The Drivers of Far-Right Populism in Western Democracies

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11 October 2026

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The vote share of far-right populist parties has almost doubled in Western countries in the last decade, yet their main drivers remain unclear. We assemble a dataset with over 26 potential determinants across over 30 countries between 1980 and 2019. Bayesian model averaging identifies robust drivers across model specifications, and Bayesian additive regression trees examine nonlinear relationships. We find that a higher trade-to-GDP ratio decreases far-right populism, whereas imports from China increase it only beyond a threshold. A higher migrant stock decreases far-right populist vote shares, confirming the contact hypothesis, while refugee migration exhibits a threshold effect. Religiosity is strongly and positively related to far-right populism, confirming the idea that religious group identity reinforces rhetoric dividing society into the moral people and the corrupt elite. Alternatively, this relationship may reflect religious voters' preference for narratives of good and evil, messianic messaging, and skepticism toward scientific discourse.

Keywords: Far-right populism, elections, Bayesian model averaging, Bayesian additive regression trees, core model

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1. Introduction

Which economic, cultural, and institutional factors explain the rise of far-right populism in Western democracies? Far-right populism, as defined by Mudde (2004), has tripled in Europe since the 1990s (Rooduijn et al., 2023). Its rise challenges liberal democracy and has prompted a growing empirical literature, but researchers disagree about the main drivers. Figure 1 shows the growth in far-right populist voting alongside the growth in related economics publications.[1]

This paper brings competing explanations of far-right populism into a common empirical framework. We assemble a dataset of 26 potential determinants across over 30 countries from 1980 to 2019, drawing on the data used in over 350 empirical papers covered by the surveys of Guriev and Papaioannou (2022) and Amengay and Stockemer (2019). We ask which determinants remain robust across model specifications and whether their relationships with far-right populist vote shares are nonlinear. Studying both questions allows us to compare explanations that are often examined separately.

The literature offers several explanations. Economic studies emphasize automation (Anelli, Colantone, and Stanig, 2019) and globalization (Colantone and Stanig, 2018a; Colantone and Stanig, 2018b); political science studies also emphasize crime (Dinas and Spanje, 2011) and electoral proportionality (Jackman and Volpert, 1996). Theoretical models connect support for populism to impatience when globalization imposes short-run costs and delayed gains (Aronsson, Hetschko, and Schöb, 2020), or to consumption inequality, financial development, and trade deficits (Pástor and Veronesi, 2021). Other work examines populist leaders' preference for loyal rather than competent bureaucrats (Sasso and Morelli, 2021). These models offer distinct explanations, with limited connections to automation, moral values (Enke, 2020), and new media (Campante, Durante, and Sobbrio, 2018). Measurement further complicates comparisons. Immigration measures differ in their definitions of migrants, treatment of transit and settlement, and use of actual or perceived migrant numbers. Cultural and identity measures are persistent and difficult to disentangle. Model uncertainty therefore makes it difficult to establish a common core of explanatory variables against which new explanations can be assessed.

We combine Bayesian model averaging (BMA) with Bayesian additive regression trees (BART). BMA identifies the most robust predictors across model specifications, allowing us to assess how findings depend on the choice of controls. BART then examines nonlinear relationships between these predictors and far-right populist vote shares. This second step matters when a relationship changes beyond a threshold, as suggested for refugee migration by Vertier, Viskanic, and Gamalerio (2023). Together, the two methods address uncertainty about both variable selection and functional form.

Our findings distinguish two dimensions of globalization. A higher trade-to-GDP ratio decreases far-right populism, whereas imports from China seem to increase far-right vote shares only beyond a threshold. The distinction helps explain why different measures of international economic integration can yield different conclusions about populist voting.

[1] Research on populism increased after 2010, with a turning point in 2014, before Donald Trump's election in the United States and the referendum on the United Kingdom's membership of the European Union.

Migration also has different relationships with far-right populism depending on how it is measured. Larger migrant stocks correlate with lower far-right populist vote shares, supporting the contact hypothesis. Refugee migration, by contrast, exhibits a threshold effect. The distinction between migrant stocks and refugee migration is therefore important for interpreting the findings.

Religiosity is positively related to far-right populism. One interpretation is that religion forms a group identity that resonates with populist rhetoric dividing society into the moral people and the corrupt elite. Alternatively, the relationship may reflect religious voters' preference for narratives of good and evil, messianic messaging, and skepticism toward scientific discourse. Both interpretations connect the finding to the role of culture and identity in far-right populist politics.

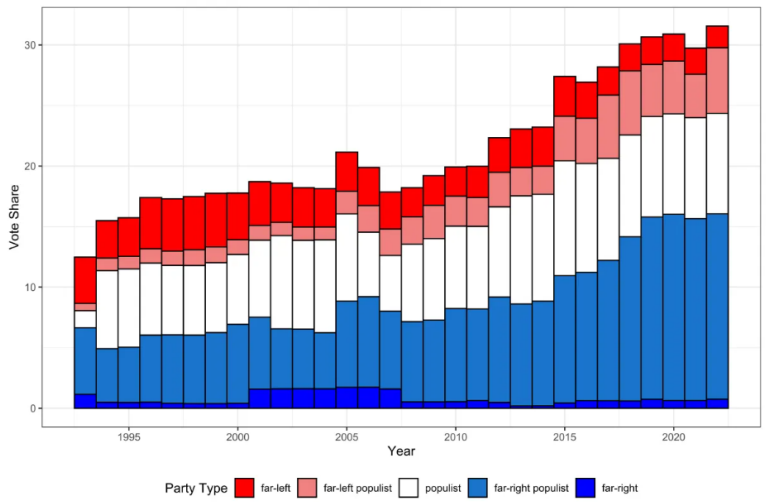
Section 2 describes the theoretical framework, Section 3 the data, and Section 4 the methods. Section 5 presents the results, Section 6 discusses them, and Section 7 concludes.

