provide interpretable outputs, albeit in different forms. Other models such as K-nearest neighbor (KNN) regression might be used but offer less interpretable results. Many other techniques such as Principal Component Regression, Support Vector machines, Linear and Quadratic Discriminant Analyses and other tree-based techniques can be applied based on the nature of the research questions and the underlying data. Several textbooks such as (James et al., 2013) provide a detailed introduction to these machine learning techniques.

A Multi-Model Interpretation Framework

Each machine learning method provides a different type of output to assist in interpreting the importance of predictors. The strength and relative importance of predictors might vary across different methods, and models may themselves have relatively different predictive capabilities. To assess the overall contribution of each predictor from across all the models considered, we develop a novel combined interpretation framework that allows for systematic aggregation of outputs from multiple models. The rationale for this combined interpretation framework is to achieve three objectives: (a) prioritize variables with higher magnitude of association within each model, (b) prioritize variables that appear as significant across multiple models, and (c) prioritize variables from models that have relatively better predictive performance.

Fig 3. A Three-Step Framework for Interpretating of Results of Multiple ML Models.



The combined interpretation framework consists of three steps (Fig 3). First, we take the list of variables from each model output and rank them according to their importance. The ranking scheme depends on the nature of output from each model. In the random forest model, we rank predictors according to their contribution to reducing the percent mean-squared error. In all other models, we rank the predictors according to the magnitude of their (standardized) coefficients. This ensures that the predictors that are more important in each model get higher ranks. Further, the predictors missing in each model and predictors that are not statistically significant in the linear regression model are penalized by assigning their rank as one greater than the total variables in the largest model. This ensures that the predictors that are not significant in each model get lower ranks.

Second, once the rank for each predictor is assigned for all models, these ranks are weighted by the respective model's predictive accuracy. In our case for example, we weight the ranks from each model by that model's 10-fold cross validation error. This ensures that the predictors in better performing models get higher weightage.

Finally, we combine the weighted ranks from all models. To do this, we take the average rank of each predictor across all models. Then, we rank those averages. This ensures that the predictors appearing across multiple models get higher ranks. This is the final measure of each predictor's overall importance in our models, as described below.

Results

The abbreviated output of the models is shown in Table 4, and the cross-validated mean squared errors (CV Error) of each of our five models are shown in Table 5.[3] The linear model performed best, followed in order by the XG Boost, random forest, subset selections and lasso regression models. In many circumstances, the process of interpreting machine learning outputs might stop here: Having discovered the best model(s), we would simply

[3] See Appendix B for a list of variable appearances across all models; and Appendix C for hyperparameter tuning plots.

interpret the results of the best-performing model. However, there is no guarantee *ex-ante* that this model always produces the least prediction errors. The tuning parameters in each model and the cross-validation errors, among other steps, are all a function of the underlying data and stochastic processes. With a different randomization routine or with a different dataset, it is entirely possible that a different model performs better [61], especially when two or more models perform closely overall such as the linear regression and random forest models in this paper. Therefore, we implement the three-step framework described above to obtain a combined single rank of importance of all variables across all models. The resulting table is shown in Table 6.

County Characteristics and Demographics

Prior research has suggested that high rates of firm creation are associated with a number of demographic and cultural characteristics of a local population, including its age distribution [11], education levels [14,62], ethnic diversity [16], culture [12], social capital [63], population growth [64], rates of immigration and age of immigrants [65], population density [16], and (oddly) the ratio of Protestant to Catholic religious adherents [11]. In the consolidated results in Table 6, some of these stand out, including age distribution, ethnic diversity, social capital, and migration, in descending order of predictive variable importance.

Table 4. Comparing Features Across Models.

	RANDOM FOREST		Multilinear regression[4]		Forward subset		Backward subset		Lasso		XG boost
Variable[5]	**% inc MSE**	**Inc node purity**	**Coef.**	**+/-**	**Coef.**	**+/-**	**Coef.**	**+/-**	**Coef.**	**+/-**	**Gain**
Newfirms_prevyear	16.64	0.184	0.74	++	0.89	++			0.78	++	0.23
Population_density	13.31	0.134									0.10
Deposits_thousands	11.62	0.072									0.00
Population	9.34	0.146	0.07	++	0.01	++			0.04	++	0.47
Total_emp	9.30	0.075	0.03	–							0.05
Business_density	8.60	0.059									0.04
Percent_age_25_44	8.38	0.004							0.00	–	
Year	8.34	0.010									
Banks	7.99	0.048			0.00	–	0.014	++			
Percent_self_employment	7.79	0.003									
Ethnic_diversity	7.29	0.003							0.00	++	0.00
Industry_diversity	7.26	0.024									0.01
County_gdp	7.22	0.015	0.03	++							0.00
Percent_industry_manufacturing	6.80	0.014									0.00
Percent_edu_college	6.79	0.004									
Percent_industry_healthcare	6.77	0.019							0.00	–	0.00
Distance_250k	6.70	0.006									
Play	5.68	0.002									

