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Populism and the Skill-Content of Globalization*

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Abstract

We propose new ways to measure populism, using the Manifesto Project Database (1960-2019) as main source of data. We characterize the evolution of populism over 60 years and show empirically that it is significantly impacted by the skill-content of globalization. Specifically, imports of goods which are intensive in low-skill labor generate more right-wing populism, and low-skill immigration shifts the distribution of votes to the right, with more votes for right-wing populist parties and less for left-wing populist parties. In contrast, imports of high-skill labor intensive goods, as well as high-skill immigration flows, tend to reduce the volume of populism.

Keywords: Globalization, Populism, Immigration, Trade.
JEL Codes: D72, F22, F52, J61, P00.

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1 Introduction

The recent rise of populism is often portrayed as a backlash against globalization. The fall of the Communist Block and the opening of EU markets to trade and immigration from Eastern Europe that followed, China's entry into the WTO in 2001, the generalization of offshoring as well as the steady increase in South-North immigration flows since the 1990s have exposed workers and firms in industrialized countries to a global competition that some (and certainly the populists) characterize as unfair. Together with an anti-elite rhetoric, providing protection against the forces of globalization is part of the DNA of populist parties. This was already the case for the late-19th-century *American People's Party*, one of the first populist parties in the modern sense (Rodrik, 2018; Guriev and Papaioannou, 2022),[1] and is evermore the case for today's European populist parties, from the right as well as from the left (Funke et al., 2023; Colantone et al., 2022). Several definitions of populism have been proposed over the years, generally combining (with varying degrees of prominence) anti-elite, anti-pluralist and anti-globalization stances as well as a commitment to protect the people (Mudde, 2004; De Vries, 2018; Algan et al., 2018; Morelli et al., 2021).[2]

This paper discusses the measurement of populism, documents its evolution over the last sixty years, and studies its determinants, focusing on the role of globalization and of its skill-content. It makes two main contributions.

The first contribution concerns the measurement of populism. Using data from the Manifesto Project Database (MPD), one of the most standardized and comparative source of data for tracking party ideology, we construct a continuous and time-varying "populism score" for each political party in 657 national elections across 55 countries from 1960 to 2019. Our measure captures two core dimensions of the populist rhetoric: (i) the anti-establishment stance (AES), and (ii) the commitment to protect (CTP) the people from perceived internal and external threats. Taken together, these two dimensions provide a coherent theoretical foundation for identifying and comparing the extent of populism across parties, ideologies and over time. Unlike measures of populism relying on expert judgments and which, as such, are vulnerable to subjective biases hindering comparability across years and countries(Meijers and Wiesehomeier, 2023), our approach is based on textual data and does not depend on external classification. We apply transparent, unsupervised methods using a parsimonious set of text-based indicators from the MPD that directly reflect the populist content of party's electoral platforms. This yields a replicable party-level score of populism that varies across elections, enabling fine-grained analysis of when and how parties adopt populist stances, regardless of whether they are classified as populist or not and avoiding arbitrary classification and aggregation rules (Di Cocco and Monechi, 2022; Celico et al., 2024). We aggregate our party-level

[1] As noted by Rodrik (2018), "the term [populism] originates from the late nineteenth century, when a coalition of farmers, workers, and miners in the US rallied against the Gold Standard and the Northeastern banking and finance establishment. Latin America has a long tradition of populism going back to the 1930s, and exemplified by Peronism."

[2] Others also emphasize the populists' shortsighted political agenda (Guiso et al., 2024) or their fascination for authority (Eichengreen, 2018) and national identity (Müller, 2016)

populism scores into two country-level measures: a ”volume margin“ (the total vote share of all parties with populist rhetoric) and a ”mean margin“ (the vote-share-weighted average populism score of all parties). The latter accounts for the fact that populist ideas are not restricted only to parties identified as populist; rather, they can spillover to parties not classified as populists.

Overall our proposed measures of populism provide significant advances compared to expert-based datasets such as POPPA (Meijers and Zaslove, 2021), the Global Populism Database (Hawkins et al., 2019) or V-Party (Düpont et al., 2022), which often suffer from limited coverage or consistency across time and space. They also improve on existing manifesto-based approaches. For example, Stöckl and Rode (2021) construct a populism index based on a broad set of issues, many of which are only loosely related to populism, whereas Di Cocco and Monechi (2022) rely on supervised learning anchored in expert-coded classifications and focus on a narrow set of Western countries.[3] In contrast, our approach systematically integrates theoretical grounding, empirical scalability, and extensive coverage. Furthermore, by linking our populism scores to the MPD's ideological indicators, we can examine how populism varies and evolves along the right-left spectrum.

The second contribution consists in a rich empirical analysis of the effects of import competition and of immigration on populism (respectively for left-wing, right-wing and total populism) according to their skill-content. Previous literature (see our review below) has looked at trade and immigration separately and often neglected their skill dimension; it has also focused almost exclusively (with some exceptions of course) on globalization and right-wing populism. Extending the scope of the analysis as we do is of value for itself, in terms of territory covered, but also methodologically, as this helps mitigating certain econometric issues such as potential omitted variable biases. For example, we show in Appendix E.1 that including migration shocks increases the magnitudes and statistical precision of the trade-related coefficients. Importantly, we instrument skill-specific imports and immigration flows relying only on exporting/origin-country (i.e., push) factors, in line with the relevant literature (Autor et al., 2020; Munshi, 2003; Boustan, 2010; Kleemans and Magruder, 2018; Monras, 2020). We find that low-skill imports and low-skill immigration both raise votes for right-wing populist parties (volume margin), while the opposite holds for high-skill immigration and imports. In addition, low-skill imports also translate into higher levels of populism at the mean margin, and low-skill immigration reduces voting for left-wing populist parties.

Our results are only partly in line with the literature on globalization and populism in a large panel of countries (Swank, 2003; Burgoon, 2009; or Milner, 2021 among others), as we detail and discuss below. This literature is not restricted to cross-country studies, it also includes important studies exploiting cross-regional variations in exposure to globalization within a country. As far as trade is concerned, several papers have focused on the differential exposure of local labor markets to the “China trade shock” and showed that the rise in Chinese imports triggered support for radical-right parties in a number of OECD countries (Autor et al., 2020; Malgouyres, 2017). Aksoy et al.

[3]Some of the above-mentioned measures appeared in the course of our investigation. In our validation exercise in Section B.2, we only refer to established datasets widely used in political science and political economy.