2. Theoretical Framework

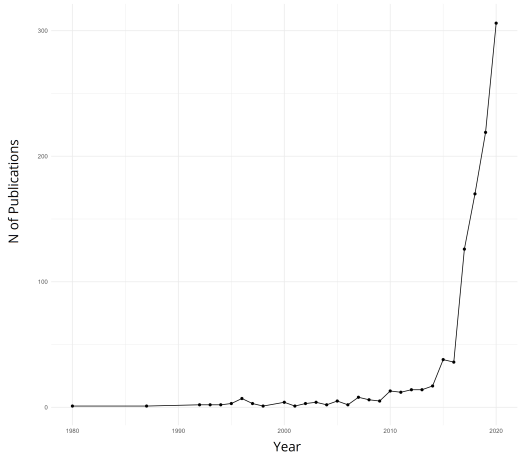
This section outlines the theoretical frameworks that shape the debate on far-right populism. Scholars disagree on the definition of far-right populism. Mudde (2004) provides a common starting point by defining populism as an anti-elitist and anti-pluralist thin-centered ideology. According to him, populists 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 does not 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 homogeneous nation-state. Any threats to the ordered society should be severely punished (authoritarianism)[2]. In contrast, the far-left rejects contemporary capitalism and its winners (the elite). They see economic inequality as

[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) Economics publications related to far-right populism, 1980–2020. Papers include "populism" in their title or as a designated topic in their abstract. Authors' illustration based on Web of Science data.

Figure 1. Populist voting and research on populism

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 role of unemployment is itself contested. 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 competing theories suggest otherwise.

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).

A central debate concerns the relative importance of economic and cultural factors in explaining the appeal 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 Midwest, these regions suffered the most, leading voters to vote for a populist, far-right candidate in the 45th U.S. presidential election. 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 of 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 dataset 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) database.

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 datasets covering the period from 2000 to 2019 and include the other datasets from 1980 and 1990 onward as controls. We also include samples covering shorter periods with more variables and longer periods with fewer variables.

We measure populism using vote shares for far-right populist parties. These provide a more consistent and comparable indicator across countries and periods than measures based on culturally dependent personal or political attitudes. To operationalize Mudde's far-right, populist definition, we turn to the PopuList dataset (Rooduijn et al., 2023), considered a reliable and comprehensive source of information on both far-left and far-right populist parties in Europe. The PopuList dataset 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 that have been represented in national parliaments.

Table 3, Table 4, and Table 5 in the appendix present 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 100,000 people, 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 and 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 model with too many predictors can overfit the data and yield unstable predictions. To avoid relying 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. The theory explains only part of the variation in y, since other factors also influence the outcome. Alternative theories might suggest that $x_3, \ldots, x_{10}$ also influence y. On the one hand, ignoring any variable might yield omitted variable bias. On the other hand, including irrelevant variables can be challenging with small samples or small to moderate effects—that is, when the signal-to-noise ratio is low. Which specification should be chosen? The additional controls alone give rise to $2^8 = 256$ possible specifications. Averaging estimates allows us to consider all models without presenting each one separately.[3] Moreover, stark changes in coefficient estimates across models will inflate the variance of the averaged estimate and stabilize 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

[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 among 21 methods for variable selection, BMA performs best. Jacob M. Montgomery and Nyhan (2010) and Steel (2020) provide excellent reviews of 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.

of the (posterior) probabilities of all models M_s, which include the regressor:

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

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, Barbieri, Berger, et al. 2004) 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 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).

Recent studies increasingly examine the functional form of these relationships. We therefore expect nonparametric estimates to reveal novel insights and yield better predictive performance, as they can consider nonlinearities and interactions. We use 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.

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

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-trees 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 a small part of the variation in the full dataset.

[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 datasets 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.

[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). BART has successfully predicted election outcomes (Kennedy, Wojcik, and Lazer, 2017), outperforming alternative approaches.

2. Sequentially grow further trees on the (partial) residuals of all other trees 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 fitted iteratively by holding the other 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. We instead plot partial dependence functions (J. H. Friedman, 2001; Hastie, Tibshirani, and J. Friedman, 2009). 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, 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 dataset. 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 presents benchmark panel regressions and BMA results for the main samples from 1990-2019 and 2000-2019. The BMA results are model-fit-weighted averages across all possible models and therefore provide the most comprehensive robustness check possible. The region and decade effects are included by construction and have a PIP of one. Their

[8] Note that this explanation is simplified. BART actually already starts with as many trees as chosen, but they all consist of a single root node and together they yield the mean of the response as a prediction. Like 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 individual trees from dominating 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.

	OLS				BMA			
Dependent Var.:	1990–2019 Region rw_pop_vote	2000–2019 Region rw_pop_vote	1990–2019 Country rw_pop_vote	2000–2019 Country rw_pop_vote	1990–2019 Region rw_pop_vote	2000–2019 Region rw_pop_vote	1990–2019 Country rw_pop_vote	2000–2019 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	Yes	Yes	Yes	Yes
country	No	No	Yes	Yes	No	No	Yes	Yes
Observations	216	140	216	140	216	140	216	140
R^2	4761	52075	66475	79194				
Within R^2	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.

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 a 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 nonparametric setting, together with better model fit. We apply estimator-independent tests and measures to compare the full linear model, BMA, and BART in the following.[10]

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 dataset.[11] BART outperforms the other models. Its RMSE is only half as large as the RMSE from the BMA model, which in turn slightly outperforms the full linear model, as was to be expected. This difference suggests that BART models the relationships best. The following analysis examines why.