[4] Coefficients significant at 10% level. Individual year dummy variables not reported in this table

[5] For ease of viewing, we have removed those variables which contributed least to MSE and which appeared in no other models. In order of least importance, They are: Percent industry community college; percent industry coal; percent industry oil and gas; solar installations; percent industry farming; presidential vote differential; and percent of residents born in-county.

Protestant_ethic	5.64	0.002									
Total_gas_boe	5.64	0.004									
Unemployment_rate	5.21	0.004							0.00	–	
Percent_industry_extraction	5.01	0.002									
Total_oil	4.95	0.006	0.00	–					0.00	–	
Income_inequality	4.61	0.003			0.00	–					
Percent_child_elder_care	4.35	0.001			0.00	++					
Percent_industry_recreational	4.30	0.011									
Land_area	4.22	0.008									
Resilience	4.19	0.003									
Percent_broadband	4.06	0.002									
Percent_poverty	4.02	0.002									
Social_capital	3.88	0.004							0.00	++	
Natural_amenity	3.78	0.004									
Percent_age_65	3.69	0.003							0.00	++	
Percent_mobility_in_mig	3.69	0.005			0.00	++	0.004	–			
Percent_industry_edu_ PRIME_SECONDARY	3.19	0.001									0.00
Percent_mobility_out_mig	3.06	0.004							0.00	–	
Percent_insured	2.55	0.004									
Patents	2.09	0.004									0.01
Fed_fund_rate[6]	2.00	0.002	0.00	–							
Wind_capacity	1.37	0.001							0.02	++	
Failedfirms	0.35	0.012			0.01	++					0.08
Play_eagle_ford					0.00	–	0.003	++			
Play_granite_wash					0.00	–					

[6] Constant across all years in a given county or, in the case of Federal Funds Rate, across all counties each year. Broadband access is available for two years.

Table 5. Comparison of 10-Fold Cross Validation Error.

Model	Test MSE
Linear Regression	0.000049
Forward Subset Selection	0.006819
Backward Subset Selection	0.006833
Lasso Regression	0.049521
Random Forest	0.000082
XG Boost	0.000085

Table 6. Multi-Model Variable Importance Rankings, Weighted by Model Performance.

Variable	Rank	Variable	Rank
Population	1	Pop. born in state (%)	32
New firms (prior year)	2	Pop. college education (%)	33
Oil production	3	Income inequality	34
Banks	4	Broadband access	35
Immigration (%)	5	Resilience	36
Industry size: healthcare	6	Land area	37
Industry size: elder and childcare	7	Distance from metro area	38
Failed firms (prior year)	8	Natural Amenities score	39
Wind capacity	9	Self-employment	40
Pop. aged 25-44 (%)	10	Patents	41
Pop. aged 65 and older (%)	11	Bank deposits	42
Ethnic diversity	12	Outmigration (%)	43
Unemployment rate	13	Population density	44
Total Employment	14	Year: 2010	45
Social capital	15	Year: 2012	46
County GDP	16	Industry size: oil and gas	47
Federal Funds Rate	17	Industry size: community college	48
Year: 2011	18	Industry size: coal	49
Year: 2013	19	Pop. in poverty (%)	50
Year: 2014	20	Percent insured	51
Year: 2016	21	Protestant Ethic	52
Industry size: farming	22	Year: 2009	53
Industry size: extraction	23	Year: 2015	54
Industry size: recreational	24	Oil play: Eagle Ford	55

Industry size: K-12 education	25	Year: 2017	56
Industry size: manufacturing	26	Oil play: Granite Wash	57
Business density	27	(Intercept)	58
Industry diversity	28	Year: 2018	59
Gas production	29	Oil play: Haynesville	60
Solar installations	30	Oil play: None	61
2020 presidential vote differential (%)	31	Oil play: Permian	62

One other factor merits discussion here: the number of new firms started in the previous year. There are at least two ways to interpret that the number of firms started in the prior year is predictive of number of firms started in this year. First, we might understand it structurally: Those factors that are associated with higher entrepreneurial rates carry over from year to year. Second, we might understand it culturally, as many of the authors in Table 1 theorize: Once an entrepreneurial culture is established in a place, it becomes more culturally appropriate to take entrepreneurial risk [27].