(2024) show that the way voters react to the skill-content of trade shocks is itself mediated by their own skill-structure. Other studies show that populism tends to flourish in contexts of economic uncertainty (Rodrik, 1997; Swank, 2003; Algan et al., 2017), which may itself be the result of trade shocks (Di Giovanni and Levchenko, 2009; Vannoorenberghe, 2012; Caselli et al., 2020). Similarly, a growing literature has explored the links between immigration and electoral outcomes in contexts as various as the United States (Mayda et al., 2022), France (Malgouyres, 2017; Edo et al., 2019), the United Kingdom (Colantone and Stanig, 2018; Becker and Fetzer, 2016; Becker et al., 2017), Germany (Dippel et al., 2022), Italy (Barone et al., 2016), Spain (Mendez and Cutillias, 2014), Austria (Halla et al., 2017; Steinmayr, 2021), Denmark (Harmon, 2018; Dustmann et al., 2019), Switzerland (Brunner and Kuhn, 2018), the city of Hamburg (Otto and Steinhardt, 2014), or Western Europe in general (Guiso et al., 2017). Most studies show positive effects of immigration on support for the far-right, driven by fears of negative labor market and fiscal effects of immigration as well as by perceived cultural threats. The skill structure of immigration is discussed in only a handful of studies (e.g., Hainmueller and Hiscox, 2010; Edo et al., 2019; Moriconi et al., 2022, 2019; Mayda et al., 2022).

The relationship between globalization and populism is no exception. Beyond trade and immigration, the cross-country literature on globalization and populism has explored other dimensions of globalization such as the expansion of internet and social media (Zhuravskaya et al., 2020; Campante et al., 2018; Guriev et al., 2021), the role of structural transformations arising from automation and de-industrialization (e.g., Frey et al., 2018; Anelli et al., 2018; Gallego et al., 2018), or the role of financial crises (Funke et al., 2016; De Bromhead et al., 2013; Algan et al., 2017). The surge of populism has also been related to cultural factors and to the perception that the elites are ignoring people's concerns about identity and fairness (Norris and Inglehart, 2019; Mukand and Rodrik, 2018; Algan et al., 2018). We account for these other determinants and explore interactions between some of them and globalization shocks.

The rest of this paper is organized as follows. In Section 2, we construct a new, continuous and time-varying populism score for around 3,900 party-election pairs using data on political manifestos across election campaigns. We show that our populism score is consistent across countries and election periods and describe its correlation with other, widely used measures of populism. In Section 3, we use this populism score to build our volume and mean margins measures of populism and describe their long-run evolution. We show that levels of populism have been fluctuating since the 1960s, with peaks after all major economic crises (including the financial crisis of 2007-08). While the recent rise of right-wing populism is not restricted to Europe, it is certainly more pronounced there, both in Eastern and Western Europe. In Section 4 we exploit dyadic data on imports, immigration and their respective skill-structure to empirically investigate the determinants of populism at different margins. The surge in populism appears closely linked to the skill structure of imports and immigration, sometimes in non-conventional ways. Section 5 concludes.

2 A Continuous, time-varying Populism Score

Populism is a multifaceted concept, which encompasses different dimensions of politics such as the ideology, political strategy and communication style of a party or politician (Van Kessel, 2015). As Rodrik (2018) puts it, however, populism is more a view of the world than anything else. It is a complex object, easier to recognize than to define, which may be partly why many studies rely on expert judgment to classify political parties (and leaders) as either populist or not. The alternative is to rely on an analysis of political speeches, platforms and agendas, which is the route we will follow in this paper. Whatever the pros and cons of each approach – expert v. text-based, holistic v. objectifying – the latter has an intrinsic advantage: it allows for measuring how much populist/non-populist parties are, something out of reach in a dichotomous classification (Sikk, 2009; Inglehart and Norris, 2016).

In this section we develop a *continuous* populism score for each political party that is *time-varying* (parties can become more or less populist) and consistent over time and across space for a large set of countries since the early 1960s. Relying on text analysis of political manifestos, our populism score can be used to define certain parties as populist (above a certain threshold score) or not, compute the share of votes accruing to those parties – what we call the *volume margin* of populism – and take the vote-weighted average of such scores for all parties as alternative measure of the extent of populism, what will be referred to as the *mean margin.* We will also internally and externally validate our methodological choices, as discussed in Section 2.2 and Section 2.3.

2.1 Populism Scoring Methodology

For each party-election pair in our sample, we construct a populism score based on a content-analysis of its political manifesto. We denote it by $S^p_{i,e,t}$ for party $p \in (1, ..., P)$ from country $i \in (1, ..., I)$, in election $e \in (1, ..., E)$ at year $t \in (1960, ..., 2019)$. Our scoring methodology is theory-based and relies on two standard dimensions of populism, the *anti-establishment* and the *commitment-to-protect* stances. In Section 2.3, we show that deviating from this parsimonious definition of populism creates additional noise and reduces comparability with existing measures and classifications.

Data. We rely on the *Manifesto Project Database (MPD)* (Lehmann et al., 2024), which characterizes a party's political preferences by counting the number of quasi-sentences associated with a specific issue compared to the length of the party's manifesto (*salience*).[4] For some variables, the MPD reports separately the salience of both positive and negative statements about an issue. In such a case we construct the *net position* as the difference between the two. The MPD covers several

[4]The MPD parsed each party manifestos in quasi-sentences. The methodological notes of MPD define them as follows: "A quasi-sentence is a single statement. A grammatical sentence can contain more than one quasi sentence, but a quasi-sentence can never span over more than one grammatical sentence."

political issues such as the position on external relations (e.g., European Union and/or internationalism), the economic system (e.g., free market economy v. market regulation), the welfare system (e.g., welfare state and public education expansion) and on the fabric of society (e.g., the relevance of traditional morality and law enforcement). The MPD captures the positioning of parties during the electoral campaign, when parties are seeking to attract electors and before accepting possible post-election compromises with other parties. The MPD covers all parties that won at least one seat in an election campaign. Although debates can be engaged on selection issues, the one-seat constraint excludes many independent candidates, and implies that parties that are very small or politically insignificant are excluded from the sample.[5] Figure A.1 and Table A.1 in the Appendix document the geographic and time coverage of the MPD database and of our sample, respectively. The MPD also provides an overall synthetic index positioning the party over the right-left political spectrum (Budge and Laver, 2016), as discussed below.

Dimensions of Populism. To provide a consistent measure of populism over space and time, we rely on a parsimonious definition of populist parties, which is based on the existing political science literature and associates populism with two main characteristics:[6]

First, the *anti-establishment stance (AES)* is the key characteristic that recurs in all definitions of populism. Populist parties build on the premise that high ethical and moral values are the hallmark of the people, and not of the ruling class (Shils, 1956; Wiles, 1969). They highlight the divide between the good, pure and homogeneous people, and the corrupt and self-centered elite (Taggart, 2000; Mudde, 2004; Van Kessel, 2015), the enemy of the people. A key reference in this literature is Mudde (2004), who defines populism as "an ideology that considers society to be ultimately separated in two homogeneous and antagonist groups: the pure people against the corrupt elite, and which argues that politics should be the expression of the general will of the people." This rationale guides our focus on attitudes toward corruption and anti-pluralist views when measuring the AES dimension. The commitment to protect, on the other hand, varies across ideologies. Such an antagonistic view implies that populists advocate the sovereignty and protection of the people against the political establishment as well as against internal and external threats (Stanley, 2008), which leaves no room for pluralism, diversity of opinions, and even for the protection of minorities (Guriev and Papaioannou, 2022). We use two variables from the MPD to proxy for the AES: the salience of, and position towards (*i*) political corruption, which includes mentions related to the need to eliminate political corruption, power abuses and "clientelist" structures; and (*ii*) political authority, which proxies for anti-pluralism views and measures parties' own statements about their relative competences and abilities.

