The Drivers of Far-Right Populism in Western Democracies

Dimitria Freitas* Patrick Zwerschke†

January 2024

Draft. Please do not cite or circulate without the author's permission.

The vote share of far-right, populist parties has almost doubled in Western countries in the last decade. This sudden increase led to a growing body of literature, especially in Economics and Political Science. Yet, due to disagreement among the disciplines, measurement, and identification issues, the main drivers of far-right populism remain unclear. It is also unclear if some of the determinants analyzed so far might have a non-linear relationship with the far-right, populist vote share. Against this backdrop, we create an extensive new dataset with over 26 determinants of far-right populism in over 30 countries between 1980 and 2019. We then employ Bayesian Model Averaging (BMA) to identify the most robust drivers of populism across all possible models. We move on to apply Bayesian Additive Regression Trees (BART) to determine non-linearities in those drivers' relationship with far-right populism. We find that while the trade-to-GDP ratio decreases far-right populism, imports from China increases it, however, only after a threshold value. Regarding the effect of immigration on far-right populism, we find that higher migrant stock decreases far-right populist vote share, confirming the contact hypothesis. In contrast, we find a threshold effect regarding refugee migration. Regarding culture, we find a strong positive relationship between religiosity and far-right populism, confirming the idea that religion forms a group identity and plays into the cards of populist rhetoric of the division of society into the moral people and the corrupt elite. Alternatively, it may reflect a predilection among religious voters for Manichean narratives, self-messianic messaging, and skepticism towards scientific discourse, all hallmarks of far-right populist rhetoric.

Keywords: Far-right Populism, Elections, Bayesian model averaging, Bayesian Additive Regression Trees, Core Model

*TU Dresden University of Technology, dimitria.freitas@tu-dresden.de

†University of Konstanz and Center of Public and International Economics, TU Dresden, patrick.zwerschke@uni-konstanz.de

1. Introduction

In recent years, the rise of far-right populist movements and parties challenging the foundations of liberal democracy has been observed in many Western democracies. Especially far-right populism, as defined by Mudde (2004a), has tripled in Europe since the 1990s (Rooduijn et al. 2023a). This rise of far-right populism and its aftermath has also attracted a growing empirical literature. Scholars in various disciplines, including economics and political science, analyze economic, cultural, and institutional factors that may explain the phenomenon. Section 1 contrast the increase in far-right populist votes on the one hand and the increasing number of related papers in economics since the 1980s on the other hand[1]. Although this surge has generated an interdisciplinary debate on the determinants of far-right populism, consensus on the primary drivers remains far. While economists see secular factors such as automation (Anelli, Colantone, and Stanig 2019) and globalization (Colantone and Stanig 2018a; Colantone and Stanig 2018b) as the main drivers, political scientists see rising crime (Dinas and Spanje 2011) and proportionality of the electoral system (Jackman and Volpert 1996) as more relevant.

A scarcity of theoretical models on far-right populism exacerbates the issue. Aronsson, Hetschko, and Schöb (2020) developed a behavioral economics model that links impatience to voters' appraisals of an income shock due to globalization associated with short-run costs and delayed gains. The model shows that impatient individuals may reject further globalization if they perceive the short-run costs to outweigh the long-run gains. Pástor and Veronesi (2021), on the other hand, focuses on cases where voters optimally elect a populist promising to end globalization in response to rising inequality in consumption. They found that countries with more inequality, higher financial development, and trade deficits are more vulnerable to populism. Sasso and Morelli (2021) explored the consequences of populism on bureaucrats' incentives by analyzing delegated policy-making. They found that populist leaders prefer loyalist bureaucrats over competent ones, which leads competent bureaucrats to engage in strategic policy-making. As valuable as these insights are, the contributions deliver very independent explanations unrelated to factors such as automation, moral values (Enke 2020), or communication and the new media (Campante, Durante, and Sobbrio 2018).

The literature also suffers from measurement and identification issues. Immigration is highly dependent on various factors, such as the criteria used to classify individuals as immigrants (foreign-born, own nationality, parent's nationality), whether we differentiate between transit and settlement, and whether we consider the real or the perceived number of migrants. Vertier, Viskanic, and Gamalerio 2023 also hint that there might be a threshold effect regarding the effect of refugee migration. The operationalization of immigration affects the results of studies, leading to different conclusions. It is difficult to identify cultural and identity factors such as social capital, morality, or perceived status due to their persistence over time and compositional complexity. In mature literature, studies often estimate a reference or core model. This model consists of the most important explanatory variables and qualitatively yields the same results in every study. This ensures that a particular data sample does not drive results and that omitted variable bias is unlikely to be a serious threat. If a newly proposed driver shows a meaningful effect when added to the core model in a study, readers of this study know that the reported effect is not an idiosyncratic finding due to a selective choice of control variables. Due to the high model uncertainty outlined above, this is not feasible in the literature on far-right populism.

This study seeks to demystify the underlying forces of far-right populism by constructing a comprehensive dataset encompassing 26 potential determinants across over 30 countries from 1980

[1]Although researchers started focusing more on populism in 2010, 2014 marks a changing point in the literature, just before the election of Donald Trump in the US and the referendum to leave the European Union in the United Kingdom.

to 2019. We examined the data in over 350 empirical papers covered by two extensive surveys by Guriev and Papaioannou 2022; Amengay and Stockemer 2019. We systematically evaluate these determinants using Bayesian Model Averaging (BMA) to find the most robust predictors within all possible model configurations. Furthermore, we deploy Bayesian Additive Regression Trees (BART) to explore potential non-linear relationships between these determinants and right-wing populist vote shares. Our findings indicate that while a higher trade-to-GDP ratio decreases far-right populism, imports from China seem to increase far-right vote shares, but only after a certain threshold. In terms of immigration, our results lend support to the contact hypothesis: larger migrant stocks correlate with lower populist vote shares. However, an intriguing threshold effect emerges in the context of refugee migration. Cultural factors also play a significant role; notably, increased religiosity aligns positively with right-wing populism. This could be attributed to the formation of group identities and the resonance of populist rhetoric, which often divides society into a 'moral populace' versus a 'corrupt elite'. Alternatively, it may reflect a predilection among religious voters for Manichean narratives, self-messianic messaging, and skepticism towards scientific discourse, all hallmarks of right-wing populist rhetoric.

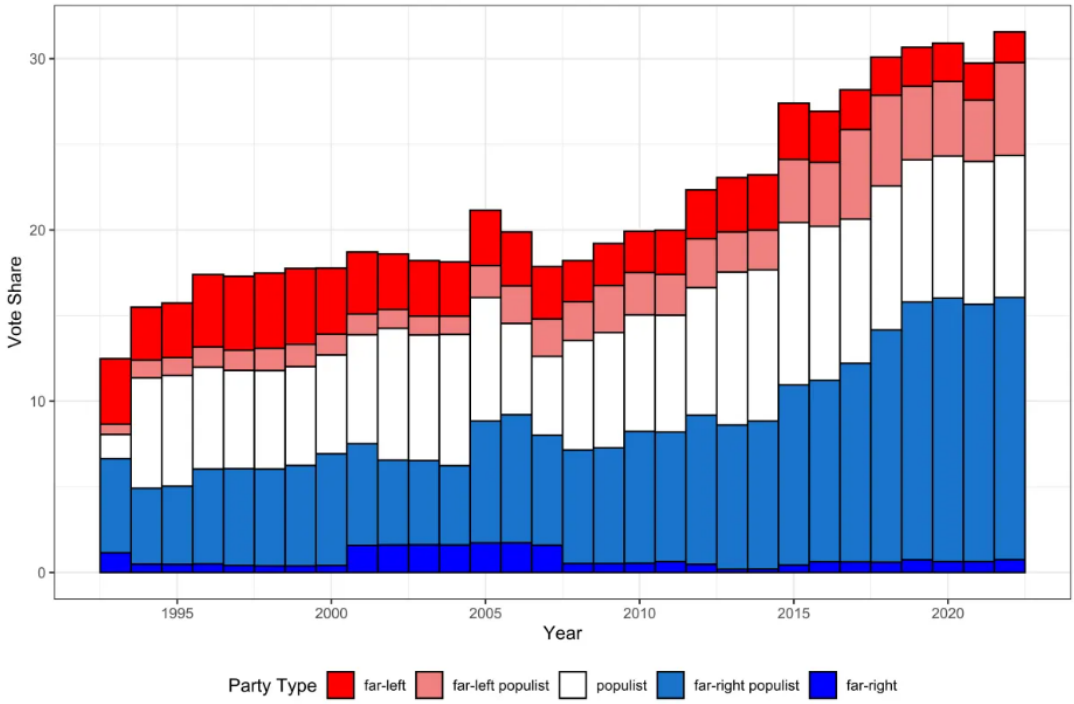
The paper is organized as follows. Firstly, Section 2 lays out the theoretical frameworks in which we embed our study. Next, Section 3 provides an overview of our data set. Section 4 details our methods. Section 5 presents our main results. Section 6 further elucidates the core findings resulting from our analysis. Finally, Section 7 concludes.

2. Theoretical Framework

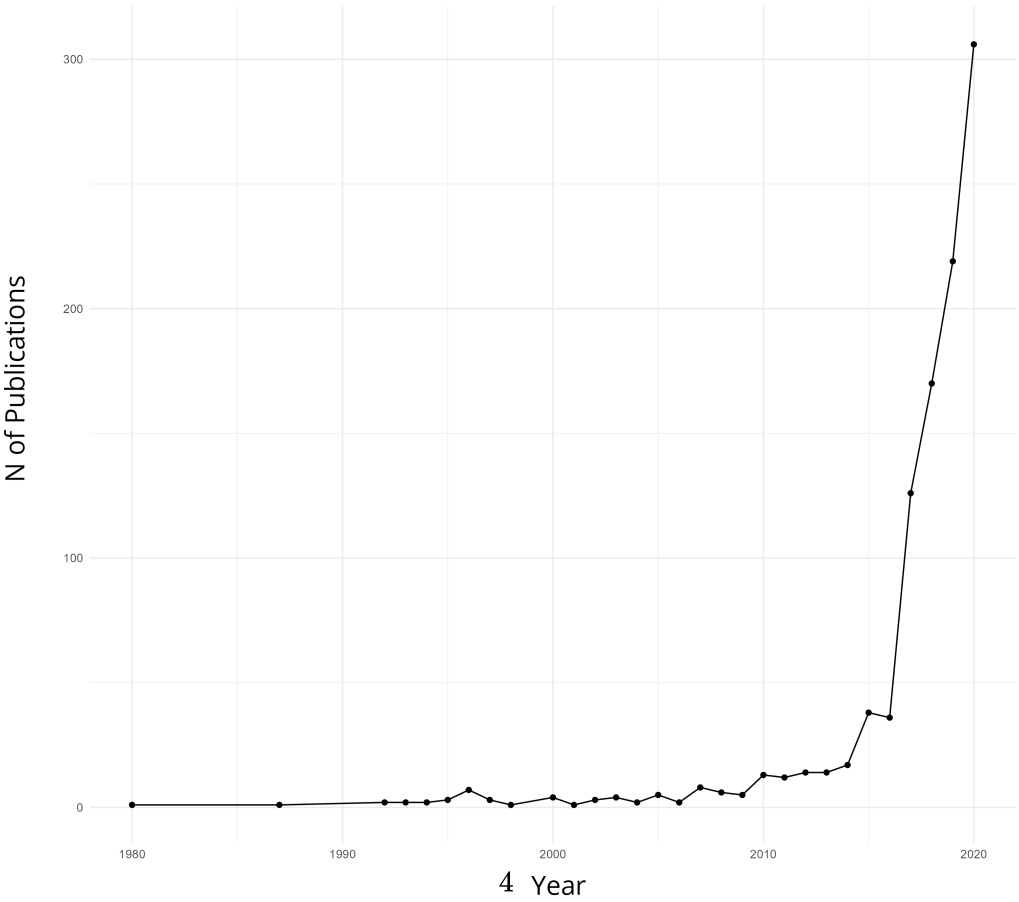
This chapter will give an overview of the underlying theoretical frameworks shaping the far-right populism debate. First, the very definition of far-right populism is a subject of a long and ongoing debate among scholars. Mudde (2004b) provides a least-common denominator by defining populism as an anti-elitist and anti-pluralist thin-centered ideology. According to him, populists see society in two homogeneous and antagonistic groups: 'the pure people' and the 'corrupt elite'. Populism prioritizes the moral superiority of the 'people' over the 'elites' rather than socioeconomic priorities. This view implies conflict with liberal democracy, as pluralism and the protection of minorities and diverse opinions are incompatible with this ideology. However, as a thin-centered ideology, it doesn't define who this homogeneous group of pure people is and who exactly the elites are. Far-right and far-left parties and politicians fill these gaps in different ways.