[9] This makes it impossible to judge the relevance of these variables but ensures interpretability across models and sensible averaging.

[10] Like most nonparametric 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 depend on the particular folds. For 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] An RMSE value of 0 indicates that the model has perfectly predicted the values for the set of data. Thus, smaller is better.

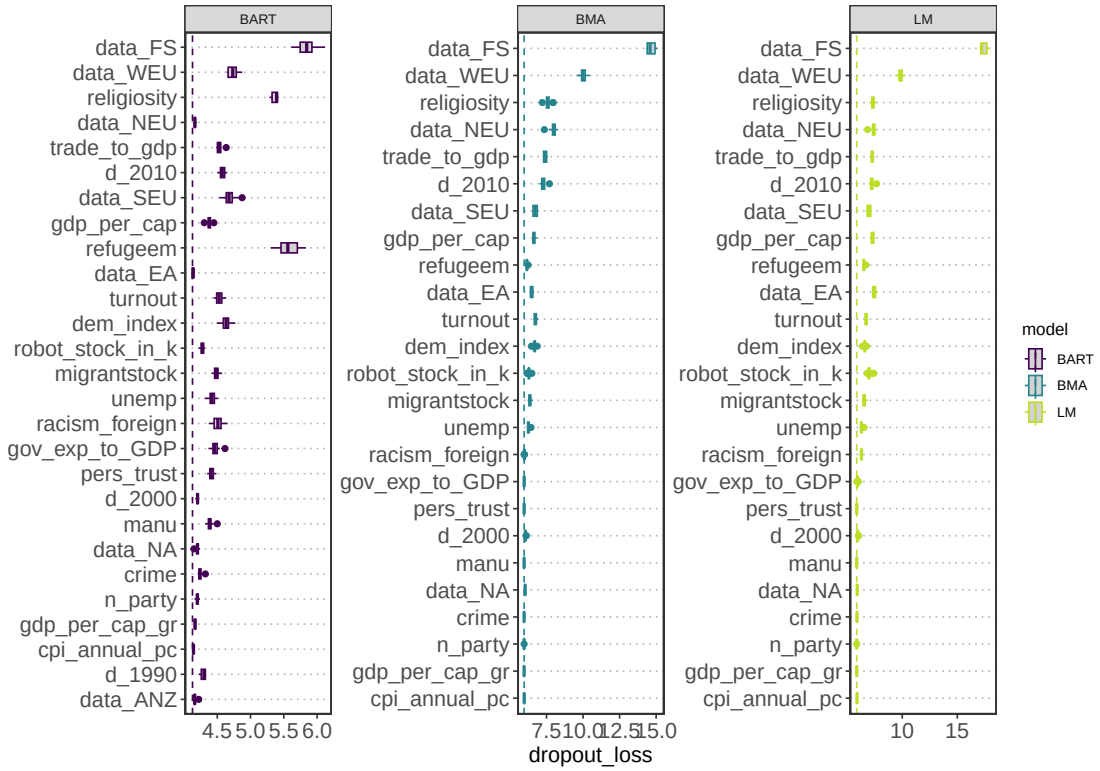


Figure 2. Permutation-test-based variable importance (dropout loss in RMSE) for 1990-2019 data.

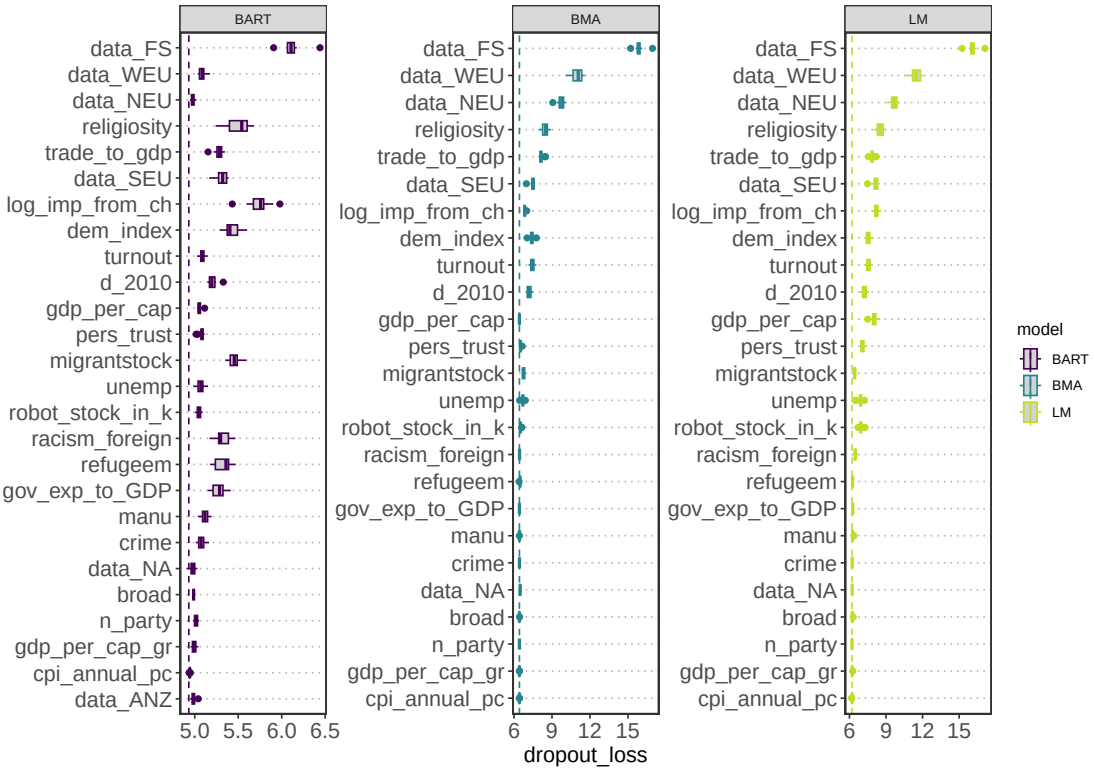


Figure 3. Permutation-test-based variable importance (dropout loss in RMSE) for 2000-2019 data.