[5]With proportional representation and high electoral thresholds, or with majority voting and narrow electoral districts, this may bias against capturing a large fraction of populist votes. Incidentally, this makes the mean margin even more relevant in such contexts. In any event, we check the robustness of our results to the type of political systems in Appendix E.7.

[6]The exact description of these characteristics is provided in Appendix B.

Second, populism involves a strong *commitment to protect (CTP)* people against various internal and external threats (Morelli et al., 2021; Guiso et al., 2017; Rodrik, 2018; Acemoglu et al., 2013; Gennaro et al., 2021). This commitment to protect is often expressed so as to nurture peoples' resentment (Taggart, 2000; Moffitt and Tormey, 2014). Left-wing populists also emphasize inequality across social classes[7] while right-wing populists tap on ethno-cultural cleavages, stressing the threat of immigration.[8] To proxy for parties *commitment-to-protect* people from external threats, we first rely on a series of variables used to measure parties' stances towards globalization (Burgoon, 2009; Colantone et al., 2022):[9] (*i*) protectionism, which captures parties' statements towards the protection of the internal market, (*ii*) internationalism, which refers to parties' mentions of international cooperation and national sovereignty, (*iii*) European Community/Union, which includes mentions of its expansion and increase in its competences.[10] We then include a fourth dimension: (*iv*) nationalization, which reflects positive mentions of government ownership of land and industries and proxies for overall support for government intervention in the economy.[11]

Populism score. To obtain a populism score based on the 6 dimensions of the MPD identified above, we perform two stages of dimensionality reduction. In the first, we perform a Polychoric Principal Component Analysis of the variables belonging to each populism dimension (AES and CTP), and construct a synthetic indicator for each of them. Panel I of Table 1 shows the results of the PPCA for the two dimensions of populism. Col. (1) gives the eigenvalues produced by the PPCA. Following the so-called Kaiser's criterion, we focus on the first component only, which retains a sizeable amount of variance and exhibits eigenvalues above one (Preacher and MacCallum, 2003). Focusing on the first component, Col. (2) gives the score associated to each variable within the first component, and Col. (3) shows the correlation between the estimated first component and each of the underlying variables. This first stage gives rise to two synthetic indicators capturing political parties' positions with respect to anti-establishment (AES) and commitment-to-protection (CTP) stances.

In Panel II of Table 1, we estimate the partial correlations between our two synthetic indices AES and CTP after controlling for country and year fixed effects and for parties right-leaning

[7]Left-wing populism is quite common in Latin America (March and Mudde, 2005). In Western Europe recent examples include *La France Insoumise* or *Podemos* in Spain.

[8]Growing right-wing populism is evidenced by rise of the *Tea Party* and Trump's MAGA movement in the U.S., the *Lega Nord* and *Fratelli d'Italia* in Italy, the *Law and Justice Party* in Poland, the *Front then Rassemblement National* in France, *Alternative for Germany* (AfD) in Germany, UKIP in the UK, *Vlaams Belang* in Belgium, etc.

[9]Discussion of differences and similarities between our approach and the net autarky stance is available in Appendix B.5.

[10]For these dimensions, MPD provides parties' favorable and negative stances. We rely on the net position, which is the difference between positive and negative mentions. For parties belonging to non-European countries, component (iii) is set to zero.

[11]See Shleifer (1998) as well as Dornbusch et al. (1989) and Bazdresch and Levy (1991) more specifically for the Latin American context.

Table 1: Construction of the populism score ($S^p_{i,e,t}$) using a two-stage PPCA

	I. PPCA (AES/CTP)			II. Corr. btw. AES & CTP				III. Descriptives		
	EV	Score	Corr.	AES	CTP	RW	R^2	SD	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Anti-establishment (AES):				-	.08† (.02)	.01† (.00)	.26	1.03	-.73	8.58
- Pol. corruption	1.07	.71	.73‡							
- Anti-pluralism	.93	.71	.73‡							
Commitment to protect. (CTP):				.12** (.04)	-	-.01* (.00)	.11	1.14	-5.80	10.78
- Protectionism	1.29	.42	.48‡							
- Internationalism	.96	-.42	-.48‡							
- EU institutions	.91	-.60	-.68‡							
- Nationalization	.83	.54	.62‡							
Populism score								.81	-3.26	5.52

Notes: Panel (I) shows the results of the polychoric principal component analysis (PPCA). Cols. (1), (2) and (3) give eigenvalues (EV) associated to each variable, their scoring, and the correlation between the first component of the PPCA and the variables in the analysis. Panel (II) shows the partial correlations between dimensions after controlling for a right-left index of parties' position over the political spectrum, country and year fixed-effects. Standard errors are clustered at the country level. Panel (III) provides some descriptive statistics. Level of significance: * p<0.05 ; ** p<0.01 ; † p<0.001 ; ‡ p<0.00001.

ideology (RW) (available in MPD, Budge and Laver, 2016).[12] The coefficients are reported in Cols. (4) to (6), and the R-squared of the regressions are provided in Col. (7). The correlation between these two components is positive, though not as strong as one might expect—0.13 when controlling for fixed effects and 0.12 without controls. This suggests that our set of parties with a high populism score includes those with both high AES and CTP scores, as well as parties with pronounced AES but low CTP, or vice versa. For example, parties such as the New Democratic Party (Canada), the UK labor Party, the Australian Labor Party, and Fine Gael (Ireland) have high CTP scores alongside low AES. Conversely, parties such as the Social Democratic Party (Denmark), the Partido Revolucionario Institucional (Mexico), the Democratic Party in the United States (1994–2008), and the Five Star Movement in Italy (in most years) are characterised by high AES but relatively low CTP. Finally, in Cols. (8) to (10) of Panel III, we provide the standard deviation (SD), the minimum (Min) and the maximum (Max) of the two synthetic indices.

In a second stage of *dimensionality* reduction, we perform an average of the two synthetic indicators extracted from the first stage, and identify a general populism score for each election-party pair. In our context, performing a PPCA would provide identical results, with the same

[12] The dependent variable is AES in the upper Panel, while is CTP in the lower Panel. Hence, the estimated coefficients from the regression should be read horizontally.

weights assigned to the two synthetic indicators. In the bottom Panel of Table 1, we show the descriptive statistics associated to the populism score, $S^p_{i,e,t}$. By construction, each index has a zero mean, while the standard deviation equals 0.81.

Right-wing vs. left-wing populism. Populism is a "thin" ideology, which can be combined with other political views and can easily adapt its position on salient political issues at stake (Taggart, 2000; Mudde, 2004; Rooduijn et al., 2014). In particular, populism is usually identified as right-wing or left-wing populism based on the type of cleavage used to create two antagonist groups in the society. Mobilization of voters along income/social class lines is associated with left-wing populism. By contrast, tapping on the ethno-national/cultural cleavages is associated with right-wing populism.