According to Mudde 2007, far-right parties are driven by nativism when defining who the 'pure people' are. Nativism is an ideology that holds that states should be inhabited exclusively by members of the native group and that non-native elements are fundamentally threatening to the homogenous nation-state. And any threats to the ordered society should be severely punished (authoritarianism)[2]. In contrast, the far-left rejects contemporaneous capitalism and its winners

[2] In addition to Mudde's definition, other scholars have identified authoritarianism, nativism, and identity politics as add-ons or special cases of far-right populism. As defined by Müller (2016), identity politics defines the "real" people based on race, ethnicity, religion, or citizenship. In contrast, as described by Eichengreen (2018) and Norris and Inglehart (2019), authoritarianism involves weakening checks and balances on the executive, attacks on minorities, and violence. It comprises two sets of ideas: rhetorical language and governing style that challenge the authority of establishment elites, tough security against threats from outsiders, xenophobic nationalism, strict adherence to conventional moral norms, and intolerance of multiculturalism. Taking this into account, the existence of different versions of populism implies that different determinants may lead to the emergence of different kinds of populism. However, there is currently very little evidence on this topic, and it is outside the scope of this paper.



(a) Vote shares of (1) far-left, (2) far-left populist, (3) populist, (4) far-right populist, and (5) far-right parties in 31 European countries, weighted by population size. Source: popu-list.org.



(b) Publications related to far-right Populism in Economics from 1980-2020. Papers that either have the word "Populism" in their title or as a designated topic in their abstract. Own illustration based on Web of Science data.

(the elite). They see economic inequality as the basis of existing political and social structures and call for redistributing resources (March 2012).

Another significant debate in the study of populism concerns its temporal dimension. Scholars are yet to reach a consensus on whether populism is caused by long-term, secular economic factors, such as the rise of automation or globalization, or short-term factors, such as crises and their aftermath, like post-crisis austerity or the rise in unemployment. The issues around the role of unemployment have some controversies of their own. The 'economic hardship breeds extremism hypothesis' argues that people experiencing economic difficulties will become more radical in their political preferences. In contrast, the 'people may turn (back) to the more established and experienced mainstream parties in times of economic uncertainty' or rally around the flag hypothesis suggests the opposite. Also, the role of material affluence or GDP in relation to populism is unclear. The 'losers of modernization hypothesis' suggests that regions experiencing economic deprivation should support radical right parties more, but there is a contesting theory. The concepts of welfare chauvinism and the welfare state paradox provide additional insights into the rise of populism in wealthy countries. While the welfare state paradox describes seemingly contradictory outcomes that can arise when a government implements policies and programs to support the well-being and economic security of its citizens, like dependency on welfare benefits and disincentives to work, welfare chauvinism describes the belief that welfare benefits should be reserved for native citizens while restricting or excluding immigrants' access. These ideas reveal how welfare policies' unintended consequences can fuel social divisions and perceived unfairness, which populist movements exploit. Populist leaders address grievances from the welfare state paradox, such as dependency and fiscal strains, by promising system reforms. Welfare chauvinism, meanwhile, resonates with populist rhetoric emphasizing native-born citizens' protection and excluding immigrants from benefits. Thus, the relationship between populism and economic factors is more nuanced, with welfare policies significantly shaping populist sentiment (see Greve 2019 for a detailed discussion).

The probably most crucial discourse within the populism literature concerns the relative significance of economic and cultural factors in shaping the allure of populism. Some scholars assert that economic factors, such as structural change and economic insecurity, are the primary drivers of populism. Autor et al. (2020) conclude that since China joined the WTO in 2000, The U.S. suffered from an import shock leading to job displacement and declining wages in the manufacturing sector. Since manufacturing industries agglomerate in the American mid-West, these regions suffered the most, leading voters to vote for a populist, far-right candidate in the 45. U.S. Presidential Elections. Other studies observe a similar effect of trade on far-right, populist voting in other high-wage countries. See Colantone and Stanig (2018b) for an overview of Western European countries. According to recent papers by Gozgor (2022) and Guiso et al. (2021), economic insecurity drives voters to far-right populist parties. The economic factors perspective generally maintains that populist movements emerge when substantial portions of the population feel economically threatened and blame the elites or incumbent governments for their fate. See Colantone and Stanig (2018a) for an example on scapegoating and Brexit. On the other hand, other scholars contend that cultural factors, such as national identity and conservative moral values, are the critical determinants of populism. According to this viewpoint, populist movements arise when large population segments feel threatened by cultural changes. Gidron and Hall (2017) find that far-right populism is most successful among Western white men. According to the authors, they fear a decline in their subjective social status because of relative improvements in the perceived status of other groups, for example, women and racial minorities. Nevertheless, other scholars propose that the interplay between economics and culture in determining populism is far more intricate than a simple dichotomy. Instead, they suggest that economic and cultural factors interact in context-specific ways. For instance, some scholars posit that economic insecurity may cause cultural anxiety and opposition to immigration (Margalit 2019). In contrast, others propose that cultural resentment may arise in response to economic globalization and the perceived weakening of national sovereignty (Algan et al. 2017). However, there is no clear consensus on the direction or magnitude of these effects.

3. Data

Our data set consists of 30 OECD countries and covers up to 26 alternative specifications and control variables, averaging over 21 potential determinants. The sample is drawn from over ten different sources, including the Organisation for Economic Co-operation and Development (OECD), World Bank Data, International Values Survey (IVS), European Social Survey (ESS), EU KLEMS database, International Federation of Robotics (IFR), Swiss Economic Institute (KOF), and the World Integrated Trade Solution (WITS) Data Base.

Our goal in compiling the data was to include as many variables used in the literature on the determinants of populism as possible while covering the longest possible period. However, we faced a fundamental trade-off between the number of independent variables and data availability. Consequently, we decided to use two primary dataset covering the period from 2000 to 2019 and include the other dataset from 1980 and 1990 onwards as controls. However, we also include controls with data including shorter periods, more variables, and longer periods but fewer variables in our analysis.

To measure populism, we utilize vote shares for far-right populist parties, as vote shares for far-right populist parties are a more consistent and, more importantly, more comparable indicator across various countries and periods compared to other measures of populism that consider, for example, culturally dependent personal or political far-right attitudes. To operationalize Mudde's far-right, populist definition, we turn to the PopuList data set (Rooduijn et al. 2023b), considered a reliable and comprehensive source of information on both far-left and far-right populist parties in Europe. The PopuList data set covers 31 European countries from 1989 to 2020 and classifies parties into four categories: populist radical right, populist radical left, other populists, and non-populist. The classification is based on expert assessments and secondary literature and includes even small parties with less than 2% of the votes but have been represented in national parliaments.

Table 3, Table 4, and Table 5 in the appendix presents a comprehensive statistical overview of all socio-economic and political variables across observations. The economic indicators include Log GDP per Capita, Consumer Price Index (CPI), government revenue and expenditure as a percentage of GDP, trade-to-GDP ratio, unemployment rate, and R&D expenditure as a percentage of GDP. It also includes infrastructure spending (in absolute terms and as a percentage of GDP), manufacturing employment percentage, crime rate per 100k, robot stock, new robots, and imports from China (logarithmic scale). Technology penetration is represented through Log ICT Capital and mobile and broadband subscriptions per 100 people. Political variables encompass the number of parties in parliament, voter turnout, average district magnitude, and the Democracy Index. Culture & Identity Variables include social and cultural factors such as racism towards different races and foreigners, trust percentage, authoritarian personality index, financial satisfaction percentage, religiosity percentage, and migrant stock percentage. It also covers the logarithmic number of refugees and mobile and broadband subscriptions per 100 people.

4. Method

As the number of candidate variables for inclusion in empirical models steadily increases, it is unclear which covariates should be included in the linear regression model. A too large model with too many predictors might result in over-fitting the data and, thus, instable predictions. To not rely on a few manually selected models, we focus on two special cases. First, we report the results from the full model, considering all covariates. Second, we use Bayesian model averaging (BMA, (Bartels 1997; Adrian E Raftery 1995; Adrian E. Raftery, Madigan, and Hoeting 1997)) and report an average model.

The basic principle behind model averaging is intuitive. Assume some theory explains the outcome y, the vote share of far-right parties, by two factors, x_1 and x_2. As always, the theory can be expected to only partially explain the variation in y because of other confounding factors influencing the outcome. Alternative theories might propose $x_3, \ldots, x_{10}$ to influence y, e.g. On the one hand, ignoring any variable might yield an omitted variable bias. On the other hand, including irrelevant variables can be challenging in case of small samples, or small to median effects - to put it slightly oversimplified: in a low signal-to-noise ratio setting. Which specification should be chosen? The additional controls alone give rise to $2^8 = 256$ possible specifications. Presenting an averaged estimate across all models is a very efficient way to consider all models without having to present them individually.[3] Moreover, stark changes in coefficient estimates across models will inflate the variance of the averaged estimate and stabilizes predictions.[4]

Within BMA, the importance of a particular covariate is assessed by its posterior inclusion probability (PIP). For the covariate indexed by k, PIP_k is defined as the sum of the (posterior) probabilities of all models M_s, which include the regressor:

$$\mathrm{PIP}_k = P\left(\beta_k \neq 0 | Y\right) = \sum_{\beta_k \neq 0} P(M_s|Y), \tag{1}$$

where β_k denotes the corresponding regression coefficient. Thus, if PIP_k approaches unity, results point to an essential role of this variable as the probabilities of all models omitting it are virtually zero.[5][6]

The median probability model (MPM, barbieri2004optimal) is our main reference. Thus, covariates with a PIP ≥ 0.5 are considered robust covariates. We also refer to conventional rules of thumb thresholds to provide some guidelines that ease judging the relevance of the variables qualitatively. Covariates are considered weakly / positively / strongly / decisively robust, if their

[3] To be more precise, a BMA estimate is the model-fit-weighted average of the single model estimates. The influence of a single model on the overall result is thus proportional to its fit to the data relative to competing specifications.

[4] Moreover, Porwal and Adrian E Raftery (2022) find that out of 21 methods, which deal with the variable selection question, BMA performs best. Jacob M. Montgomery and Nyhan (2010) and Steel (2020) provide excellent reviews for the wide applicability of Bayesian model averaging. See also Jiang and Li (2019) for a recent discussion of the oracle properties of BMA. For a more formal treatment of BMA see the online appendix.

[5] Note that all model probabilities sum to one.

[6] Evaluating such a large model space exhaustively is computationally infeasible (but also unnecessary). Therefore, we apply birth/death Markov Chain Monte Carlo sampling to draw 10 million times from the model space. 1 million draws serve as burn-in. The posterior inference is based on the top 10,000 models. Although most variables have excellent coverage, a few also show missing values. To avoid loss of information, we use the Amelia II package (Honaker, King, Blackwell, et al. 2011) for imputation. To ensure uncertainty is reasonably captured, we consider five imputed data sets in the following and aggregate the results according to Rubin's rules (Wood, White, and Royston 2008; Yang, Belin, and Boscardin 2005). Unfortunately, however, this prevents us from presenting posterior distributions.

PIPs exceed 0.5 / 0.75 / 0.95 / 0.99 (Eicher, Helfman, and Lenkoski 2012; Jeffreys 1998; Kass and Adrian E Raftery 1995; Adrian E Raftery 1995; Robert, Chopin, Rousseau, et al. 2009).

As discussed in the literature section above, most recently, authors increasingly start speculating about the functional form of various relationships. We therefore expect non-parametric estimates to reveal novel insights and yield better predictive performance, as they can consider non-linearities and interactions. We therefore consider another, nonlinear estimator, Bayesian additive regression trees (Chipman, George, and R. E. McCulloch 2010; Hill, Linero, and Murray 2020).[7] BART also allows for nonparametric statistical inference, which separates it from many other ensemble tree-based methods.

The general idea of BART is to approximate the unknown data generating process by a sum-of-trees model.

$$f(\boldsymbol{X}) + \boldsymbol{\varepsilon} \approx h(\boldsymbol{X}) = \mathcal{T}_1^{\mathcal{M}}(\boldsymbol{X}) + \cdots + \mathcal{T}_m^{\mathcal{M}}(\boldsymbol{X}) + \boldsymbol{\varepsilon}, \qquad \text{with } \boldsymbol{\varepsilon} \sim N(\boldsymbol{0}, \sigma^2 \boldsymbol{I}_n) \tag{2}$$

In a classic regression framework $f(\boldsymbol{X})$ is assumed to be linear in the regression parameters, but BART does not make such an assumption. Instead, BART approximates the unknown function by a sum-of-trees model $\sum_{t=1}^{m} \mathcal{T}_t^{\mathcal{M}}(\boldsymbol{X}) = \mathcal{T}_1^{\mathcal{M}}(\boldsymbol{X}) + \cdots + \mathcal{T}_m^{\mathcal{M}}(\boldsymbol{X})$. The sum-of-tree model consists of many shallow and simple trees. This also makes the estimation of smooth relationships easier.