5.2.1. Variable selection

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

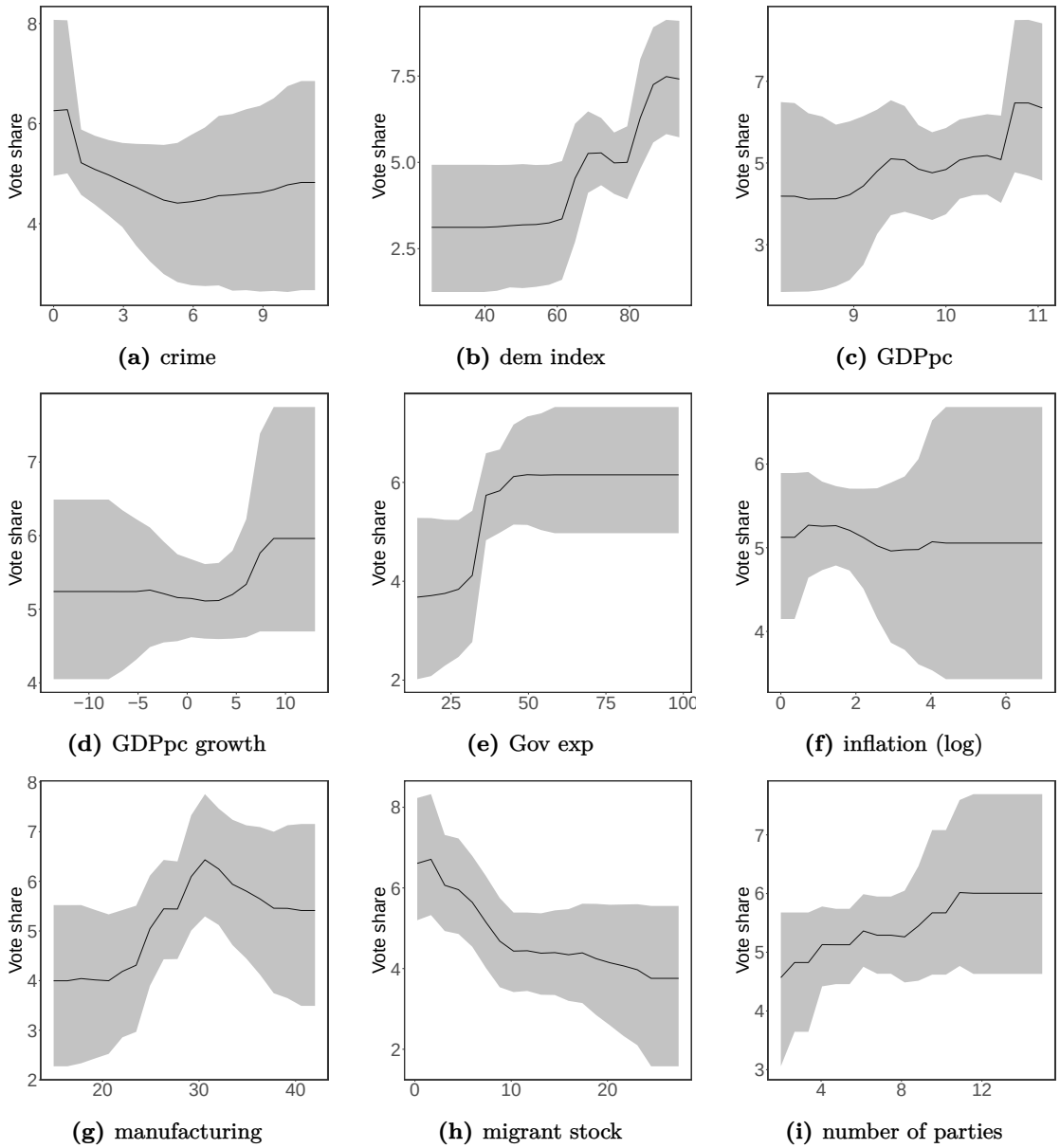
The permutation tests yield very similar results for the full linear model and the BMA, while BART differs significantly. Across all models, the dummy variable for Eastern European countries (data_FS) was the most important for predictive performance. RMSE roughly doubled for all models if the variable 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 BMA, it narrowly misses the robustness threshold. Its predictive relevance appears even weaker in BART. Automation does not seem to have any predictive power in the nonparametric 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. The vertical axis of each panel in Figure 4 represents 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., Figures 4b and 4l, some effects are nonlinear. For example, the effect of manufacturing on the populist vote appears to be inverted U-shaped, the PDP of unemployment follows a rounded L shape, and trade,