Based on the work of Budge and Laver (2016), we position parties over the right-left political scale using the right-left index (*rile*) available in the MPD. We consider as left-wing (as right-wing, respectively) those belonging to the first tercile (third tercile, respectively) of the right-left political scale distribution. Those in the second tercile are classified as centrist. It is worth emphasising that this classification along the right-left spectrum is governed by several factors such as parties' attitudes towards redistribution and political preferences that are related to moral values (e.g. on law and order, traditional morality, importance of military forces, anti-imperialism, etc.). In Table B.5 we show that our populism scores is positively related with parties' likelihood to belong either to radical right and radical left political families – using the classification provided in the Chapel Hill Expert Survey for the 1994-2014 period. By contrast, the we do find a negative association with the likelihood to belong to other families (i.e., liberal, Christian-democratic and socialists).

2.2 Comparison with existing measures of Populism

Other populism indices and classifications have been developed in the political science literature; they cover different sets of countries and periods. As a validation exercise, we focus on six widely used databases (detailed description of the different dataset is available in Appendix B.2):

- ☐ Four dichotomous classification of parties: the *Van Kessel* database (Van Kessel, 2015); the *Swank* database (Swank, 2018); the *PopuList* database (Rooduijn et al., 2019); and the *GPop 1*, known as the Global Populism data (Grzymala-Busse and McFaul, 2020). The latter is particularly relevant for our analysis, since it allows us to cross-validate our time-variant measure over a time-invariant definition of populist parties for the whole 1960-2019 period.

- ☐ Two (continuous) indexes of populism based either on textual analysis of party leaders' political discourses (for the *GPop 2*, also known as the *Global Populism Data* (Hawkins et al., 2019)) or on expert surveys evaluation (for the *Chapel Hill Expert Survey* database (Bakker et al., 2015)).

In Panels I to IV of Table B.4 in Appendix, we regress the four dichotomous classifications above on our populism score ($S^p_{i,e,t}$) and on its two components (AES and CTP). We estimate

Probit models (denoted by PRB). Partial correlations are provided for Van Kessel in Panel I, for Swank in Panel II, for the PopuList database in Panel III, and for the GPop 1 database in Panel IV. In all cases, we control for country and election-year fixed effects, to capture countries' time-invariant unobserved heterogeneity and common year trends. The estimates suggest a positive and highly robust correlation between our populism score and the probability to be classified as a populist party.[13] In Panels V and VI of Table B.4, we show the partial correlations between the GPop 2 and CHES continuous indicators and our populism score. As can be seen, they are positive and highly significant.

We then produce our own classification of parties using our continuous and centered (i.e., zero-mean) score of populism. This classification is needed to define the volume margin of populism. We classify a party as populist when its populism score $S^p_{i,e,t}$ exceeds a certain threshold, which can be expressed as a multiplying factor η of the standard deviation of the distribution (SD). We define a dummy $\mathbf{1}^p_{i,e,t}$ equal to 1 if the party p from country i is classified as populist in election e at year t, and 0 otherwise:

$$\mathbf{1}^p_{i,e,t} = \begin{cases} 1 & \text{if } S^p_{i,e,t} \geq \eta \times SD \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

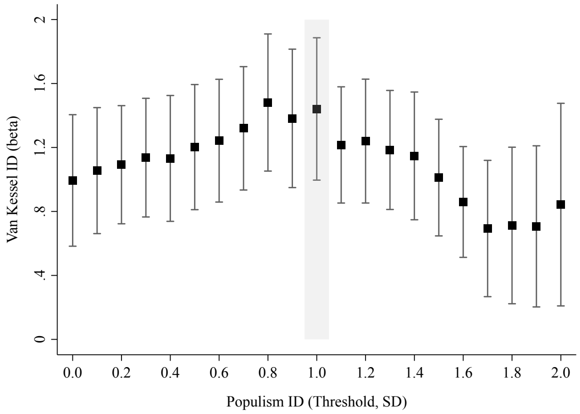
The classification depends on the populism threshold determined by η. To identify a relevant threshold, we compare our classification of populist parties with those of existing studies when we gradually increase η from 0 to 2 (i.e., 0 to 2 standard deviations above the mean). As our database includes more parties and elections than alternative databases, the statistics are computed for the party-election pairs included in each alternative database – namely those of Van Kessel, Swank, PopuList and GPop 1. We investigate the capacity of our populism score to predict the probability to be classified as populist in these databases. We estimate new Probit models for each of the four dependent variables with three sets of explanatory variables, a dummy $\mathbf{1}^p_{i,e,t}$ equal to one if the party is classified as populist according to our criteria (η),[14] country and year fixed effects.

Figure 1 shows that $\eta = 1$ determines a relevant threshold, maximizing the partial correlation with three existing classifications. A more restrictive threshold might be desirable to maximize the partial correlation with the GPop 1 database. However, in the Appendix B.6 we show that $\eta = 1$

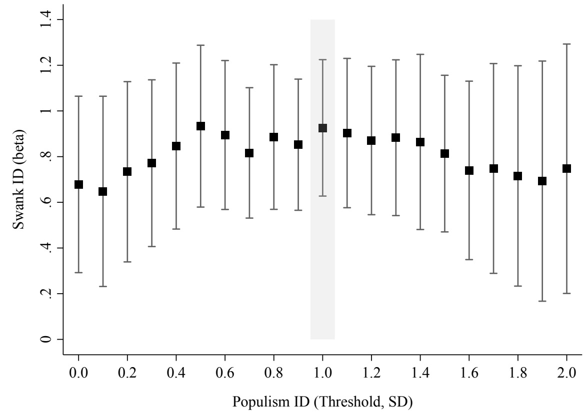
[13] To better grasp the quality of the fit of our Probit models with respect to the different binary definitions of a populist party, we first compute the predicted probability of being defined a populist party using the estimated models, and we define the set of predicted populist parties as the ones characterized by a predicted probability of being populist above 0.5. Following Naik and Leuthold (1986) we then compute the ratio of accurate forecasts (RAF), which is the percentage of predicted populist identifiers (either 0 or 1) corresponding to the actual data set of reference. The ratio of accurate forecasts takes value between 80% to 91%, suggesting that our predictions nicely fit alternative classifications. Interestingly, the highly significant correlation levels obtained for Global Populism data (GPop 1) over the 1960-2019 minimize concerns related to comparability and consistency issues over our long period of analysis. Controlling for the right-left index hardly affects the correlations between alternative definitions of populism and our populism score or its *commitment-to-protect* component. The correlation with the anti-establishment index is less robust, suggesting that parties' ideological orientation captures part of the *anti-establishment* stance.

[14] In Table B.4, we regressed existing populist dummies on our continuous score ($S^p_{i,e,t}$).