All trees are grown sequentially according to the following procedure

1. Grow a tree that explains only little on all data.
2. Sequentially grow further trees on the (partial) residuals of all other tree(s), to improve the fit of the sum-of-trees model.
3. Cycle over all trees for a chosen number of iterations, make proposals to change the tree structure to improve the fit of the sum-of-trees model (update).

Trees are fit (re)iteratively by holding other already grown trees constant. This way BART tries to gradually improve the overall fit of the model and quantify uncertainty.[8]

As BART is a nonparametric procedure, it is not possible to present a classical single point estimate. Partial dependence functions (J. H. Friedman 2001; Hastie, Tibshirani, and J. Friedman 2009) will be plotted in the following, instead. To summarize the marginal effect of any subset $\boldsymbol{X}_S$ of all predictors $\boldsymbol{X} = [\boldsymbol{X}_S, \boldsymbol{X}_{-S}]$, which was used to approximate $f(\boldsymbol{X})$, the partial or average dependence of $f(\boldsymbol{X})$ on $\boldsymbol{X}_S$ can be computed, which is defined by $f_S(\boldsymbol{X}_S) = E_{\boldsymbol{X}_{-S}}[f(\boldsymbol{X}_S, \boldsymbol{X}_{-S})]$. Assuming $\boldsymbol{X}_S$ consists of a single variable, $f_S(\boldsymbol{X}_S)$ is the marginal average of f for any given value of $\boldsymbol{X}_S$ after having controlled for the average effects of all variables $\boldsymbol{X}_{-S}$. In other words,

[7] For a gentle introduction into the concept of tree based models in general and BART in particular, see James et al. (2021). The advantages of tree-based methods in general are discussed with increasing frequency (Athey and Imbens 2017; Jacob M Montgomery and Olivella 2018; Mullainathan and Spiess 2017; Varian 2014). Previously, BART already successfully predicted election outcomes (Kennedy, Wojcik, and Lazer 2017), outperforming alternative approaches.

[8] Note that this explanation made a couple of simplifications. BART actually already starts with as many trees as chosen, but they all consist of a singe root node and together they yield the mean of the response as a prediction. As all Bayesian methods, BART is regulated by a set of priors. Strong shrinkage, as recommended by Chipman, George, and R. E. McCulloch (2010) and Sparapani, Spanbauer, and R. McCulloch (2021), prevents single trees to dominate the entire sum-of-trees model and avoids overfitting. The key in sampling from the posterior is a special form of Bayesian backfitting "to cycle over and over through the m trees" and make proposals to change the tree structure (Chipman, George, and R. E. McCulloch 2010, p. 272). This sampling procedure separates Bayesian tree methods from other popular approaches, which make no proposals to change — possibly improve — the trees and quantify uncertainty. BART was fitted with the recommended default priors, which are known to work well.

the partial dependence function for a single predictor gives the value of f that one would expect given a specific value of $\boldsymbol{X}_S$ after having controlled for all other influences $\boldsymbol{X}_{-S}$. They can be calculated by averaging over all observed values of $\boldsymbol{X}_{-S}$ while holding $\boldsymbol{X}_S$ constant:

$$\bar{f}_S(\boldsymbol{X}_S) = \frac{1}{N} \sum_{i=1}^{N} \hat{f}(\boldsymbol{X}_S, \boldsymbol{x}_{(i)-S}), \tag{3}$$

where $\hat{f}$ is the estimated approximation of f, N is the number of observations and $\boldsymbol{x}_{(i)-S}$ are the realizations of the joint values of $\boldsymbol{X}_{-S}$ that occur in the data set. Because BART estimates posterior densities, it is possible to calculate not only a point estimate (posterior mean) but also uncertainty intervals to conduct inference.

5. Results

5.1. Model Averaging

Table 1 displays benchmark panel regressions, and BMA results for the main samples from 1990-2019 and 2000-2019. Effectively, the BMA results model the fit weighted averages across all possible models and, therefore, the most comprehensive robustness check possible. Theoretically, the first variables, with a PIP of one, are the enforced region and decade effects. Their PIP is unity by design.[9] We also find religiosity and the trade-to-GDP ratio to be decisively robust. The BMA analysis also reveals positive evidence for the relationship between populism and unemployment and turnout. Afterward, PIP values drop quickly, with only refugee migration and migrant stock still at least being weakly associated with populist vote shares. Industrial robots, which measure automation, and imports from China are just below the common median probability model threshold of robustness (0.5).

Surprisingly, some widely discussed crisis measures, such as economic growth, inflation, crime, and austerity (government expenditure), are not robustly associated with the dependent variable. Similarly, fractionalization (number of parties), social capital (personal trust), and structural change (manufacturing employment) do not significantly predict far-right populist voting. Ultimately, our BMA analysis only partly confirms the panel regression results accentuating the negative relationship between unemployment and far-right populist voting, but mainly shifts the focus towards the significance of other factors such as the democracy index, the trade-to-GDP ratio, and especially religiosity.

5.2. Non-parametric Results

The previous regressions showed that only few variables correlate robustly with the dependent variable. As more recent publications cast doubt on the linearity and independence assumptions usually applied, we expect more covariates to be relevant in the non-parametric setting, together with an increased model fit. We apply estimator-independent tests and measures to compare the full linear model, BMA, and BART in the following.[10]

[9]This makes it impossible to judge the relevance of these variables but ensures interpretability across models and sensible averaging. Figure **??** in the appendix shows the best 100 models from the BMA exercise, together with the sign stability of the posterior means.

[10]As most non-parametric methods, BART relies on many tuning-parameters, which must be chosen. While it is generally suggested to set all of them (model priors) to their default values, one parameter, the number of trees, does not have a general default. To find the most appropriate number of trees for the model, we apply 10-fold cross-validation. We repeat this 10 times to ensure our results do not

Dependent Var.:	r90 rw_pop_vote	r00 rw_pop_vote	r90c rw_pop_vote	r00c rw_pop_vote	rbma_UIP_1990_region rw_pop_vote	rbma_UIP_2000_region rw_pop_vote	rbma_UIP_1990_country rw_pop_vote	rbma_UIP_2000_country rw_pop_vote
gdp_per_cap	5.1 (5.4)	-5.2 (16.3)	11.8 (12.4)	-13.5 (8.0)	**3.26 (3.85 / 0.50)**	-0.04 (2.78 / 0.13)	3.97 (5.07 / 0.42)	-0.40 (3.25 / 0.06)
cpi_annual_pc	0.005 (0.003)	0.11 (0.11)	0.0004 (0.004)	0.25** (0.12)	0.00 (0.00 / 0.06)	0.01 (0.06 / 0.07)	-0.00 (0.00 / 0.01)	0.17 (0.20 / 0.47)
gdp_per_cap_gr	0.12 (0.10)	0.11 (0.17)	0.10 (0.09)	0.009 (0.21)	0.01 (0.04 / 0.07)	0.01 (0.06 / 0.06)	0.01 (0.04 / 0.04)	0.00 (0.03 / 0.02)
gov_exp_to_GDP	0.07 (0.12)	0.07 (0.09)	0.02 (0.08)	0.21* (0.11)	0.00 (0.02 / 0.08)	0.00 (0.03 / 0.06)	-0.00 (0.01 / 0.02)	0.00 (0.02 / 0.02)
trade_to_gdp	-0.06** (0.02)	-0.07 (0.04)	-0.04 (0.05)	0.08 (0.07)	**-0.06 (0.02 / 0.99)**	**-0.07 (0.03 / 0.94)**	-0.00 (0.00 / 0.02)	0.00 (0.01 / 0.02)
dem_index	0.17 (0.11)	0.25 (0.23)	-0.13 (0.19)	-0.11 (0.23)	**0.16 (0.08 / 0.89)**	**0.20 (0.09 / 0.90)**	-0.00 (0.01 / 0.01)	-0.00 (0.02 / 0.02)
racism_foreign	-0.12* (0.06)	-0.11 (0.10)	-0.06 (0.18)	0.09 (0.20)	-0.01 (0.05 / 0.12)	-0.01 (0.06 / 0.08)	-0.00 (0.01 / 0.01)	0.00 (0.03 / 0.02)
pers_trust	0.01 (0.04)	0.18** (0.06)	0.21* (0.12)	0.02 (0.27)	0.00 (0.02 / 0.07)	0.04 (0.09 / 0.24)	0.00 (0.02 / 0.02)	0.00 (0.03 / 0.02)
refugeem	0.72 (0.46)	0.24 (0.79)	0.43 (0.99)	-0.74 (0.89)	0.32 (0.45 / 0.40)	0.18 (0.44 / 0.20)	0.04 (0.20 / 0.05)	-0.01 (0.12 / 0.02)
religiosity	2.1*** (0.24)	2.7*** (0.56)	0.90 (1.4)	-5.6 (3.3)	**2.15 (0.49 / 1.00)**	**2.63 (0.77 / 0.98)**	0.00 (0.21 / 0.01)	-0.18 (1.05 / 0.04)
n_party	0.02 (0.29)	0.03 (0.69)	0.39 (0.33)	0.21 (0.29)	0.00 (0.07 / 0.06)	-0.00 (0.09 / 0.06)	0.02 (0.10 / 0.05)	0.01 (0.09 / 0.03)
turnout	0.16 (0.09)	0.20 (0.14)	0.17 (0.13)	0.11 (0.12)	**0.16 (0.07 / 0.91)**	**0.18 (0.12 / 0.77)**	**0.10 (0.09 / 0.57)**	0.02 (0.05 / 0.10)
manu	-0.0010 (0.15)	0.10 (0.22)	-0.21 (0.25)	-0.49 (0.44)	-0.00 (0.05 / 0.08)	-0.00 (0.07 / 0.07)	-0.00 (0.03 / 0.02)	-0.01 (0.09 / 0.03)
crime	0.16 (0.40)	0.16 (0.57)	1.5 (1.0)	1.5 (0.98)	-0.00 (0.09 / 0.06)	-0.03 (0.19 / 0.08)	0.12 (0.37 / 0.12)	0.32 (0.66 / 0.22)
unemp	-0.35* (0.17)	-0.49 (0.29)	-0.15 (0.27)	-0.86*** (0.27)	**-0.27 (0.20 / 0.72)**	**-0.25 (0.25 / 0.58)**	-0.08 (0.17 / 0.24)	-0.19 (0.25 / 0.44)
migrantstock	-0.33 (0.18)	-0.20 (0.34)	-0.60 (0.44)	-0.51 (0.44)	**-0.24 (0.20 / 0.65)**	-0.21 (0.25 / 0.49)	-0.02 (0.10 / 0.04)	-0.01 (0.07 / 0.02)
robot_stock_in_k	-0.008 (0.006)	-0.01 (0.008)	0.005 (0.004)	-0.004 (0.006)	-0.00 (0.00 / 0.45)	-0.00 (0.01 / 0.30)	0.00 (0.00 / 0.01)	-0.00 (0.00 / 0.02)
log_imp_from_ch		1.9 (2.8)		3.2* (1.7)		0.79 (0.94 / 0.49)		0.24 (0.74 / 0.12)
broad		0.03 (0.07)		-0.09 (0.11)		0.00 (0.03 / 0.07)		0.00 (0.01 / 0.02)
Fixed-Effects:								
region	Yes	Yes	No	No	Yes	Yes	No	No
decade	Yes	Yes	Yes	Yes	es	Yes	Yes	Yes
country	No	No	Yes	Yes	No	No	Yes	Yes
Observations	216	140	216	140	216	140	216	140
R2	4761	52075	66475	79194				
Within R2	35765	42957	17743	30116				

Table 1. Explaining populist vote share, full model (benchmark)

OLS: Clustered (region/country) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; BMA: Posterior SD and PIP in parentheses.