Economic Variables

Prior research has also identified strong associations between firm creation and economic variables, including access to capital [9], industry diversity [24], interest rates, changes in technology, and the rate of business failures [11]. From this perspective, demographics—education levels, unemployment rates, income equality—become measure of labor market readiness, and the availability of local workers has been shown a predictor of entrepreneurial outcomes [8]. We included a wide range of economic variables in our analysis; The most important across all models include the unemployment rate. Not salient were hypothesized economic factors such as total employment, county GDP, patents, interest rates, and business density.

Understood through the lens of labor market economics, the absence of an association between total employment and firm creation stands in contrast to prior research, which suggests that low levels of unemployment make it less attractive for would-be entrepreneurs to start businesses and more difficult for them to hire employees [26]. More in line with previous research is the association between the number of local banks and firm creation: Internationally-focused research on firm creation across countries often includes variables regarding access to finance [10,14], though US-focused research has not. This may be in part because banking in the United States has become so consolidated that the importance of *local* banking institutions with a physical presence has been overlooked.

Two surprising results are the relatively low predictive power of patents and or business density on firm creation. Literature on patents suggests a strong set of links among patents, innovation and entrepreneurship [11]. But in two of our models, that relationship is significant and negative. This lines up with some recent scholarship suggesting that the United States is unusual in how much patents are concentrated in its large cities [66] and that patents are a less helpful proxy for innovation in rural areas than urban ones [67,68]. Future work might examine this more closely by decomposing patents into invention, design, and plants patents. Business density, too, has been shown by prior research to be associated with economic resilience [2]. But our results suggest that it is not greatly predictive of firm creation. Interpreting these two outcomes together, it may be that the agglomeration effects present in large cities may not be as powerful in urban areas, where more dedicated work is needed to induce spillover effects of innovation [69].

One variable receiving considerable attention across the country and in Texas specifically is access to broadband [21,70]. While perhaps of importance in areas like equitable access to health care and education, broadband access does not emerge in this data as predictive of firm creation. We should note here that broadband access data was only available for two years; this is absence of evidence, not clear evidence of absence.

Energy and Other Industry Variables

Recent scholarship has explored the relationship between the oil and gas industry, using oil production both as an instrumental variable [71] and an explanatory one [26], finding that oil and gas expansion is negatively associated with firm creation. In our analysis, we re-examined this relationship, along with two other energy industries (solar and wind) that have grown rapidly in Texas in the last twenty years, along with other sectors (manufacturing, farming, extraction, education, healthcare, and elderly care) that are of particular importance in many rural areas.

Of our industry variables, three emerged as most important: wind, oil, and healthcare. The negative association between oil production and firm creation in two of our parametric models is not surprising, given prior research suggesting that large extractive industries depress firm creation [26]. It may be that firms that spring up in support of that industry are outnumbered by the firms crowded out by higher wages in the oil industry. That oil, but not gas, is negatively associated requires some explanation. One possibility is that extraction of oil and gas in Texas are more properly considered two industries than one, with different value chains—something that makes practical sense given the global integration of oil markets as compared to the primarily domestic use of natural gas in the United States.

The relationship between wind energy and firm creation is clear, novel, and worthy of further study, especially in comparison with the absence of a relationship between solar energy and firm creation. Prior research has examined the positive economic impacts of specific wind energy projects [72], but to our knowledge this is the first test of the association between wind energy and entrepreneurship.

Comparing Predictors of Urban and Rural Entrepreneurship

In addition to the models above, which predict firm creation in rural counties, we ran a second set of models for non-rural counties. Table 7 compares these results. It includes the top fifteen predictive features in both rural and non-rural counties, according to our multiple-model variable importance rankings (holding aside the control variables for specific years). The list of factors that predict non-rural firm creation is materially different from those predicting non-rural entrepreneurship. Patents, local bank deposits, education levels, and natural gas production emerged as influential predictors of urban firm creation. The first three of these, at least, are well-studied in existing (and mostly urban-focused) scholarship on firm creation but did not emerge as important predictors of firm creation in rural areas.

Table 7. Comparing Urban and Rural Predictors of Firm Creation.