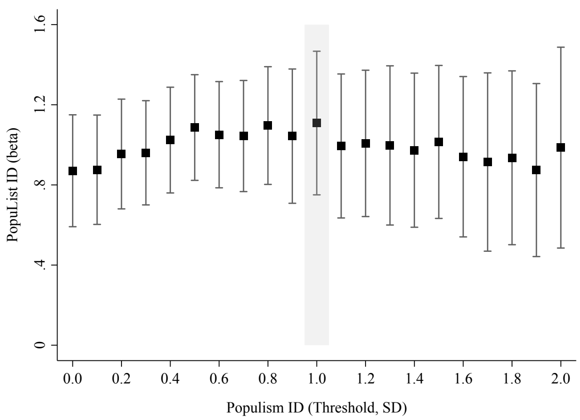
Figure 1: Populist parties – Threshold definition



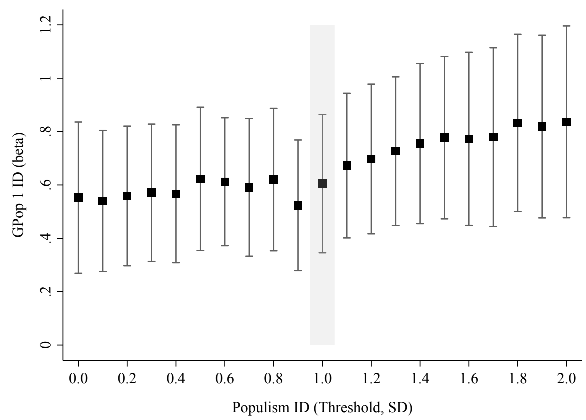
(a) Van Kessel



(b) Swank



(c) PopuList



(d) GPop 1

Note: The Figure shows the partial correlations between a dummy which defines a party as populist based on different threshold of the populism score (x-axis) and a populist identifier based on: Van Kessel (2015) (Panel a), Swank (2018) (Panel b), Rooduijn et al. (2019) (Panel c) and Grzymala-Busse and McFaul (2020) (Panel d). The partial correlations are estimated from a probit model, including country and year fixed effects. The rate of accurate forecasts for the overall set of parties and for populist parties only are provided in Appendix B.6.

also maximizes the rate of accurate forecasts for the overall set of parties and for populist parties only, whatever the classification used as a reference (even when using the GPop 1 classification). Moreover, descriptive evidence at the party-level presented in Appendix C.2 support our methodological choices for the selection of the threshold. For instance, parties classified as populist in the UK are the *UK Independence Party* (UKIP) before the Brexit referendum and the *Labour* Party from the 1974 to the early 1980s', due notably to its opposition to the entrance of the UK to the European Common Market.[15] Another example is France, where two parties exhibit a populism score consistently above the $\eta = 1$ threshold for several elections: the *Parti Communiste Français* (PCF) and the *Front National* (FN). Moreover, for the last election available (2017), *La France Insoumise* (LFI) has a populism score above the selected threshold. Consequently, when using a dichotomous classification of parties to compute the volume of populism, we classify parties with a populist score exceeding one standard deviation as populist in the rest of the paper.[16] We classify 454 party-year observations as populist (205 as right-wing, 153 as left-wing and 96 as centrist), representing 12.3% of our sample.

While we consider alignment with existing measures as a "blessing," our approach offers several important advantages. Our populism score is continuous, available at both the party and national levels, spans a wide range of countries and years, and applies to all parties—whether or not they are classified as populist. For this reason, we see our measurement framework and related stylized facts as a relevant contribution with respect to the existing metrics and literature.

2.3 Extensions

Although our populism score is a good predictor of existing measures and classifications, its construction relies on a parsimonious definition of populism, and its validation is based on a comparison with widely used measures of populism from the political science literature. These aspects are further discussed below, in various ways.

We first investigate whether a better predictor of existing measures can be obtained by departing from the parsimonious (bidimensional) definition of populism. By focusing on two distinctive characteristics of populism identified in the literature (i.e., AES and CTP), our measurement approach builds on two dimensions that are not necessarily simultaneously present in parties' manifestos. See also Table 1, which shows that while the correlation between AES and CTP is positive, it is not particularly strong: 0.13 when controlling for fixed effects, and 0.12 without controls. Moreover, our populism score abstracts from a significant amount of relevant information available in the MPD. In Appendix B.4, we use similar dimensionality reduction techniques to construct two *extended populism scores* that exploit additional potential characteristics of populist parties, and check whether these extended scores (say $\hat{S}^p_{i,e,t}$) better correlate with existing measures. Our first extended score accounts for the fact that populist parties are sometimes characterized by their

[15] As noted by Lazer (1976), the European Common Market was perceived by the Labour Party as a "capitalist club" against the British population. Harold Wilson, Labour Party leader at the time, clarified the position of his party at the end of the parliamentary debate around this issue: "What we have seen (the debate) has been a classic confrontation - the Establishment against the common sense of the British people".

[16] When describing trends and exploring the determinants of populism, we will assess the robustness of our findings when considering threshold levels equal to 0.9 standard deviations (referred to as the lax threshold, $\underline{\eta}$) and to 1.1 standard deviations (referred to as the strict threshold, $\overline{\eta}$). As shown in the Appendix, all stylized facts highlighted in the subsequent sections are highly robust to the choice of the threshold level.

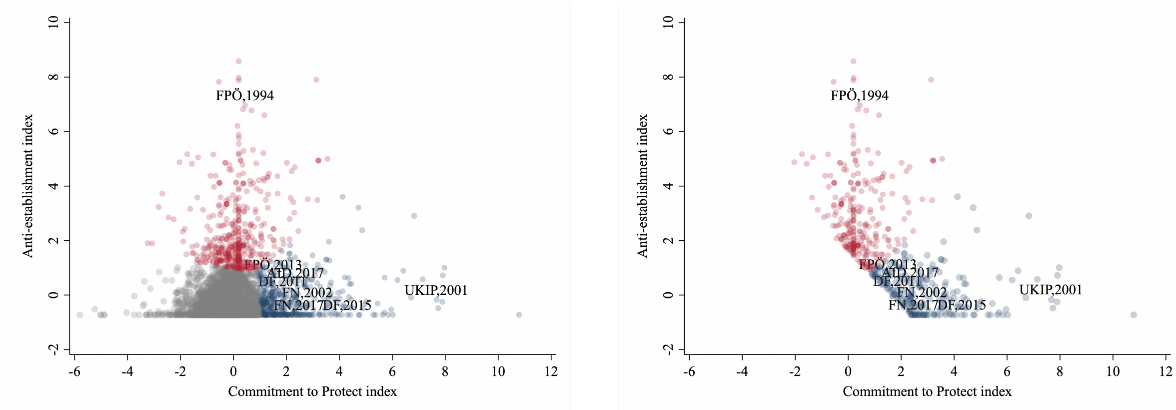
shortsighted and opportunistic research agenda, which guides their political strategy (Guiso et al., 2017). We combine two additional MPD variables covering aspects which are primarily influenced by policies with a long-term perspective such as education and environmental issues. Our second extended score accounts for the whole set of information available in MPD. We construct synthetic indices of political preferences using the remaining set of 44 variables available from the MPD. We then compute correlations with existing measures and classifications. Although the extended populism scores account for a larger number of political characteristics, they do not provide significantly better proxies for populism, as suggested by the smaller magnitudes of the estimated partial correlations (in other words, adding more information to the populism score can create additional noise).