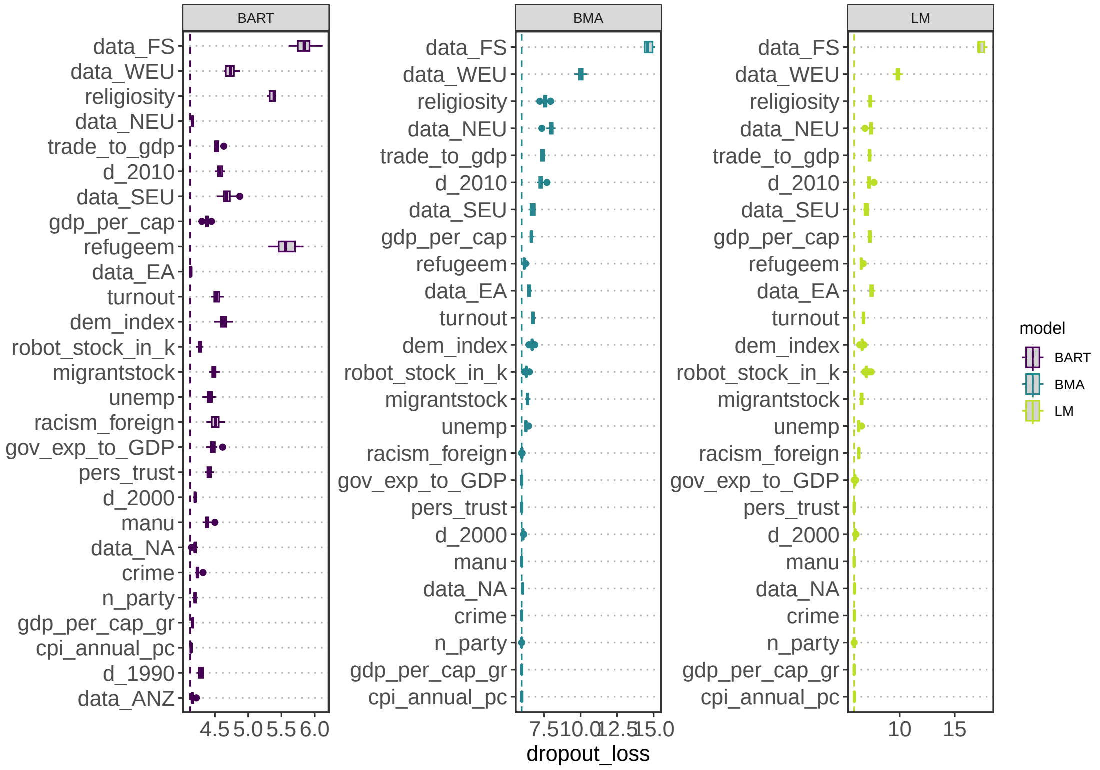


Figure 2. Permutation test based variable importance (dropout loss in RMSE) for 1990-2019 data.

First, we compare the Root Mean Squared Error (RMSE) of all three models to judge differences in overall performance. Second, we compare the dropout loss in RMSE for every variable to judge its relevance for the overall model performance. Figure 2 compares the RMSE and permutation variable importance of three estimators.

The dotted vertical line in each subfigure represents the RMSE of the actual model, fitted on the whole data set.[11] As can be seen, BART outperforms the other models. Its RMSE is only half as big as the RMSE from the BMA model, which in turn slightly outperforms the full linear model, as was to be expected. This difference suggests BART models the relationships best, and the remainder of the paper aims to show why.

5.2.1. Variable selection

A natural estimator-independent way to assess variable importance is to use a permutation test. This is, we take a variable 'out of the equation' and check the change in RMSE. Specifically, we

depend on the particular folds. For the BMA we vary the coefficient prior. For the linear model, no parameters need to be chosen. In the online appendix, we present the results from the cross-validation exercise and compare the performance of the different estimators.

[11]A RMSE value of 0 indicates that the model has perfectly predicted the values for the set of data. Thus, smaller is better.

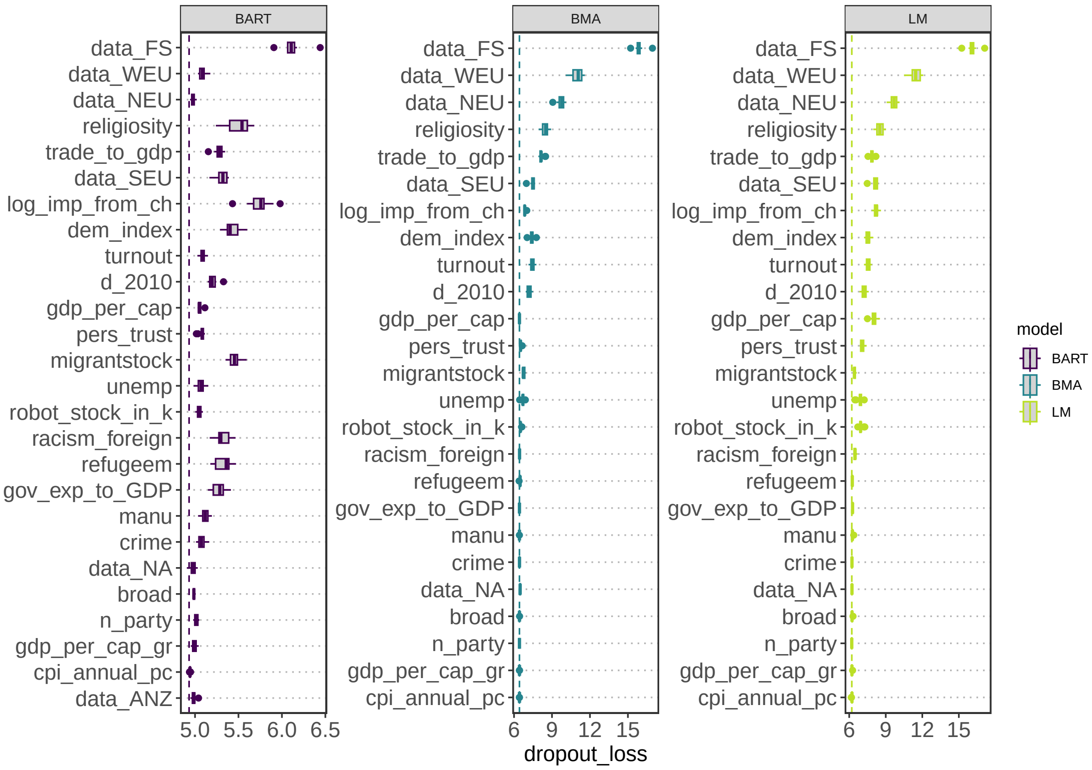


Figure 3. Permutation test based variable importance (dropout loss in RMSE) for 2000-2019 data.

permute the data column of every variable, one at a time, re-estimate the model, and compare the resulting RMSE with the RMSE of the model with the actual data. To avoid our results being driven by a particular permutation, we apply this procedure 25 times. A large increase in RMSE suggests a variable is important for prediction, and a small increase in RMSE suggests the variable of interest is unimportant.

As seen immediately, the permutation tests yield very similar results for the full linear model and the BMA, while BART differs significantly. Across all models, the dummy variable for Eastern European countries (data_FS) was the most important for predictive performance. RMSE roughly doubled for all models if the variable was permuted. The 2010 decade dummy also had a relevant influence across models. However, BART did not consider Northern Europe and Eastern Asia effects important in terms of predictive power, unlike BMA and the linear model. All methods concluded that the democracy index and religiosity were relevant for predictive performance and, to a lesser extent, the trade-to-GDP ratio.

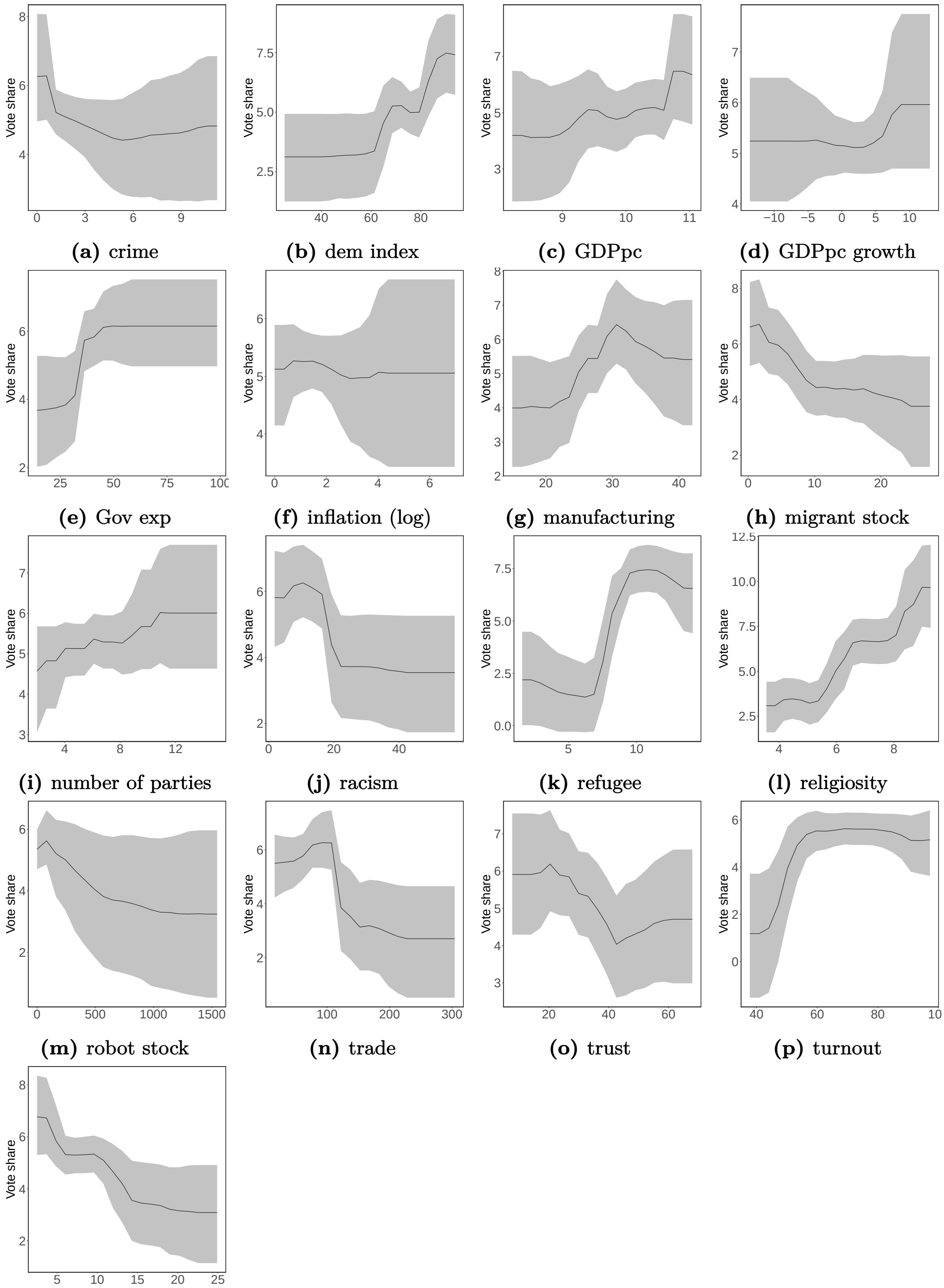
Interestingly, automation appeared to be significant in the full regression model. In the BMA, it already barely missed the robustness threshold. Concerning predictive performance, its relevance, especially for BART, seems to deteriorate even further. Automation does not seem to have any predictive power in the non-parametric model. On the other hand, BART assigned higher predictive power to personal trust, crime, and the manufacturing employment share than the other models.

In conclusion, BART outperforms BMA and the linear model regarding predictive power. Some variables appear relevant across models, but for BART, other variables appear more relevant than for the linear models. Our results indicate that regional effects play an important role in predictive performance, as do a surprisingly small number of covariates, such as the democracy index, religiosity, and the trade-to-GDP ratio. The ambiguous results regarding the predictive power of automation highlight the importance of exploring different estimation techniques and considering the potential impact of different covariates on the results.