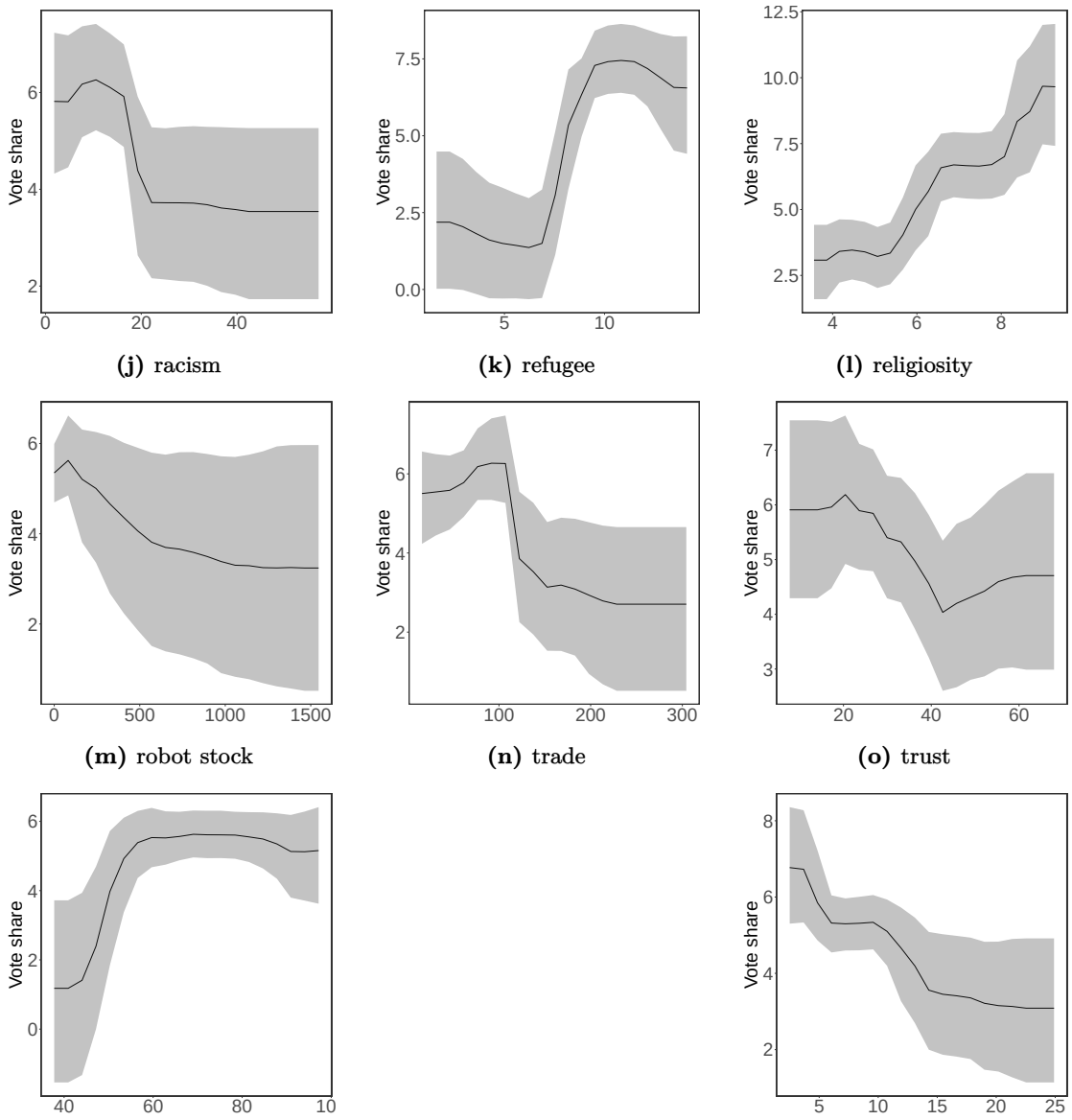


(a) crime **(b)** dem index **(c)** GDPpc

(d) GDPpc growth **(e)** Gov exp **(f)** inflation (log)

(g) manufacturing **(h)** migrant stock **(i)** number of parties

Figure 4. Partial dependence plots

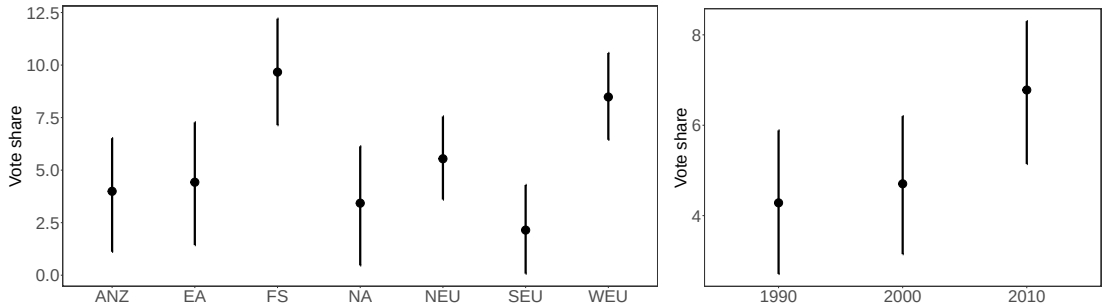


(j) racism **(k)** refugee **(l)** religiosity

(m) robot stock **(n)** trade **(o)** trust

(p) turnout **(q)** unemployment

Figure 4. Partial dependence plots (continued)



(a) regions, PDP **(b)** decades

Figure 5. Partial dependence plots of decade and regions

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 flexibility reduces the overall RMSE and yields different dropout-loss values. Table 2 summarizes the main differences and commonalities between the BART model and the full linear model. 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 the number of parties and automation. In both cases, the linear model suggests a relationship which BART does not find (Figures 4i and 4m). There are several possible explanations that we cannot test. First, it is possible that given the rather moderate effect sizes, the dataset is simply too small for BART to capture the effects. The improvement in RMSE from additional splits may be too small. Thus, 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. The BMA results, which average linear models, provide 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 or 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 whether 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

[12]The sudden dip in the PDP of the democracy index should not be interpreted too 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.