Second, our parsimonious definition of populism voluntarily disregards MPD statements that directly capture the salience of cultural and immigration-related aspects. The reason is that right-wing parties (cleavage based on cultural identity) and left-wing populist parties (cleavage based on social classes) are likely to differ drastically on these issues, and proxies for these variables are available in MPD only from 2006. Nonetheless, we computed partial correlations between our populism score $S^{p}_{i,e,t}$ and four MPD variables capturing preferences for immigration and multiculturalism.[17] In line with intuition, we find that the populism score of centrist and right-wing parties is associated with negative attitudes towards immigration and multiculturalism. The correlation is insignificant when the sample is restricted to left-wing parties. We also computed pairwise correlations between our populism score and proxies for (i) cultural conservatism, and (ii) preferences for government intervention and economic planning. We find that the populism score of centrist and right-wing parties is positively and significantly correlated with cultural conservatism; this is not the case among left-wing parties. Interventionism and populism are positively and significantly correlated on both sides of the right-to-left spectrum (and more so for left-wing populism). Results are provided in the Appendix B.3.

Finally, instead of considering existing databases as a reference basis, we stick to our parsimonious selection of political dimensions, and check whether an unsupervised machine-learning algorithm can validate our dichotomous classification of parties ($\mathbf{1}^{p}_{i,e,t}$). Remember that classifying parties with a populism score exceeding one standard deviation as populist matches well alternative definitions of populism from existing literature. As an alternative approach, we also perform a cluster analysis on the two dimensions of populism identified in the left Panel of Table 1 (i.e., AES and CTP). We use the unsupervised k-means clustering method (with the Euclidean distance as dissimilarity measure), which does not require an *a priori* classification or measurement of populism. Figure 2 (left panel) considers all election-party pairs and identifies three clusters of parties colored in grey, red and blue in the two-dimensional space. On the right panel, we select election-party pairs with populism score above the one standard deviation threshold. The clustering approach

[17] Namely, (i) immigration is negative for country's national way of life, (ii) immigration is positive for country's national way of life, (iii) immigration positively contributes to multiculturalism, and (iv) immigrant should assimilate to the country culture.

Figure 2: Unsupervised clustering analysis on two dimensions of populism



(a) All parties (b) Populist parties only

Notes: We perform a clustering analysis using the two dimensions associated to the standard populism score: anti-establishment and commitment-to-protection stances. The left panel presents the space including all the parties, while the right panel presents the space once we focus on populist parties only.

clearly shows that parties above the one standard deviation threshold belong to a specific cluster in the two-dimensional space, which means that they are both anti-establishment and committed to protect, or that they exhibit a very large index along one of those two dimensions.[18]

While the above discussions give credence to our methods, a few caveats should be stressed. First and foremost, our characterization of populism relies on the salience and stance (positive or negative) of two selected dimensions (AES and CTP) in parties' manifestos and, therefore, neglects other dimensions such as populist leaders' tone and communication style. For instance, as Figure C.13 in the Appendix shows, the US Republican Party in 2016 is not categorized as populist according to our methodology, in spite of the fact that its candidate (and eventual winner) in the 2016 Presidential election is clearly one of the most prominent populist figures of our times. Besides, our approach is *only* able to measure populism at the time of the electoral campaign and neglects whatever happens in between elections.

3 Trends in Populism over 60 Years

In this section, we analyze the evolution of the distribution and mean level of populism focusing on 55 countries over almost six decades. As stated above, we distinguish between the mean level of populism of all political parties – a concept that captures voters' exposure to (and the extent of) populism without requiring a dichotomous classification of parties – and the vote share of populist

[18]It is worth emphasizing that this pattern is less clear-cut when applying the same unsupervised machine-learning algorithm to extended populism scores (see Appendix B.4).

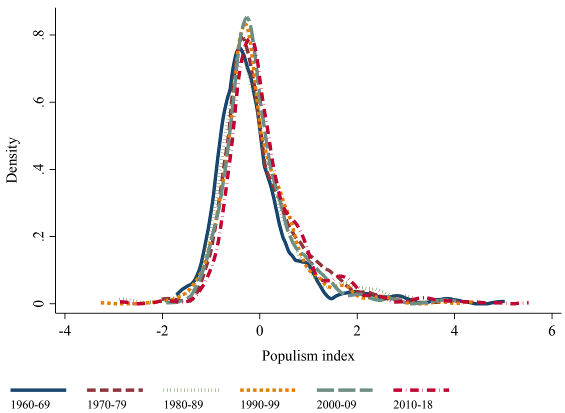
parties – a concept that has been abundantly used in cross-country and case studies. Overall, our analysis shows that: (i) populism is not a recent phenomenon, (ii) both margins of populism have waxed and waned over the last decades, and (iii) populism in general, and right-wing populism in particular has become much stronger in Europe over the last decade. In the Appendix B.8 we show that very similar trends are obtained when using a balanced sample of countries from 1960 to 2019, suggesting that those evolutions are not driven by changes in the composition of our sample.

Distribution of, and trends in populism scores. We first abstract from the dichotomous classification of parties and aggregate the populism scores of all parties included in the sample by period. Figure 3 describes the distribution of populism scores across parties (top panel) and shows different measures of the evolution of the average level of populism over time (bottom panel).

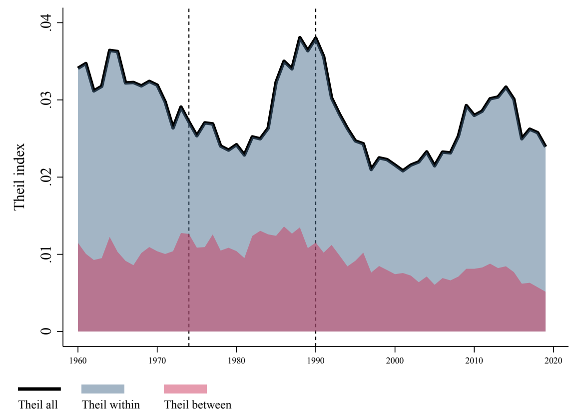
Panels (a) depicts the changes in the density of the populism score across all political parties and countries. The populism score is normally distributed in all decades. We observe a slight increase in the mean, variance, and right skewness (at least, an increase in the density in the range of 1 to 2) during the last decade. Panel (b) depicts the evolution of the Theil index of inequality in populism, and of its between-country and within-country components. Inequality in populism declined between the sixties and early eighties, peaked in the early nineties before declining again, and increased between the financial crisis of 2008 and 2015. The between-country component has been rather stable until the mid-eighties, and has gradually decreased since then. On the contrary, the within-country component – the dominant component in most periods – has shown greater variations and significant increased during the eighties and after 2008, which may reflect a polarization of populist stances in these periods.