5.2.2. Effects

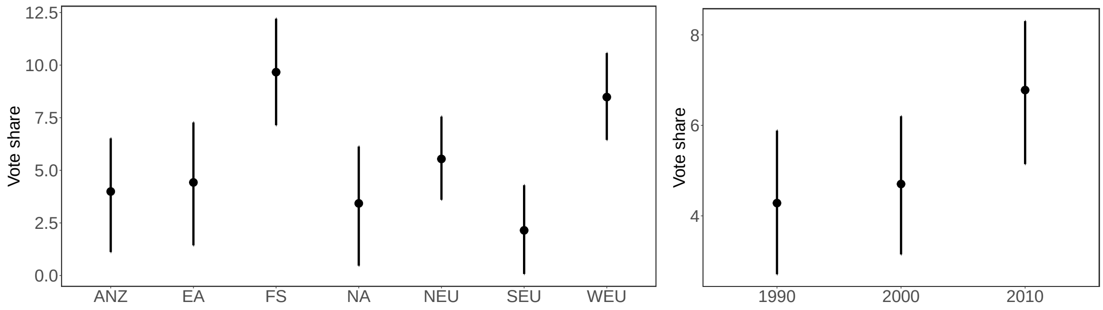
For nonlinear estimators, effects are commonly presented in the form of partial dependence plots, as described above. They represent the pointwise partial dependence of the outcome on a chosen explanatory variable, i.e., the total marginal effect at a specific point. Every vertical axis of the subfigures in figure 4 represent the model's predicted outcome for different values of a variable of interest after having accounted for the effects of all remaining variables (similar to a component-plus-residual plot for linear regressions). The depicted relationships reveal why BART selects different variables. While some relationships appear to be approximately linear, e.g., figure **??** and **??**, some effects are nonlinear. For example, the effect of manufacturing on the populist vote appears to be inverse-U shaped, the PDP of unemployment follows a round L, and trade, crime, and the effect of immigration seem to be best represented by a step function.[12] This explains why BART showed rather different results during the permutation test. BART can capture nonlinearities, which will be missed in linear models. A U-shaped relationship, for example, will show up as null-effect in a linear model. This ability of BART also reduces RMSE of the overall model and also yields different dropout-loss values. Table 2 summarizes the main differences and commonalities between the BART model and the full linear model. As can be seen, BART mainly coincides with the results from the linear model if the effect is indeed linear, but captures many more relationships, which are nonlinear in nature. The only exceptions are

[12]The sudden down-peak in the PDP of the democracy index should not be interpreted to strictly. Given the overall trend in the graph, this is more likely caused by an overly sensitive reaction of BART to a couple of outliers.



(a) crime **(b)** dem index **(c)** GDPpc **(d)** GDPpc growth **(e)** Gov exp **(f)** inflation (log) **(g)** manufacturing **(h)** migrant stock **(i)** number of parties **(j)** racism **(k)** refugee **(l)** religiosity **(m)** robot stock **(n)** trade **(o)** trust **(p)** turnout **(q)** unemployment

Figure 4. Partial dependence plots



(a) regions, PDP

(b) decades

Figure 5. Partial dependence plots of decade and regions

the number of parties and automation. In both cases, the linear model suggests a relationship which BART does not find (Figures **??** and **??**). This can have multiple reasons which cannot be tested. First, it is possible that given the rather moderate effect sizes, the data set is simply too small for BART to capture the effects. Meaning: The improvement in RMSE for making more splits is too small. Thus, it must be kept in mind, that nonparametric methods require more data to identify small effects compared to a conventional regression, if the effect is truly linear. Second, it might also be the case that the full regression results report a false-positive finding. BMA result, which consists of linear models, provides at least some evidence for this hypothesis, as both variables fail the median probability model. Hence, they are considered to be non-robust.

5.2.3. Interactions

Simple PDPs can only depict the total marginal effect of a variable. Thus, they might hide relevant interactions / heterogeneity. It is possible, for example, that the relevance of some variables cannot be seen in the PDP if their effect depends on another variable. To assess if this is the case, we calculate the H-statistic, as suggested by J. H. Friedman and Popescu (2008). In simplified terms, the H-statistic, ranging between 0 and 1, decomposes the partial dependence function into a main and an interaction effect and returns the interaction effect's share of the total effect.[13]

Figure 6 depicts the overall H-statistic for our model, which are very low across the board. The H-statistic of roughly 0.45 suggests that only 4.5% of the total effect of decade 2010 are due to interactions with other variables. Unfortunately, no formal test exists to evaluate the statistical relevance of the interactions, but such low values suggest fluctuations are most likely due to random variations in the ensemble structure. To make sure the H-statistic really accurately represents the relationships, also we calculated (centered) individual conditional expectation plots (ICE) for all variables (Goldstein et al. 2015). These disaggregate the partial dependence plots, which represent the average marginal effect, into individual effects at the level of the observations (also called ceteris paribus profiles). If interactions are present in the model, we should observe diverging patterns in the individual effects. For example, if the effect of religiosity is null prior 2010 but is strongly positive after 2010, we should observe horizontal lines for many ICE curves and steep curves for those observations post-2010. However, we do not find such patterns in any

[13]Greenwell, Boehmke, and McCarthy (2018) suggest a related approach, based on the flatness of two-dimensional partial dependence functions. As their approach is less well established, we present results for this approach in the appendix. The detected interactions are the same, in slightly different order.

Table 2. Comparing BART with the full linear model

1990-2019	linear model	BART
crime	/	- (↘→)
dem index	+***	+ (→↘)
GDP per capita	/	+ (↗)
Gov Expenditure	/	+ (↗→)
GDPpc growth	/	/ (→
inflation (log)	/	/ (→)
manu	/	+/- (↗↘)
migrants	-*	- (↘)
number of parties	+***	+ (↗)
Racism	/	- (→↘→)
refugees	+*	+ (→↗→)
religiosity	/	+ (↗)
robots	-***	- (↘)
Trade	/	- (→↘→)
Trust	/	- (→↘→)
turnout	/	+ (↗→)
unemployment	-***	- (↘)

Note: The number of stars reflects the significance level from the main regression; / indicates insignificance; blue / red indicates agreement / disagreement

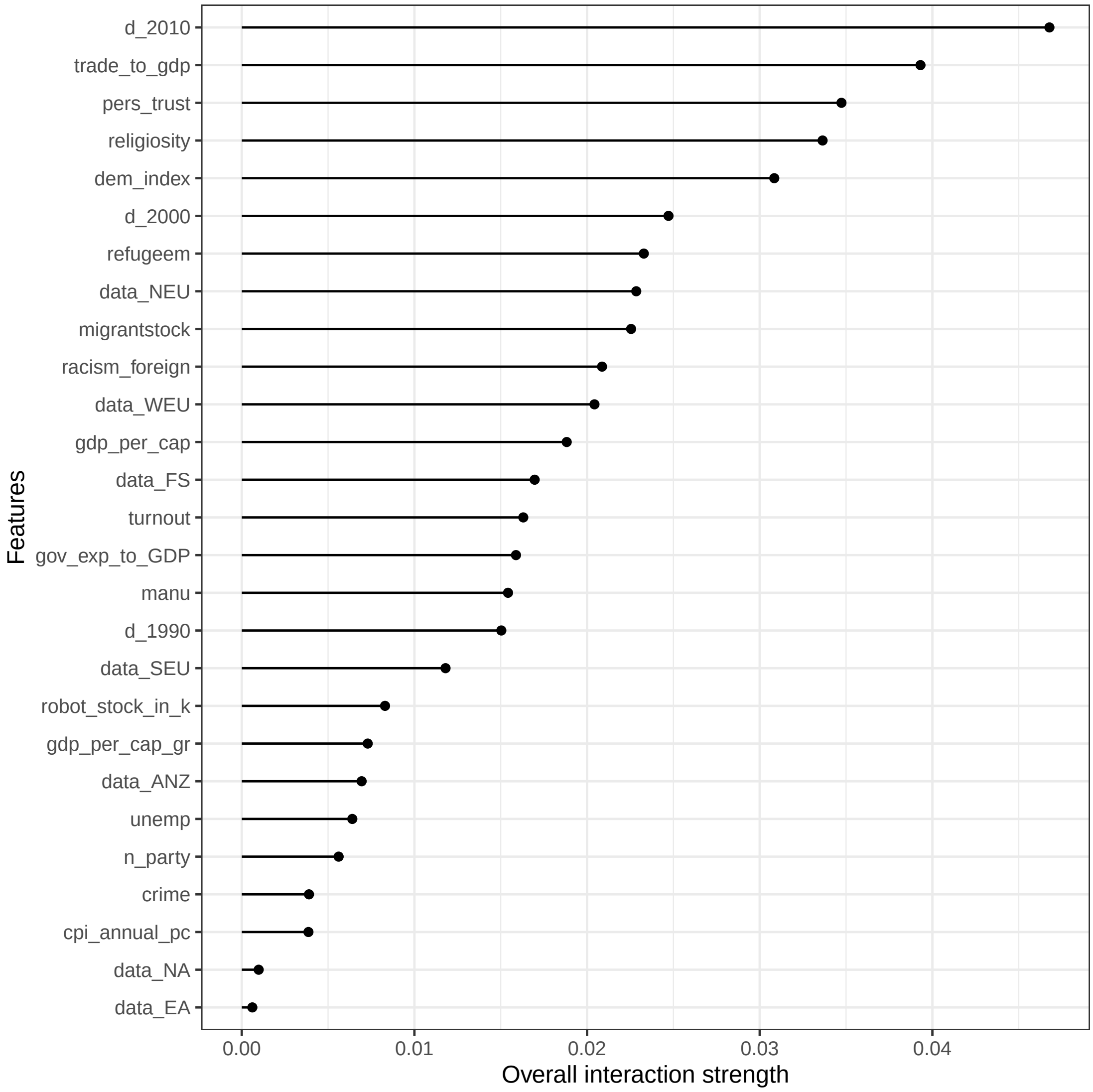
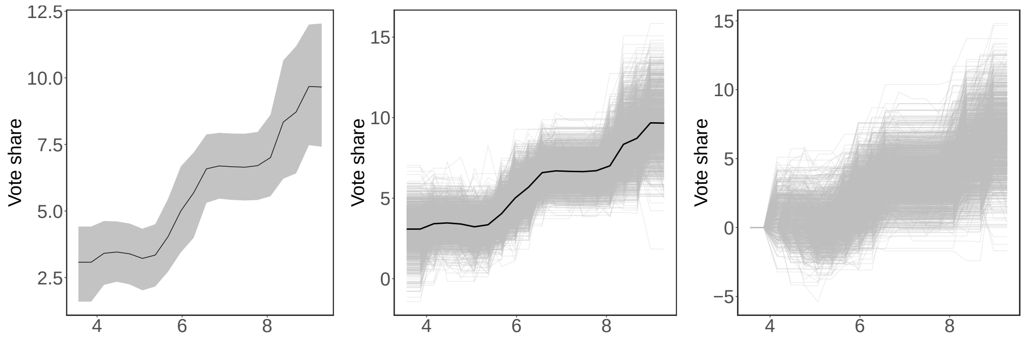


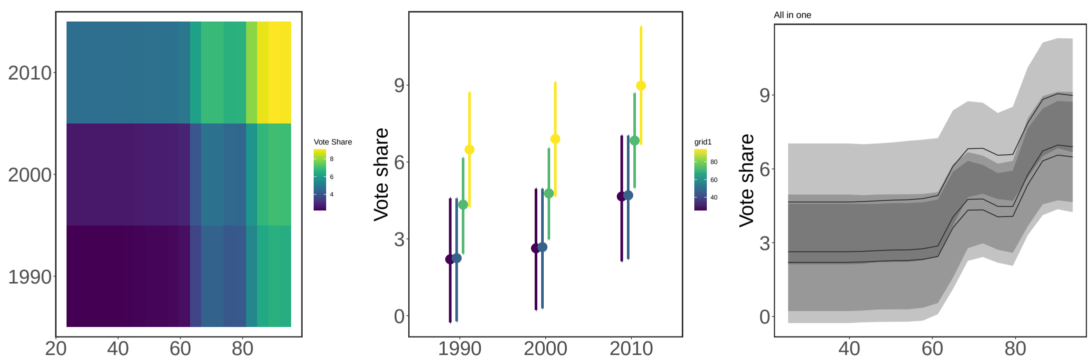
Figure 6. H-statistic for interaction detection.

Notes: The ranking is based on the variance of the partial dependence function in the two-dimensional space, measuring how much the predictions of a particular variable vary, depending on the values of a second variable. For instance, if the variable of interest is religiosity and the second variable is refugees, this procedure estimates the partial dependence of religiosity while fixing the refugee variable at a specific value. If the partial dependence of religiosity varies strongly between different values of refugees, this indicates that the partial dependence of religiosity is not independent of refugees.