Variable	Rural Ranking [a]	Urban Ranking
New firms (prior year)	3	1
Population	6	10
Wind capacity	8	12
Industry size: healthcare	10	26
Oil production	11	20
Pop. aged 25-44 (%)	12	27
Pop. aged 65 and older (%)	13	46
Ethnic diversity	14	16
Unemployment rate	15	32
Social capital	16	49
Outmigration (%)	17	28
Banks	19	37
Immigration (%)	20	25

Oil play: Eagle Ford	21	35
Failed firms (prior year)	22	36
Income inequality	25	17
Bank deposits	29	5
Total Employment	32	2
Pop. college education (%)	33	11
2020 presidential vote differential (%)	34	22
Gas production	43	13
Patents	46	18
Federal Funds Rate	49	3
Industry size: extraction	51	19
Oil play: None	60	14

[a] Individual Year Variables Removed

Predictive in rural areas, but less so in urban areas are the size of the healthcare industry, oil production, age distribution, the unemployment rate, social capital, the number of local banks, and to a lesser degree in-migration and out-migration. Common to both are population size, the number of firms created in the previous year, wind capacity, and ethnic diversity.

Discussion

These results contribute to an overlapping set of conversations among both academics and practitioners of public policy. First, they contribute to research on rural entrepreneurship, by identifying a set of variables that merit deeper study (e.g. the size of the healthcare industry, age distribution, unemployment, social capital, ethnic diversity, the number of local banks, and the size of the wind and oil industries) and others that might not be as important as suggested by prior research primarily focused on entrepreneurship in urban areas (e.g. patents, education levels, and access to broadband). Second, they offer a roadmap for public policy scholars that might be interested in using machine learning in other policy disciplines. Third, they offer policymakers interested in rural entrepreneurship a different set of tools for initially approaching policy problems than do traditional econometric models. Fourth, in the process they suggest a different way for policymakers to interface with academics on complex policy problems where tightly identifying causal mechanisms may be elusive or even unnecessary.

In reading each of the sections below, it is important to consider how and whether the results from Texas are generalizable to another context. In some ways, Texas makes up a reasonable starting point for studying the United States as a whole, in that it makes up nearly a tenth of its population and economic output; many of the dynamics present in the broader American economy are represented or even driven by Texas. But Texas is unique in many ways, including that its economy grew throughout most of the Great Recession, thanks in large part due to its hydraulic fracturing boom, which occurred during the period under study.

What is more generalizable than the specific results are the methods we propose that researchers—and more importantly, policymakers—can use to identify where to focus their limited attention. Researchers and policymakers in other geographies will want to add other geographically unique parameters to these models, to test local hypotheses about what might contribute to economic growth in that area. In Texas, for example, boosters of solar panels might claim that installation of solar panels will lead to greater economic and job growth. That feature did not prove predictive here, but it might in another geography.

Implications for Rural Entrepreneurship Research

Existing research on rural entrepreneurship is epistemologically and empirically disjointed. That is not a surprise on an issue as complex as the creation of new firms. One logically sound approach to such a complex issue is to break it into smaller, model-able parts. This approach has led researchers to clarify on the causal relationship between some variables and firm creation. But it has also led to an econometric version of the parable of multiple blindfolded investigators attempting to describe the proverbial elephant. A full, clear description of a single feature of an elephant may get us a little closer to describing the whole beast, but it is hard to know that we have isolated the most useful piece of information.

For research on entrepreneurial determinants, a machine learning-driven approach offers an avenue for us to take a step back from a complex problem and observe its multiple theoretical parts *empirically*, identifying which facets merit greater attention. In the case of rural entrepreneurship, those factors include the age distribution, ethnic diversity, migration patterns and social capital of a rural population; specific industries, such as oil, wind, healthcare, and local banking; and some economic variables, such as the unemployment rate. It may also reveal which features might have gotten too much attention, either because of political palatability (such as access to broadband) or because existing research, focused on urban areas, focuses on factors (such as patents) that fail to translate into rural contexts.

Implications for Rural Entrepreneurship Policy

These results can help policymakers in two ways. First, they can help policymakers base decisions on better predictions of what kind of firm creation to expect in their rural counties and states. Second, they can help policymakers identify what factors should get more or less time on the research and policy agenda. In many of these cases, a direct policy may not be possible—a county cannot grow its population by fiat, for example. But it can work together, as some small towns across the U.S. have, to create enough linkages with other nearby areas to operate as a bloc, perhaps mimicking some of the advantages of larger populations.

In other areas, this research suggests other potential levers that rural policymakers might want to examine more closely, including the number of local banks; attracting younger and more racially diverse workforces; investing more in healthcare infrastructure; and (where geographically feasible) exploring wind energy production, for example. It should be reiterated here that this research establishes predictive relationships, not causal ones: It can help us prioritize which policies to investigate more deeply and which to deprioritize. However, estimating the potential effects of a particular policy option requires a shift from examining prediction to establishing causation.