Panels (c) and (d) characterize the evolution of the mean level of populism since the early sixties. In Panel (c), we compute the mean populism score of all parties running for election in all years, disregarding their electoral success (i.e., $\sum_{i=1}^{I} \frac{\sum_{p=1}^{P} S^p_{i,e,t}}{I_{e,t} P_{i,e,t}}$ where $I_{e,t}$ is the number of countries in election e at year t, and $P_{i,e,t}$ is the number of parties in country i). This mean level may be seen as a (continuous) proxy for the supply of populism. However, one needs to be very careful with this interpretation as the populism stance of parties is endogenous to the potential demand for populism. The populism score has fluctuated since the early sixties, with peaks aligned with major economic crisis – the oil crisis of the seventies, the deep crises of the nineties, and the years after 2005. The average level observed in 2019 is larger than the level observed in 1960, but smaller than the peak of the late seventies. This masks disparities between European (EU28) and non-European (RoW) countries. In the European Union, the level observed in 2019 is way larger than the level observed in 1960, and slightly greater than the level of the late seventies. It is worth emphasizing that this evolution is not solely driven by the rise of radical right parties in Eastern European countries. We show in the Appendix C.4 that very similar trends are observed when focusing on the EU15 countries. In non-European countries, current levels are lower than those observed in the seventies.

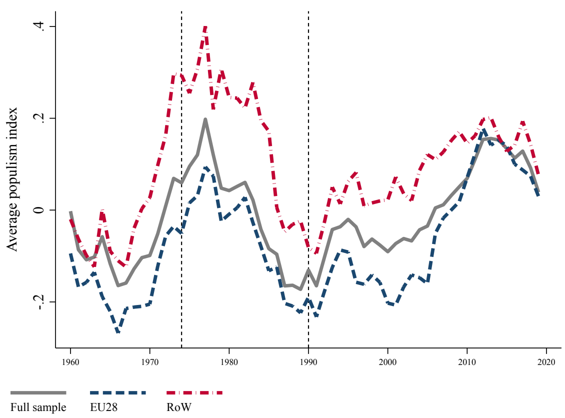
Figure 3: Stylized facts I – Distribution of populism scores and mean margin of populism



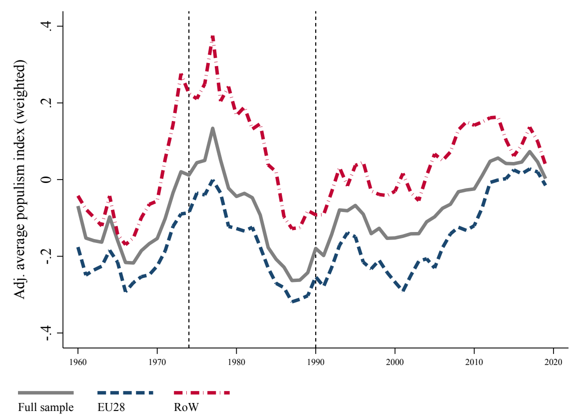
(a) Density of populism score by period



(b) Inequality across parties (Theil)



(c) Mean populism score of all parties (unweighted)



(d) Mean margin of populism ($\Pi^M_{i,e,t}$)

Notes: Fig. (a) shows the kernel-density of the populism score by decade. Fig. (b) depicts the Theil index of inequality in populism across parties, and gives its between-countries component and the within-countries components (Cadot et al., 2011). Fig. (c) plots the average populism score of all parties running for election in a given year. Fig. (d) plots the *mean margin of populism*, a weighted average of the populism scores with weights equal to the party's share in votes. Fig. (c) and (d) show moving averages including 3 years before and 3 years after each date. The vertical lines indicate shifts in our sample size: inclusion of Greece, Portugal and Spain around 1975, and inclusion of Latin American and former Soviet Union countries around 1990. Similar trends are obtained in the balanced sample (see Appendix B.8).

Finally, Panel (d) accounts for the vote shares and depicts the "post-election" mean level of exposure to populism. In line with the electoral center-of-gravity definition proposed by Gross and Sigelman (1984), we define this weighted average as the **mean margin of populism**, which is computed at the aggregate level as:

$$\Pi_t^M = \frac{\sum_{i=1}^{I}\sum_{e=1}^{E}\sum_{p=1}^{P} S_{i,e,t}^{p}\pi_{i,e,t}^{p}}{\sum_{i=1}^{I}\sum_{e=1}^{E}\sum_{p=1}^{P} \pi_{i,e,t}^{p}}, \tag{2}$$

where $\pi_{i,e,t}^{p}$ is the vote share for party p in election e of country i at year t.[19] Note that the mean margin can also be computed at the level of each country-election-year ($\Pi_{i,e,t}^{M}$) by removing the summation over i and e in the above equation. The latter variable will be used as a dependent in our regression framework.

Panel (d) shows that the evolution of the mean margin of populism is very similar to that of the unweighted average level (i.e., peaks aligned with economic crisis). The rise observed in European countries after 2005 is more pronounced, and the European and non-European mean levels are currently almost identical. Hence, although the surge of populism in the last decades appear as a European phenomenon, populism appears as a widespread "pathology" in both European and not European countries.

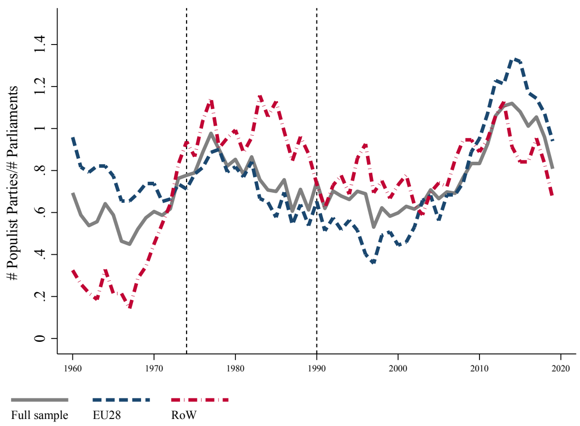
To understand which parties influence the evolution of the mean margin of populism, in Appendix B.9 we decompose the set of parties into two groups: parties that have never been classified as populist, and parties that have been classified as populist at least once. We also categorize them along the right-left axis. Two important findings emerge from this exercise. First, the changes in the mean margin up to the late 80s were primarily driven by the first group (i.e., parties classified as populist at least once) while the last three decades have seen a growing presence of populism in the manifestos of traditional parties. Second, left-wing populism played a significant role up to the collapse of the Soviet Union, whereas right-wing populism became more prominent in the later half of our period of analysis.

In the Appendix C.3, we provide stylized facts for four types of countries, namely Western European countries (France, Germany and the UK), Eastern European countries (Czech Republic, Hungary and Poland), traditional settlement countries (Australia, Canada and the U.S.), and Latin American countries (Argentina, Chile and Mexico). We point to large variations in the mean populism across elections in many countries (such as Hungary, Poland, Australia, Mexico, etc.). These are the sources of variation that we will use in the next section to assess the effect of globalization on populism.