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

and returns the interaction effect's share of the total effect.[13]

Figure 6 depicts the H-statistics 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 the 2010 decade is 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 check whether the H-statistic accurately represents these relationships, we also calculate (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 zero before 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 ICE plot. To illustrate the absence further, Figure 8 illustrates the absence of an interaction between any decade and trust. The PDPs of trust are almost parallel across decades. 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?

Both culture and economic conditions 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.

Countries with more religious populations seem more receptive 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, do not explain the rise of populism.

Populism seems to be caused by long-term, secular factors such as globalization, especially growing trade flows and imports from low-wage countries such as China, rather than by short-term crises. 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

[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 a slightly different order.

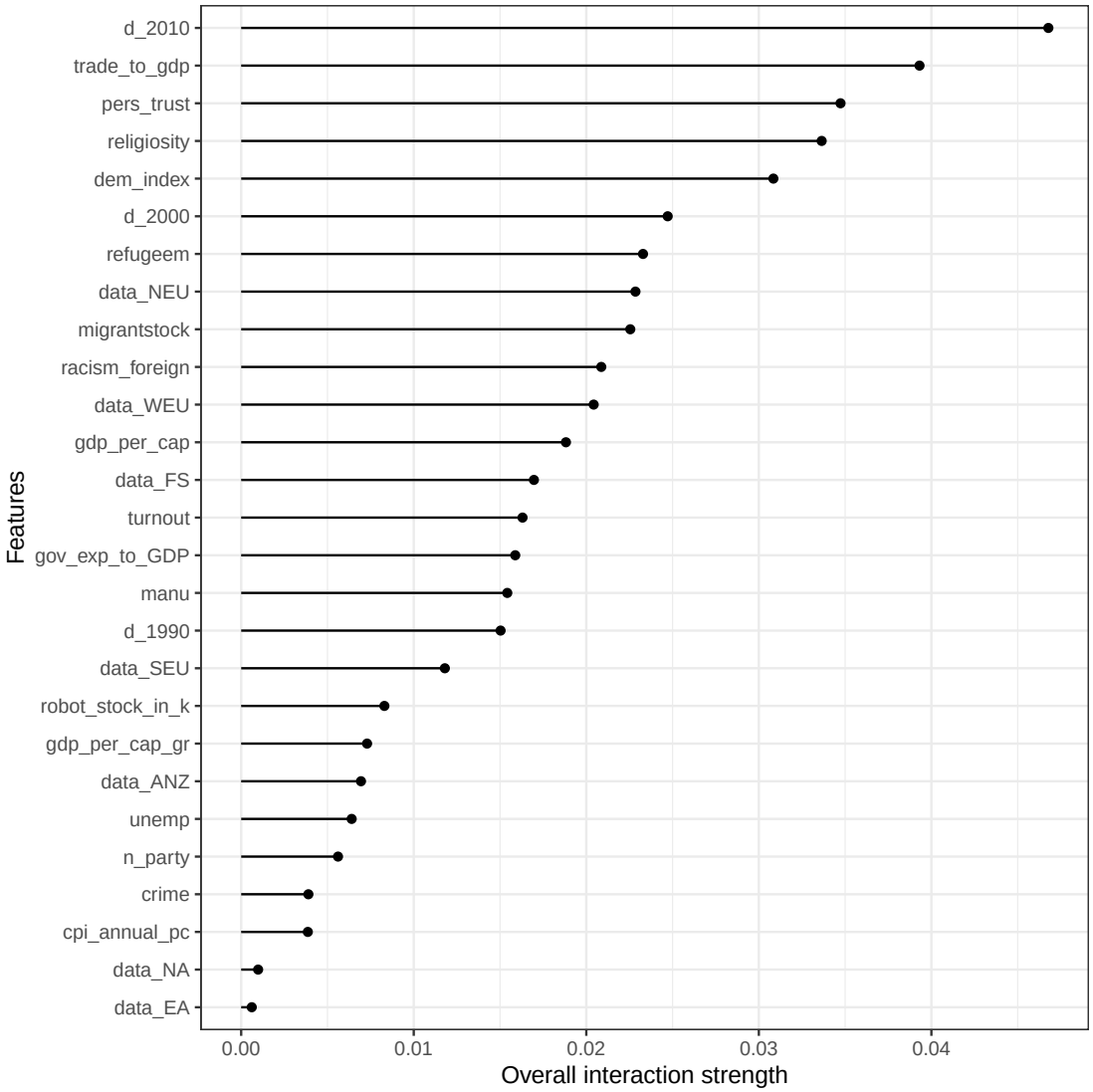
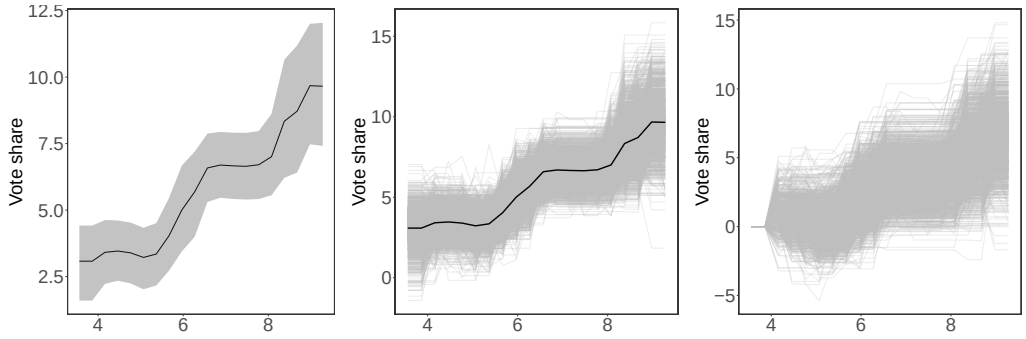