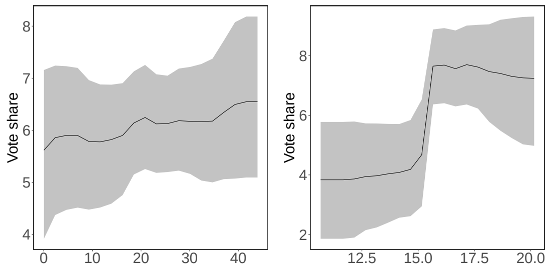
(a) religiosity, PDP **(b)** religiosity, ICE **(c)** religiosity, centered ICE

Figure 7. The null-effect of crime



(a) decade×trust PDP panel **(b)** decade×trust **(c)** decade×trust

Figure 8. decade×trust interaction heatmap and PDP slides



(a) broadband **(b)** imports from China

Figure 9. Additional PDP

ICE plot. To illustrate the absence further, Figure 8 illustrates the absense of an interaction between any decade and trust. All PDP of trust are almost perfectly in parallel, irrespective for which decade they are calculated. The only difference is a level effect, which represents the main effect of the decade. The same holds if we plot the effect of the decades for multiple slices of trust. Thus, both effects are independent of each other, just as the H-statistic suggested.

6. Discussion

How do these findings compare to the existing literature on far-right populism? How do variable selection and functional forms relate to survey results, theory, and previous empirical findings?

On the one hand, culture, and economics seem to play a role in the rise of populism. Economic factors like the trade-to-GDP ratio (unexpectedly) decrease populist voting, while imports from China seem to increase it, but only after a certain threshold.

On the side of culture, countries, where the people are more religious seem more open to populist parties. However, populism is also positively linked to the crisis of democratic values. Other cultural variables widely discussed in the literature, like social capital or trust and status (loss) as in self-stated financial satisfaction, don't explain the rise of populism.

It seems populism is rather caused by long-term, secular factors like globalization, especially the increase in trade flows and imports from low-wage countries like China, than short-term, crisis-related factors. However, when we say 'long-term,' we find that the last 20 years were relevant for the rise of populism, especially the decade around the 2010s. Surprisingly, certain crisis measures, such as GDP per capita changes, inflation, crime rates, and government expenditure to GDP ratio as a measure of austerity, are not linked to populist far-right voting despite being widely discussed.

A higher migrant stock decreases far-right populist voting, confirming the contact hypothesis. At the same we find a non-linear relationship between the log number of refugees and the vote share for populist parties after a certain threshold. However, the relationship is weaker than other economics (globalization as in trade-to-GDP) or cultural factors (like religiosity).

Unemployment is negative and significantly correlated with populism. Hence, we don't find evidence for the 'Economic hardship breeds extremism hypothesis.' In contrast, our results align with the more recent literature on populism, pointing to the hypothesis that 'people may turn (back) to the more established and experienced mainstream parties in times of economic uncertainty. ' Also, the non-parametric analysis revealed that the PDP of unemployment follows a round L, suggesting that the relationship between unemployment and the dependent variable is more complex and nonlinear than previously assumed. How rich a country is in terms of GDP only seems to play a role in the rise of populism before the 1990s.

7. Conclusion

In conclusion, our research elucidates the complex dynamics underpinning the rise of far-right populism in Western democracies over the last four decades. Our extensive dataset, covering 26 variables across over 30 countries from 1980 to 2019, allowed us to employ Bayesian Model Averaging (BMA) and Bayesian Additive Regression Trees (BART) to discern the most influential determinants of far-right populist vote shares and their potential non-linearities.

We identified that economic integration, as measured by the trade-to-GDP ratio, inversely correlates with populist tendencies, while the impact of Chinese imports on populism manifests beyond a certain threshold, highlighting the nuanced interplay between global trade and domestic political sentiments. The contact hypothesis is supported; higher migrant stocks correlate with reduced far-right populism, suggesting that exposure to diverse populations may alleviate xenophobic propensities. However, a complex relationship is observed with refugee migration, indicating a nuanced public response that varies with the intensity of the influx.

Culturally, religiosity emerges as a significant predictor, with a strong positive correlation with far-right populism. This finding is twofold: it reflects the use of religious identity in populist narratives that dichotomize society, and it may also capture the resonance of binary good-versus-evil storylines, messianic undertones, and anti-elite sentiment with religiously inclined voters.

These insights contribute substantially to the discourse on political economy and the socioeconomic determinants of political behavior, offering a more granular understanding of the rise of far-right populism. Our study demonstrates the value of nuanced, data-driven analysis in disentangling the drivers of complex sociopolitical phenomena and lays a foundation for policymakers to address the underlying causes of populist movements.

References

Algan, Yann et al. (2017). “The European Trust Crisis and the Rise of Populism”. In: *Brookings Papers on Economic Activity*, pp. 309–382.

Amengay, Abdelkarim and Daniel Stockemer (2019). “The Radical Right in Western Europe: A Meta-Analysis of Structural Factors”. In: *Political Studies Review* 17.1, pp. 30–40. DOI: 10.1177/1478929918777975.

Anelli, Massimo, Italo Colantone, and Piero Stanig (2019). “We Were the Robots: Automation and Voting Behavior in Western Europe”. In.

Aronsson, Thomas, Clemens Hetschko, and Ronnie Schöb (2020). *Globalization, Time-Preferences, and Populist Voting.* SSRN Scholarly Paper 3671252. Rochester, NY: Social Science Research Network. DOI: 10.2139/ssrn.3671252.

Athey, Susan and Guido W. Imbens (2017). “The state of applied econometrics: Causality and policy evaluation”. In: *Journal of Economic Perspectives* 31.2, pp. 3–32. DOI: 10.1257/jep.31.2.3.

Autor, David et al. (2020). “Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure”. In: *American Economic Review* 110.10, pp. 3139–3183. DOI: 10.1257/aer.20170011.

Bartels, Larry M. (1997). “Specification uncertainty and model Averaging”. In: *American Journal of Political Science* 41.2, pp. 641–674. DOI: 10.2307/2111781.

Campante, Filipe, Ruben Durante, and Francesco Sobbrio (2018). “Politics 2.0: The Multifaceted Effect of Broadband Internet on Political Participation”. In: *Journal of the European Economic Association* 16.4, pp. 1094–1136. DOI: 10.1093/jeea/jvx044.

Chipman, Hugh A., Edward I. George, and Robert E. McCulloch (2010). “BART: Bayesian additive regression trees”. In: *Annals of Applied Statistics* 4.1, pp. 266–298. DOI: 10.1214/09-AOAS285.

Colantone, Italo and Piero Stanig (2018a). “Global Competition and Brexit”. In: *American Political Science Review* 112.2, pp. 201–218. DOI: 10.1017/S0003055417000685.

— (2018b). “The Trade Origins of Economic Nationalism: Import Competition and Voting Behavior in Western Europe”. In: *American Journal of Political Science* 62.4, pp. 936–953. DOI: 10.1111/ajps.12358.

Dinas, Elias and Joost van Spanje (2011). “Crime Story: The role of crime and immigration in the anti-immigration vote”. In: *Electoral Studies* 30.4, pp. 658–671. DOI: 10.1016/j.electstud.2011.06.010.

Eicher, Theo S, Lindy Helfman, and Alex Lenkoski (2012). “Robust FDI determinants: Bayesian model averaging in the presence of selection bias”. In: *Journal of Macroeconomics* 34.3. Publisher: Elsevier, pp. 637–651.

Enke, Benjamin (2020). “Moral Values and Voting”. In: *Journal of Political Economy.* tex.copyright: © 2020 by The University of Chicago. All rights reserved. DOI: 10.1086/708857.

Friedman, Jerome H (2001). “Greedy function approximation: A gradient boosting machine”. In: *Annals of statistics* 5.29. Publisher: JSTOR, pp. 1189–1232.

Friedman, Jerome H and Bogdan E Popescu (2008). “Predictive learning via rule ensembles”. In.

Gidron, Noam and Peter A. Hall (2017). “The politics of social status: economic and cultural roots of the populist right”. In: *The British Journal of Sociology* 68 (S1), S57–S84. DOI: 10.1111/1468-4446.12319.

Goldstein, Alex et al. (2015). “Peeking inside the black box: Visualizing statistical learning with plots of individual conditional expectation”. In: *journal of Computational and Graphical Statistics* 24.1. Publisher: Taylor & Francis, pp. 44–65.

Gozgor, Giray (2022). “The role of economic uncertainty in the rise of EU populism”. In: *Public Choice* 190.1, pp. 229–246. DOI: 10.1007/s11127-021-00933-7.

Greenwell, Brandon M., Bradley C. Boehmke, and Andrew J. McCarthy (2018). *A simple and effective model-based variable importance measure.* arXiv: 1805.04755[stat.ML].

Greve, Bent (2019). *Welfare, Populism and Welfare Chauvinism.* Bristol University Press. DOI: 10.46692/9781447350460.

Guiso, Luigi et al. (2021). *The Financial Drivers of Populism in Europe.* Place: Rochester, NY Type: SSRN Scholarly Paper. DOI: 10.2139/ssrn.3922661.

Guriev, Sergei and Elias Papaioannou (2022). “The Political Economy of Populism”. In: *Journal of Economic Literature* 60.3, pp. 753–832. DOI: 10.1257/jel.20201595.

Hastie, Trevor, Robert Tibshirani, and Jerome Friedman (2009). *The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Second Edition*. 2nd ed. Springer Series in Statistics. New York: Springer-Verlag.
Hill, Jennifer, Antonio Linero, and Jared Murray (2020). "Bayesian additive regression trees: A review and look forward". In: *Annual Review of Statistics and Its Application* 7. Publisher: Annual Reviews, pp. 251–278.
Honaker, James, Gary King, Matthew Blackwell, et al. (2011). "Amelia II: A program for missing data". In: *Journal of Statistical Software* 45.7, pp. 1–47.
Jackman, Robert W. and Karin Volpert (1996). "Conditions Favouring Parties of the Extreme Right in Western Europe". In: *British Journal of Political Science* 26.4. Publisher: Cambridge University Press, pp. 501–521. DOI: 10.1017/S0007123400007584.
James, Gareth et al. (2021). *An introduction to statistical learning*. 3. Springer.
Jeffreys, H. (1998). *The theory of probability*. Oxford classic texts in the physical sciences. OUP Oxford.
Jiang, Wenxin and Cheng Li (2019). "On bayesian oracle properties". In: *Bayesian Analysis* 14.1. Publisher: International Society for Bayesian Analysis, pp. 235–260. DOI: 10.1214/18-BA1097.
Kass, Robert E and Adrian E Raftery (1995). "Bayes factors". In: *Journal of the American Statistical Association* 90.430. Publisher: Taylor & Francis, pp. 773–795.
Kennedy, Ryan, Stefan Wojcik, and David Lazer (2017). "Improving election prediction internationally". In: *Science (New York, N.Y.)* 355.6324, pp. 515–520. DOI: 10.1126/science.aal2887.
March, Luke (2012). *Radical Left Parties in Europe*. Google-Books-ID: xF3FBQAAQBAJ. Routledge. 295 pp.
Margalit, Yotam (2019). "Economic Insecurity and the Causes of Populism, Reconsidered". In: *The Journal of Economic Perspectives* 33.4, pp. 152–170.
Montgomery, Jacob M and Santiago Olivella (2018). "Tree-based models for political science data". In: *American Journal of Political Science* 62.3. Publisher: Wiley Online Library, pp. 729–744.
Montgomery, Jacob M. and Brendan Nyhan (2010). "Bayesian Model Averaging: Theoretical developments and practical applications". In: *Political Analysis* 18.2, pp. 245–270.
Mudde, Cas (2004a). "The Populist Zeitgeist". In: *Government and Opposition* 39.4. Publisher: Cambridge University Press, pp. 541–563. DOI: 10.1111/j.1477-7053.2004.00135.x.
— (2004b). "The Populist Zeitgeist". In: *Government and Opposition* 39.4. Publisher: Cambridge University Press, pp. 541–563. DOI: 10.1111/j.1477-7053.2004.00135.x.
— (2007). *Populist Radical Right Parties in Europe*. Cambridge: Cambridge University Press. DOI: 10.1017/CBO9780511492037.
Mullainathan, Sendhil and Jann Spiess (2017). "Machine learning: An applied econometric approach". In: *Journal of Economic Perspectives* 31.2, pp. 87–106. DOI: 10.1257/jep.31.2.87.

Pástor, Lubos and Pietro Veronesi (2021). “Inequality Aversion, Populism, and the Backlash against Globalization”. In: *The Journal of Finance* 76.6, pp. 2857–2906. DOI: `10.1111/jofi.13081`.

Porwal, Anupreet and Adrian E Raftery (2022). “Comparing methods for statistical inference with model uncertainty”. In: *Proceedings of the National Academy of Sciences* 119.16. Publisher: National Acad Sciences, e2120737119.

Raftery, Adrian E (1995). “Bayesian model selection in social research”. In: *Sociological Methodology* 25. Publisher: JSTOR, pp. 111–163.

Raftery, Adrian E., David Madigan, and Jennifer A. Hoeting (1997). “Bayesian Model Averaging for linear regression models”. In: *Journal of the American Statistical Association* 92.437, pp. 179–191.