In other cases, these results may suggest levers that policymakers cannot pull. Counties in Southeast Texas, for example, might not be able to develop wind capacity. But there may be other major infrastructure projects whose contracting could be made to look more like those used in the wind industry, potentially creating conditions for firm creation.

The results also suggest that the importance of some pro-entrepreneurship policies proposed by lobbying groups and think tanks, such as greater access to broadband, is not clear when ranked against other predictive variables. And these results suggest that some well-studied variables shown to be important in urban areas, such as the number of patents, are less predictive of firm growth in rural areas. If the presence of variables provides a clue as to what policymakers should prioritize, the repeated absence of variables suggests variables they should consider deprioritizing.

Some of the variables that emerged in these models as important are just as complex as those of firm creation. How would a rural county increase the number of local banks, for example? This question, too, is surrounded by a fog of often-disconnected policy briefs and consultant recommendations; getting a clear answer of where to focus lends itself equally well to the type of multi-method machine learning we have conducted in this paper.

Implications for Public Policy Scholarship

The process laid out here offers a model for how policy scholars might approach other kinds of questions, under certain conditions. First, these methods are most helpful when scholars are concerned with comparing policy options rather than identifying the impact of a particular intervention. If an independent variable of interest has been identified, traditional regression methods may be more appropriate. But when dealing with policy problems as complex yet nascent as rural entrepreneurship, scholars often apply multiple theoretical approaches to a particular problem and seem to talk past each other. In such an example, the initial research goal may be to establish the *relative* importance of the independent variable to others.

Second, these methods are most useful under certain data conditions: Specifically, with large data sets, and those where the number of predictors (p) is much larger than the number of observations (n). Over the last couple of decades, many machine learning methods have been designed precisely to overcome this curse of dimensionality, which is expressed in shorthand as $p>>n$. Conversely, where there are a great many more observations than predictors than observations ($n>>p$), classical econometric models may be more appropriate depending on the nature of the data and may provide the necessary leverage for pointing to causal mechanisms. For $p>n$ and even $n>p$ (as in this dataset), there is less clear-cut guidance on the types of models to use. The same is true for complex datasets with many features (independent variables) in applied domains, such as rural entrepreneurship, that are still evolving and so do not have a firmly established set of features that are standard across all models. Under these circumstances, the analytical framework we present in this paper could serve well to advance understanding of the underlying data and to offer fruitful pointers for deeper study.

Lessons for Policymakers Interested in Complex Problems

For decades, policymakers looking to implement evidence-based policy have turned to research for answers. That research has turned most often to a set of linear regression models designed to identify as tightly as possible the causal relationship between two variables, often transformed into just the right shape for analysis. Even when those results are meaningful, they can only answer one type of question that policymakers might ask. Machine learning techniques offer a new and growing set of tools to help policymakers answer additional questions about what policy inputs they should prioritize given a particular policy outcome of interest. Answering such questions is especially important in the early phases during which the policy agenda is still taking shape before fully crystallizing. In instances where policymakers' task is to identify where to put scarce public resources to develop deeper and more robust understanding of potential solutions, or in scenario planning situations where prediction is the central task, predictive machine learning methods can prove useful additional tools to traditional causality-seeking approaches.

These models are not silver bullets, for at least two reasons. First, the added complexity of the models means that they are open to misinterpretation or intentional manipulation (or what might be called *disinterpretation*). [28] and [38] provide two recent discussions of these issues with the application of machine learning in public policy research. Second, machine learning models are just a tool, and when wielded without care have the potential to be discriminatory. In the human context, data is one manifestation of reality, created in a particular socio-political context, and as such is often shrouded with complex, idiosyncratic drivers. Who gets to interpret the data and models is inextricable from questions of power in that context. [73] and [74] offer discussions of these dangers and how they might be addressed.

This is not a new problem, however, nor one unique to the kind of computational methods we use in this paper. In fact, the potential for policy actors to abuse emerging methods was one inspiration for the multi-method approach we lay out here. Data is always collected by and filtered through the hands of humans embedded in institutions with their own biases. This multi-method approach has the potential to mitigate that in two ways: first, it provides a mechanism through which more data can be incorporated into analysis, lowering the possibility of omitted variable bias. Second, it makes it harder for a policy actor to choose a single model that supports their agenda. Third, it has the potential to spur cross-agency coordination on data collection, and especially for the variables that show up as important in limited variable analyses and our larger variable pool study. With these dangers and possibilities in mind, we interpret our and others' models humbly—and we encourage our readers to do the same, especially when our results line up with our prior beliefs and biases.

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