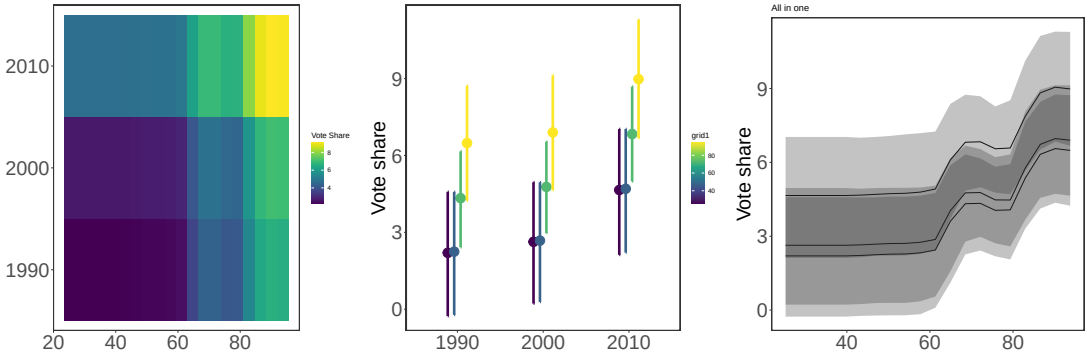
Figure 6. H-statistic for interaction detection.

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.



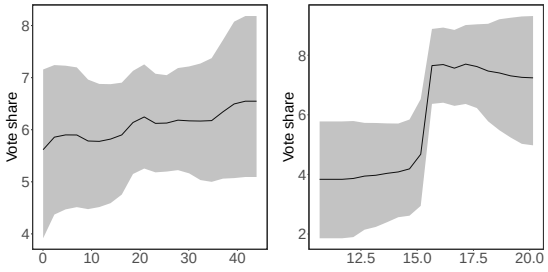
(a) religiosity, PDP **(b)** religiosity, ICE **(c)** religiosity, centered ICE

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

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 time, we find a nonlinear 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 economic factors, such as globalization measured by the trade-to-GDP ratio, or cultural factors, such as religiosity.

Unemployment is negatively and significantly correlated with populism. Hence, we do not 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 turn back to established and experienced mainstream parties in times of economic uncertainty. The nonparametric analysis revealed that the PDP of unemployment follows a rounded L shape, suggesting that the relationship between unemployment and the dependent variable is more complex and nonlinear than previously assumed. A country's level of GDP seems to play a role only in the rise of populism before the 1990s.

7. Conclusion

This paper examines the drivers of far-right populism in Western democracies over the last four decades. Our 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 identify the most influential determinants of far-right populist vote shares and their potential nonlinearities.

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, showing that different forms of trade have different relationships with populist voting. 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 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 findings contribute to the study of political behavior by distinguishing the roles of economic integration, migration, and religion in far-right populism. Combining model averaging with nonlinear analysis helps separate these explanations and provides a basis for policymakers to address the underlying causes of populist movements.

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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