Robert, Christian P, Nicolas Chopin, Judith Rousseau, et al. (2009). “Harold Jeffreys’s theory of probability revisited”. In: *Statistical Science* 24.2. Publisher: Institute of Mathematical Statistics, pp. 141–172.

Rooduijn, Matthijs et al. (2023a). “The PopuList: A Database of Populist, Far-Left, and Far-Right Parties Using Expert-Informed Qualitative Comparative Classification (EiQCC)”. In: *British Journal of Political Science*, pp. 1–10. DOI: `10.1017/S0007123423000431`.

— (2023b). “The PopuList: A Database of Populist, Far-Left, and Far-Right Parties Using Expert-Informed Qualitative Comparative Classification (EiQCC)”. In: *British Journal of Political Science*, pp. 1–10. DOI: `10.1017/S0007123423000431`.

Sasso, Greg and Massimo Morelli (2021). “Bureaucrats under Populism”. In: *Journal of Public Economics* 202, p. 104497. DOI: `10.1016/j.jpubeco.2021.104497`.

Sparapani, Rodney, Charles Spanbauer, and Robert McCulloch (2021). “Nonparametric machine learning and efficient computation with bayesian additive regression trees: The BART R package”. In: *Journal of Statistical Software* 97.1, pp. 1–66. DOI: `10.18637/jss.v097.i01`.

Steel, Mark F. J. (2020). “Model averaging and its use in economics”. In: *Journal of Economic Literature* 58.3, pp. 644–719.

Varian, Hal R. (2014). “Big Data: New tricks for econometrics”. In: *Journal of Economic Perspectives* 28.2, pp. 3–28. DOI: `10.1257/jep.28.2.3`.

Vertier, Paul, Max Viskanic, and Matteo Gamalerio (2023). “Dismantling the “Jungle”: migrant relocation and extreme voting in France”. In: *Political Science Research and Methods* 11.1. Publisher: Cambridge University Press, pp. 129–143. DOI: `10.1017/psrm.2022.26`.

Wood, Angela M., Ian R. White, and Patrick Royston (2008). “How should variable selection be performed with multiply imputed data?” In: *Statistics in Medicine* 27.17. tex.copyright: Copyright © 2008 John Wiley & Sons, Ltd., pp. 3227–3246. DOI: `10.1002/sim.3177`.

Yang, Xiaowei, Thomas R. Belin, and W. John Boscardin (2005). “Imputation and variable selection in linear regression models with missing covariates”. In: *Biometrics. Journal of the International Biometric Society* 61.2, pp. 498–506. DOI: `10.1111/j.1541-0420.2005.00317.x`.

A. Appendix

A.1. Data

Table 3. Summary Statistics - All countries 1980 - 2019

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Log GDP per Capita	322	9.985	0.738	8.18	9.532	10.547	11.56
CPI	322	21.361	98.467	-1.74	1.53	5.888	1058.37
RW Populist Vote (%)	322	4.32	7.779	0	0	6.55	43.6
LW Populist Vote (%)	322	0.799	2.768	0	0	0	20.1
Gov Revenue to GDP	322	34.137	9.007	16.4	28.875	38.82	82.73
Gov Expenditure to GDP	322	36.707	10.505	14.08	31.742	42.755	98.48
Trade to GDP	322	85.193	52.139	16	47.25	110	321
Log N. of Refugees	322	8.908	2.772	1.61	6.815	11.148	14.12
Democracy Index	322	73.333	11.457	25.25	66.773	80.368	92.34
Racism - different race (%)	313	12.949	7.53	1.21	7.77	17.57	40.22
Racism - Foreigners (%)	313	17.586	9.789	1.82	9.81	23.21	57.04
Trust (%)	322	33.522	14.878	7	23	42	68
Authoritarian Personality Index	312	0.054	1.055	-2	-1	1	3
Financial Satisfaction (%)	261	48.467	26.788	1	32.35	61.06	100
Religiosity (%)	322	6.004	1.528	3.56	4.885	7.463	9.07
N of Parties in Parliament	322	5.391	2.405	1	4	7	15
Turnout (%)	322	74.708	13.991	37.79	64.532	86.185	100
Average District Magnitude	322	15.432	34.165	1	2	12	150

Table 4. Summary Statistics - All countries 1990 - 2019

Category	Determinant	Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Dependent Variable	Populism	RW Populist Vote (%)	253	5.175	8.454	0	0	8.1	43.6
		LW Populist Vote (%)	253	0.954	3.062	0	0	0	20.1
Economic Factors	Crises	Log GDP per Capita	253	10.021	0.756	8.21	9.53	10.62	11.56
		CPI	253	22.308	108.187	-1.74	1.36	4.22	1058.37
		Unemployment (%)	253	8.374	4.395	1.2	5.11	10.31	24.9
		Crime Rate per 100k	253	2.41	2.761	0	0.99	2.36	17.17
	Automation	Robot Stock	233	121.567	311.212	0	1	55	1546
		New Robots	233	12.91	32.443	0	0	7	184
	Austerity	Gov Revenue to GDP	253	34.817	9.105	16.4	30.61	39.11	82.73
		Gov Expenditure to GDP	253	37.394	10.742	14.08	32.2	42.92	98.48
	Structural Change	Manufacturing Employment (%)	253	27.643	6.344	12.04	22.75	32.13	44.99
Globalization	Trade	Trade to GDP	253	90.917	53.82	16	54	120	321
	Immigration	Migrant Stock (%)	253	9.598	7.036	0.24	3.81	12.89	38.04
		Log N. of Refugees	253	8.802	2.871	1.61	6.8	11.12	14.12
Political Factors	Fractionalization	N of Parties in Parliament	253	5.759	2.466	2	4	7	15
	Electoral System	Average District Magnitude	253	15.66	34.228	1	2	13	150
Identity and Culture	Xenophobia	Racism - different race (%)	246	13.417	7.815	1.21	7.77	19.34	40.22
		Racism - Foreigners (%)	246	18.554	10.209	1.82	10.547	23.418	57.04
	Social Capital	Trust (%)	253	32.968	15.078	7	22	41	68
		Turnout (%)	253	72.078	13.698	37.79	61.74	83.62	97.16
	Moral Values	Authoritarian Personality Index	245	0.106	1.011	-2	-1	1	3
		Democracy Index	253	72.827	11.891	25.25	64.53	79.52	92.34
	Culture	Religiosity (%)	253	5.951	1.519	3.56	4.8	7.2	9.07
	Status	Financial Satisfaction (%)	205	47.011	26.429	1	30.88	52.72	100

Table 5. Summary Statistics - All countries 2000 - 2019

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Log GDP per Capita	165	10.157	0.683	8.278	9.695	10.713	11.565
CPI	165	2.422	3.958	-1.736	1.137	3.039	45.667
RW Populist Vote (%)	165	6.14	9.494	0	0	11.7	43.6
LW Populist Vote (%)	165	1.218	3.598	0	0	0	20.1
Gov Revenue to GDP	165	34.339	8.366	16.403	30.684	38.904	82.728
Gov Expenditure to GDP	165	36.564	9.69	15.052	31.956	42.386	98.477
Trade to GDP	165	98.05	55.907	19.562	58.416	129.733	320.534
Log N. of Refugees	165	9.023	2.595	1.609	7.425	11.183	13.795
Democracy Index	165	72.444	12.021	25.25	65.13	79.148	92.345
Racism - different race (%)	160	13.281	7.836	1.215	7.756	19.62	39.29
Racism - Foreigners (%)	160	18.963	10.887	1.82	10.602	24.14	57.04
Trust (%)	165	33.395	15.482	7.185	22.235	41.07	67.97
Authoritarian Personality Index	159	0.191	1.066	-1.553	-0.582	1.043	2.528
Financial Satisfaction (%)	133	46.779	25.607	1	32.35	50.98	100
Religiosity (%)	165	5.923	1.508	3.695	4.805	7.205	9.065
N of Parties in Parliament	165	5.945	2.438	2	4	7	15
Turnout (%)	165	69.519	13.727	37.79	59.68	80.04	95.7
Average District Magnitude	165	16.836	36.128	1	1.95	13.3	150
Manufacturing Employment (%)	165	25.843	5.986	12.04	21.13	30.39	40.13
Crime Rate per 100k	165	1.924	1.993	0	0.876	1.871	10.707
Unemployment (%)	165	8.232	4.419	2.55	5.11	9.67	24.9
Migrant Stock (%)	165	10.092	6.759	0.574	4.461	13.758	38.043
Robot Stock	152	144.322	323.483	0	1.316	78.025	1491.258
New Robots	152	16.039	36.599	0	0.1	9.994	183.728
Infrastructure Spending to GDP	149	0.987	0.501	0.139	0.624	1.236	3.205
Log Infrastructure Spending	161	21.678	1.888	15.899	20.349	23.278	25.29
Log Imports from China	158	15.468	2.05	10.665	14.087	17.034	20.149
R&D Expenditure to GDP	165	1.664	0.923	0.237	0.793	2.413	3.618
Log ICT Capital	158	9.384	2.767	4.099	6.962	10.754	16.812
Mobile Subscriptions per 100 people	165	105.239	29.091	11.289	90.103	123.119	165.862
Broadband Subscriptions per 100 people	165	21.101	12.178	0.031	11.09	30.392	43.946

Table 6. Summary Statistics - EU countries 2000 - 2019

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Log GDP per Capita	123	10.085	0.67	8.28	9.61	10.66	11.56
CPI	123	2.209	1.965	-1.74	1.16	3.11	10.93
RW Populist Vote (%)	123	7.274	9.667	0	0	12.6	37.6
LW Populist Vote (%)	123	1.466	3.732	0	0	0	16.9
Gov Revenue to GDP	123	36.434	5.337	26.2	32.975	39.475	62.84
Gov Expenditure to GDP	123	38.96	6.294	26.26	34.075	43.48	62.3
Trade to GDP	123	107.699	48.057	48	66.5	134	321
Log N. of Refugees	123	8.698	2.649	1.61	6.86	10.73	13.8
Democracy Index	123	73.87	11.182	37.78	69.795	79.52	92.34
Racism - different race (%)	119	14.024	7.932	1.21	8.08	19.925	39.29
Racism - Foreigners (%)	119	19.708	11.755	1.82	10.68	28.76	57.04
Trust (%)	123	32.333	15.819	7	22	40	68
Authoritarian Personality Index	118	0.017	0.952	-2	-1	1	3
Financial Satisfaction (%)	95	50.451	24.368	1	43.47	64.64	100
Religiosity (%)	123	5.713	1.351	3.7	4.91	6.34	8.73
N of Parties in Parliament	123	6.317	2.223	3	5	7	15
Turnout (%)	123	69.66	11.751	46.18	60.74	79.07	91.98
Average District Magnitude	123	21.285	40.866	1	4	14	150
Manufacturing Employment (%)	123	26.583	6.306	12.04	21.835	30.7	40.13
Crime Rate per 100k	123	1.863	2.036	0.18	0.88	1.76	10.71
Unemployment (%)	123	9.007	4.647	2.55	5.415	11.13	24.9
Migrant Stock (%)	123	9.833	6.044	0.67	5.205	13.085	38.04
Robot Stock	110	57.491	128.151	0	1	42.5	758
New Robots	110	5.936	12.422	0	0	5.75	79
Infrastructure Spending to GDP	112	0.967	0.425	0.339	0.643	1.173	2.441
Log Infrastructure Spending	119	21.277	1.551	18	20	22	24
Log Imports from China	123	15.132	1.775	10.67	13.995	16.595	18.57
R&D Expenditure to GDP	123	1.522	0.856	0.24	0.775	2.065	3.62
Log ICT Capital	123	8.825	2.158	4.91	6.875	10.435	13.21
Mobile Subscriptions per 100 people	123	107.772	28.419	15	91	124	166
Broadband Subscriptions per 100 people	123	20.358	12.134	0	10	30	44
Liberalism Index	121	0.047	1.543	-6.681	-0.671	1.071	2.547
Redistribution Acceptance	123	41.706	24.827	1	22.75	51	100
Traditionalism	121	54.762	16.67	13.1	44.565	65.5	100