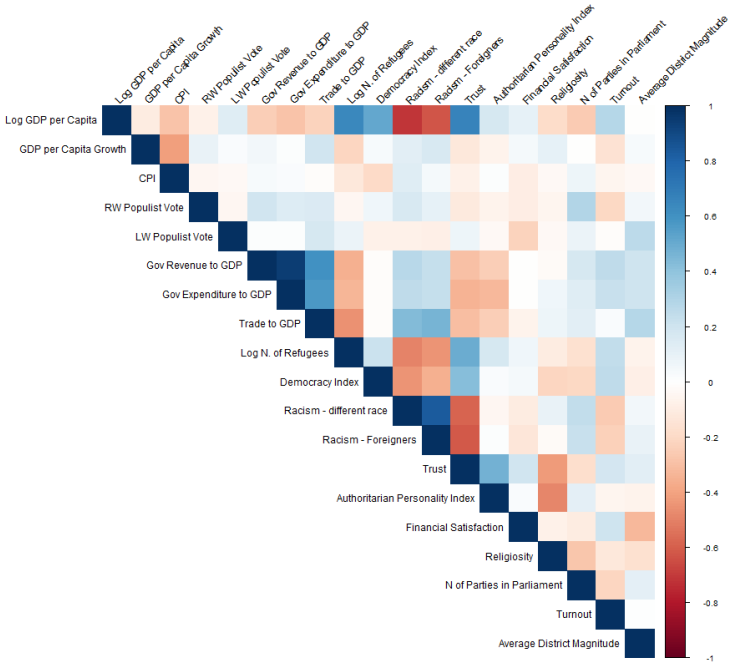


Figure 10. Correlation Table - All Countries 1980 - 2019

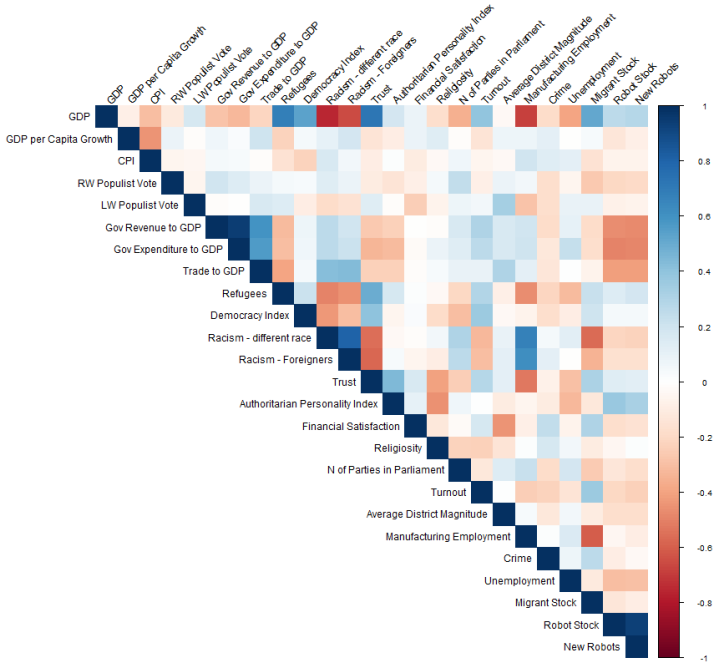


Figure 11. Correlation Table - All Countries 1980 - 2019



Figure 12. Correlation Table - All Countries 2000 - 2019

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

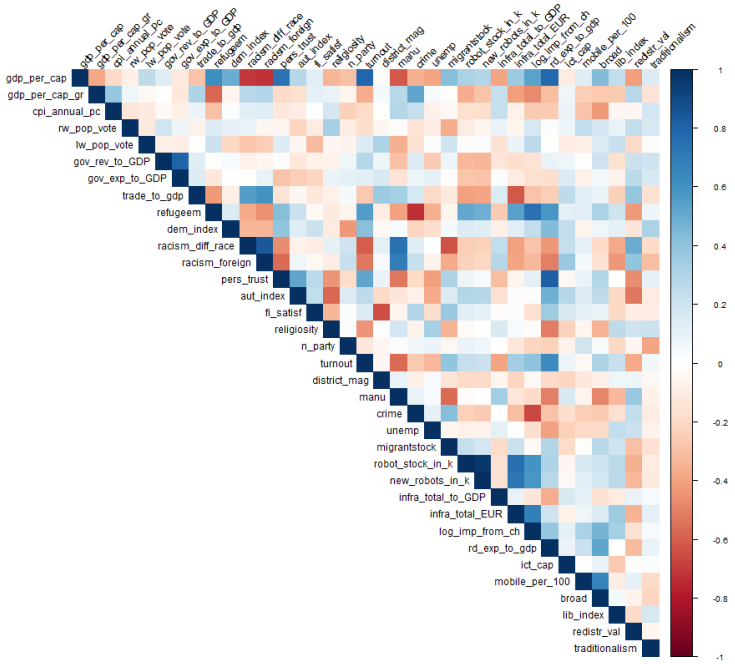


Figure 13. Correlation Table - European Countries 2000 - 2019

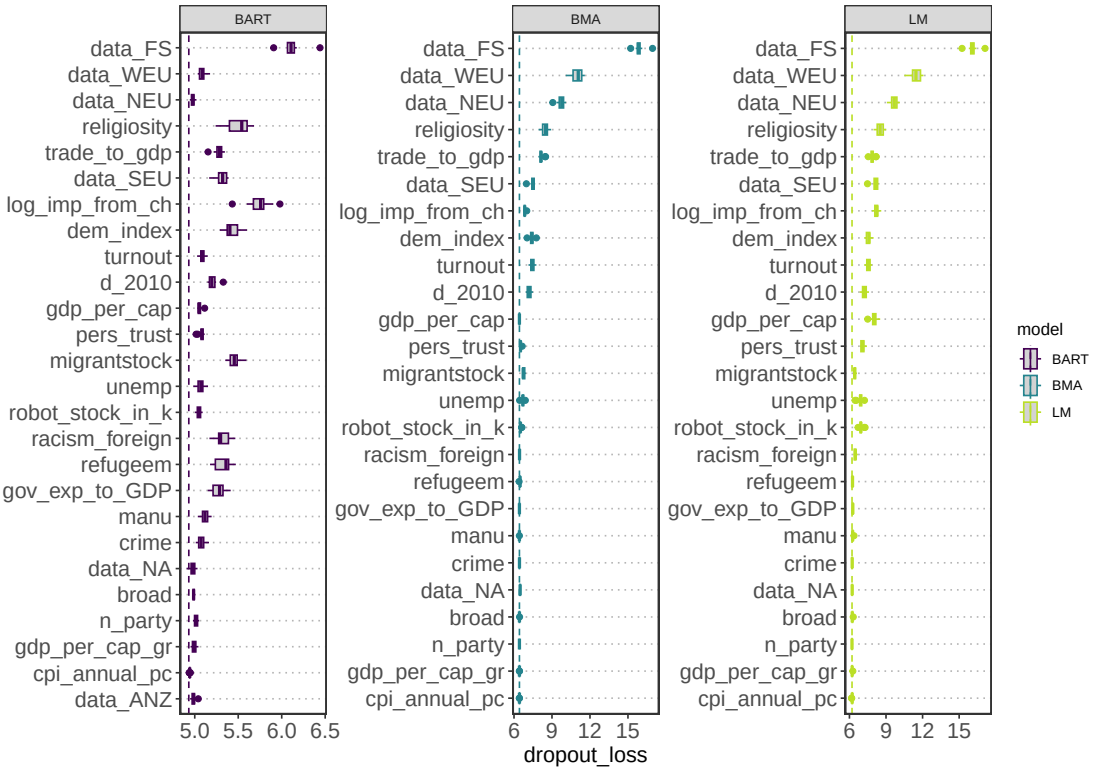


Figure 14. Permutation-test-based variable importance (dropout loss in RMSE) for 2000-2019 sample.