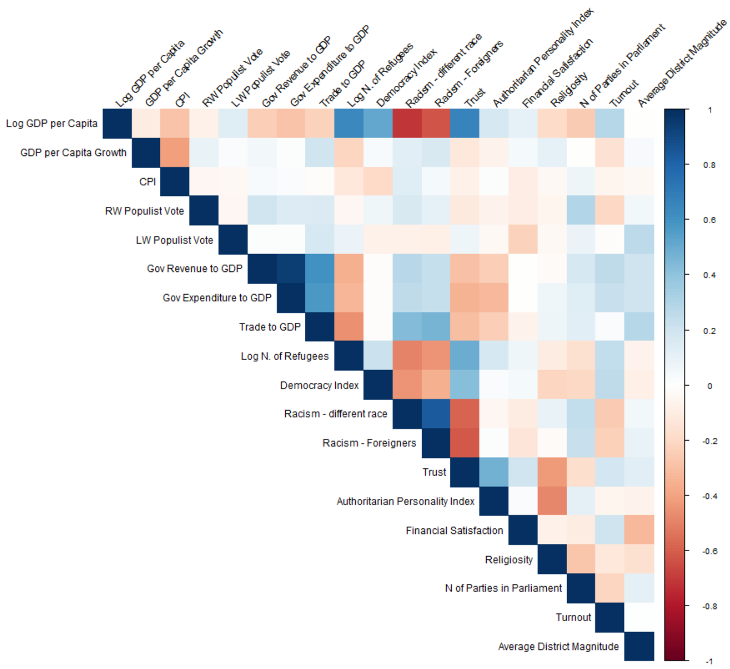


Figure 10. Correlation Table - All Countries 1980 - 2019

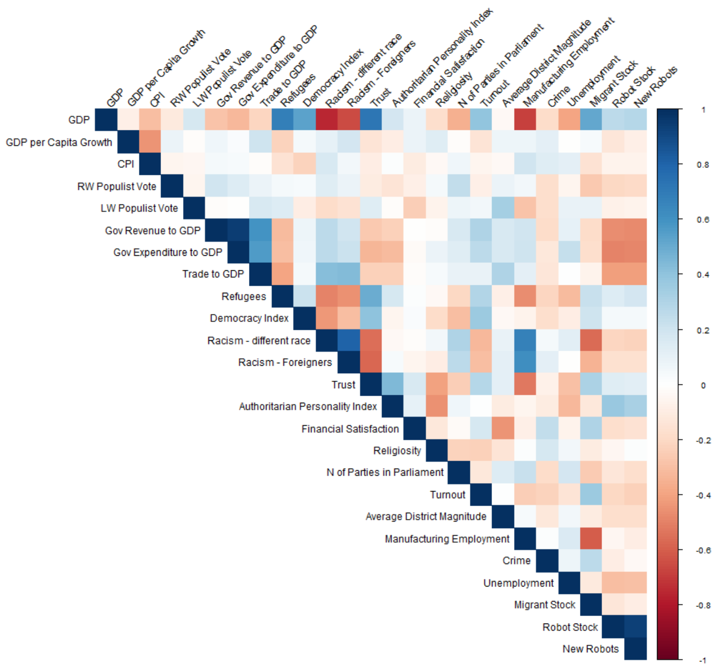


Figure 11. Correlation Table - All Countries 1980 - 2019

Figure 12. Correlation Table - All Countries 2000 - 2019

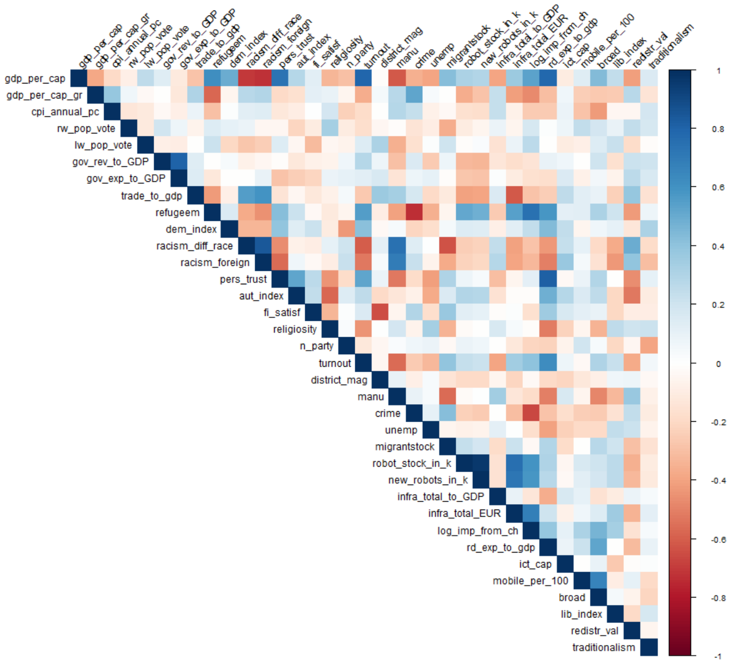


Figure 13. Correlation Table - European Countries 2000 - 2019

Dependent Variable:	Vote Share for far-right Populist Parties			
Model:	All countries 1980-2019	All countries 1990-2019	All countries 2000-2019	EU countries 2000-2019
Variables				
Constant	-11.24	20.31	46.01	13.26
	(10.55)	(18.96)	(30.48)	(42.43)
GDP	-0.2361	-3.189*	-13.36***	-8.241
	(1.026)	(1.903)	(3.150)	(5.338)
CPI	-0.0014	-0.0034	0.1303	-0.5154
	(0.0045)	(0.0051)	(0.1741)	(0.4188)
Gov Expenditure to GDP	0.1133**	0.0406		
	(0.0510)	(0.0690)		
Trade to GDP	0.0117	-0.0059		
	(0.0112)	(0.0145)		
Democracy Index	0.1438***	0.2035***	0.3298***	0.1569
	(0.0417)	(0.0569)	(0.0783)	(0.1011)
Racism - Foreigners	0.0585	0.0195	-0.1757*	-0.2448**
	(0.0547)	(0.0726)	(0.0911)	(0.1083)
Trust	0.0138	0.0413	0.2740***	0.3337**
	(0.0424)	(0.0601)	(0.0814)	(0.1456)
Refugees	0.5729**	0.7044**	0.3721	0.9885
	(0.2244)	(0.2958)	(0.5850)	(0.8122)
Religiosity	-0.0070	0.4010	1.799**	2.938***
	(0.3606)	(0.4766)	(0.7028)	(1.043)
N of Parties in Parliament	0.7017***	0.7991***	0.4339	-0.0336
	(0.1997)	(0.2238)	(0.3346)	(0.4008)
Turnout	-0.1067***	-0.0680	0.0153	0.0983
	(0.0338)	(0.0480)	(0.0748)	(0.1305)
District Magnitude	-0.0019	0.0068	0.0013	-0.0345
	(0.0129)	(0.0147)	(0.0182)	(0.0231)
Manufacturing Employment		-0.1148	0.0861	0.2905
		(0.1353)	(0.2616)	(0.3557)
Crime		-0.2056	0.4439	0.2082
		(0.2468)	(0.5002)	(0.6537)
Unemployment		-0.5285***	-0.5853***	-0.5167**
		(0.1372)	(0.2011)	(0.2208)
Migrant Stock		-0.0715	-0.1057	0.0147
		(0.1293)	(0.1879)	(0.3308)
Robot Stock		-0.0053**	-0.0087	-0.0362***
		(0.0021)	(0.0064)	(0.0128)
Infrastructure Spending			-1.38×10^{-10}	1.34×10^{-10}
			(8.43×10^{-11})	(2.48×10^{-10})
Imports from CH (log)			3.157***	2.315*
			(0.7998)	(1.200)
Broadband			0.1213	0.1401
			(0.0828)	(0.0977)
Northern Europe				-13.08
				(8.656)
Southern Europe				-11.01**
				(4.989)
Western Europe				-8.871
				(6.677)
Liberalism Index				1.220*
				(0.6689)
Redistribution Acceptance				0.0288
				(0.0387)
Traditionalism				-0.1223**
				(0.0535)
Fit statistics				
Observations	313	226	140	106
R^2	0.17355	0.25064	0.41385	0.53881
Adjusted R^2	0.14050	0.18939	0.32665	0.40217

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7. Fixed Effects Regressions - All countries 1980 - 2019

Dependent Variable:	Vote Share for far-right Populist Parties	
Model:	Eastern European Countries 1990-2019	Eastern European Countries 2000-2019
Variables		
Constant	-6.865	94.68
	(57.00)	(99.39)
GDP	-2.786	-27.72***
	(4.551)	(9.229)
CPI	-0.0029	0.1921
	(0.0058)	(0.2030)
Gov Expenditure to GDP	-0.6413***	
	(0.2103)	
Trade to GDP	0.0505	
	(0.0443)	
Democracy Index	0.2585**	0.2225
	(0.1025)	(0.1969)
Racism - Foreigners	-0.2614*	-0.1300
	(0.1348)	(0.2060)
Trust	0.0792	0.5175
	(0.2386)	(0.3580)
Refugees	1.877**	0.9107
	(0.8906)	(1.991)
Religiosity	2.541**	2.732
	(1.247)	(2.315)
N of Parties in Parliament	0.4409	0.5522
	(0.3741)	(0.5773)
Turnout	0.2833**	0.1223
	(0.1070)	(0.2483)
District Magnitude	-0.0213	0.0558
	(0.0359)	(0.0566)
Manufacturing Employment	-0.1856	-0.3068
	(0.3944)	(0.9700)
Crime	-0.1299	0.8984
	(0.4521)	(0.9419)
Unemployment	0.2370	-0.1191
	(0.3093)	(0.4871)
Migrant Stock	0.2017	1.184
	(0.3901)	(0.8512)
Robot Stock	0.3069***	0.2756**
	(0.0875)	(0.1255)
Infrastructure Spending		-4.08×10^{-11}
		(1.01×10^{-9})
Imports from CH (log)		7.817**
		(3.096)
Broadband		-0.0504
		(0.2787)
Fit statistics		
Observations	76	48
R^2	0.62356	0.78178
Adjusted R^2	0.51322	0.64633

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8. Fixed Effects Regressions - Eastern Europe 1990 - 2019

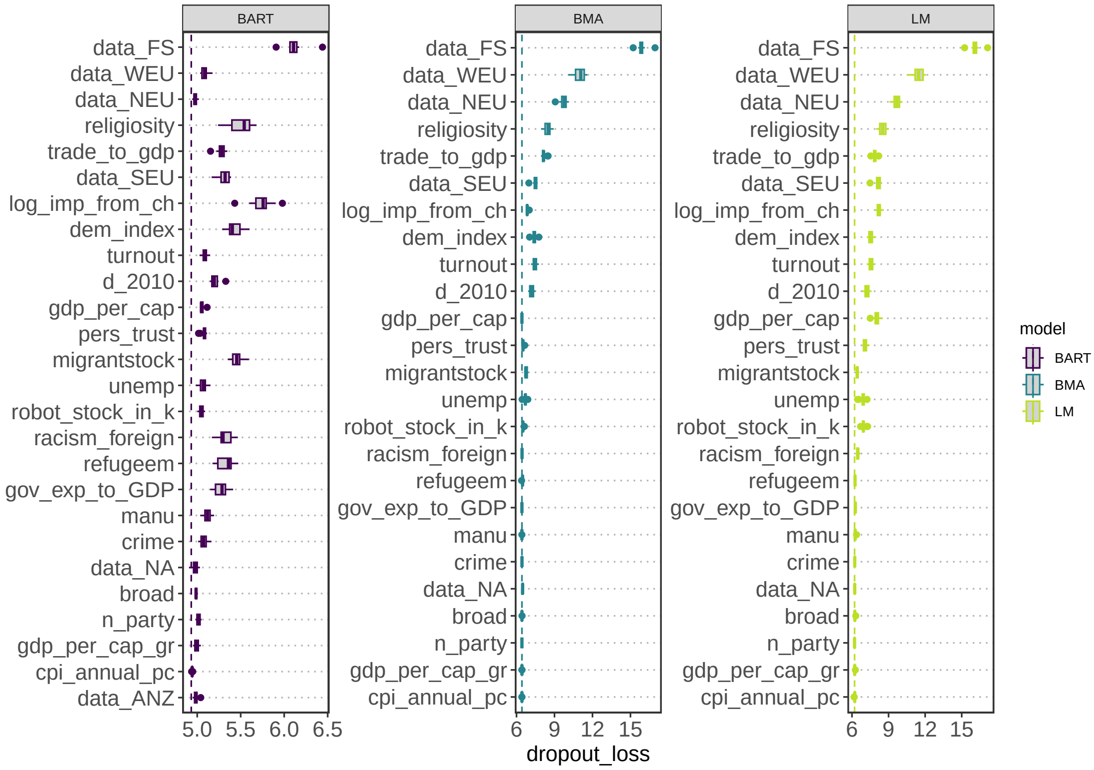


Figure 14. Permutation test based variable importance (dropout loss in RMSE) for 2000-2019 sample.