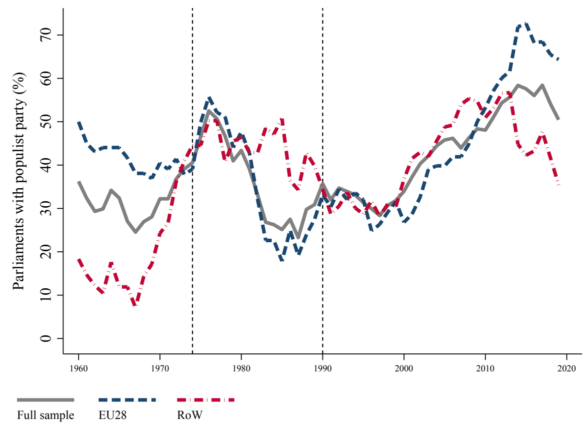
Trends in the presence and success of populist parties. We now account for the dichotomous classification of parties and focus on the presence and electoral success of populist parties, defined as in the previous section as those with a populism score exceeding the one standard deviation threshold ($\mathbf{1}_{i,e,t}^{p} = 1$). Stylized facts are presented in Figure 4.

[19] We do summation over elections $e \in \{1, 2\}$ since for an handful of countries we have two elections in the same year: United Kingdom (1974), Ireland (1982), Greece (1982, 2012 and 2015), Turkey (2015), Israel (2019), and Spain (2019).

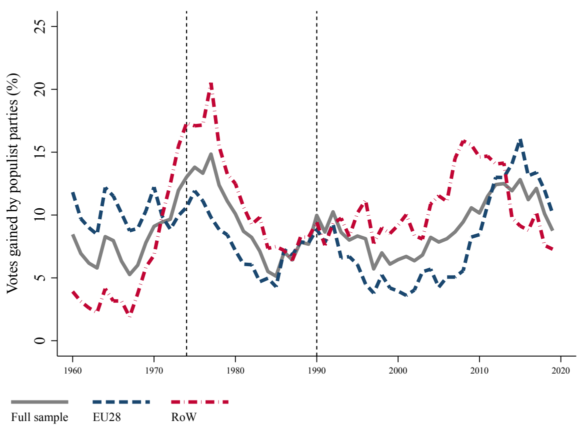
Figure 4: Stylized facts II – Presence, electoral success and score of populist parties



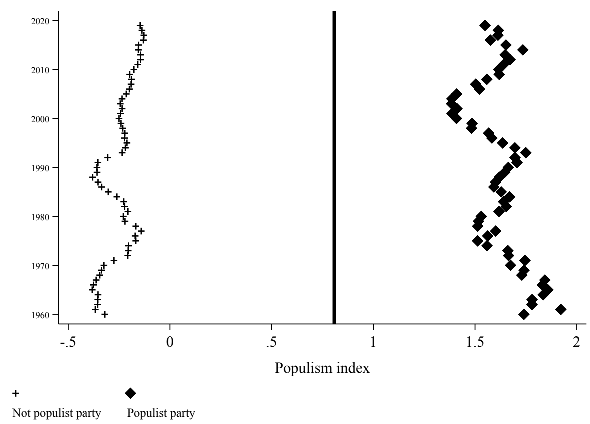
(a) Number of populist parties per parliaments



(b) Parliaments with a populist party (%)



(c) Volume margin of populism ($\Pi^V_{i,e,t}$)



(d) Mean score of populist vs. non populist

Notes: Fig. (a) shows the total number of populist parties per parliaments. Fig. (b) gives the percentage of parliaments with at least a Populist party. Fig. (c) depicts the average share of votes for populist parties (the volume margin). Fig. (d) presents the average populism score of populist and non populist parties. Populist parties are defined as those with a score exceeding 1 standard deviation (0.81). Fig. (a), (b), (c) and (d) show moving averages including 3 years before and 3 years after each date. The vertical lines indicate shifts in our sample size: inclusion of Greece, Portugal and Spain around 1975, and inclusion of Latin American and former Soviet Union countries around 1990. Similar trends are obtained in the balanced sample (see Appendix B.8).

Panels (a) and (b) illustrate the increasing presence of populist parties in political elections. Panel (a) shows the evolution of the average number of populist parties per election, conditional on obtaining one seat (to be part of our sample). The total number of populist parties in the 55 countries included in our sample has increased steadily since the sixties, with peaks observed in the late seventies, mid-nineties and in the recent years. This suggests that changes in the mean level of populism highlighted in the bottom panel of Figure 3 have been governed, at least partly, by changes in the number of populist parties. The trends are similar in European and non-European countries, except for the recent years. The last peak is clearly determined by the rising number of populist parties in the European Union. As a corollary, Panel (b) shows that the share of elections with a least one populist party has also increased steadily since the early nineties. Populist parties are present in about 55 percent of contemporaneous elections, and in more than 70 percent of European elections.

Turning our attention to the success of populist parties, we define the **volume margin of populism** as the vote share of populist parties, and compute it at the aggregate level as:

$$\Pi_t^V = \frac{\sum_{i=1}^{I}\sum_{e=1}^{E}\sum_{p=1}^{P}\mathbf{1}_{i,e,t}^{p}\pi_{i,e,t}^{p}}{\sum_{i=1}^{I}\sum_{e=1}^{E}\sum_{p=1}^{P}\pi_{i,e,t}^{p}}, \tag{3}$$

where, as before, $\pi_{i,e,t}^{p}$ denotes the vote share. Note that the volume margin can also be computed at the level of each country-election-year ($\Pi_{i,e,t}^{V}$) by removing the summation over i and e in the above equation. The latter variable is also used as a dependent in the regression analysis.

Panel (c) depicts the evolution of the volume margin of populism over time. The evolution of the volume margin is by and large similar to that of the mean margin, suggesting again that changes in the mean margin have been strongly governed by the number and electoral success of populist parties. Stylized facts for four types of countries are provided in the Appendix C.3. Variations in the volume of populism are way greater than variations in the mean margin. This is due to the fact that parties frequently enter or exit the populist group either by changing their political discourses, or by exiting or entering our sample (remember that our sample only includes countries with at least one seat in the Parliament). Hence, in line with the trade literature, changes in the volume of populism (total share of votes won by populist parties) can be studied along the extensive margin (number of populist parties running for election) and the intensive margin (average share of votes won by each populist party). Changes in the extensive margin are illustrated in Panel (a) and appear stronger than those identified in the volume margin of populism.

Other variables of interest are the average populism score of populist parties (Sikk, 2009) and its difference with the score of traditional/non-populist ones (Inglehart and Norris, 2016). In Panel (d), we compute the average populism score of traditional or non-populist parties (gray crosses), and of populist parties (black diamonds). The figure shows that the populism score of traditional parties has been rather stable over time. As far as populist parties are concerned, their average score has had its ups and downs. Before the year 2000, the mean score of populist parties was negatively correlated with the volume margin of populism. This can be due to the fact that more parties becomes “moderately” populist (changes along the extensive margin) or that “moderately” populist parties start obtaining seats when there is a window of opportunity for sanction votes (i.e., times of crisis). As a mirror effect, the score of traditional parties decreases in these periods.

Perhaps more worrisome is that the correlation between the mean score of populist parties and the volume of populism has turned positive after 2005. The gap with traditional parties has widened since then, which is in line with the recent evolution of the within-country component of inequality illustrated in Figure 3.

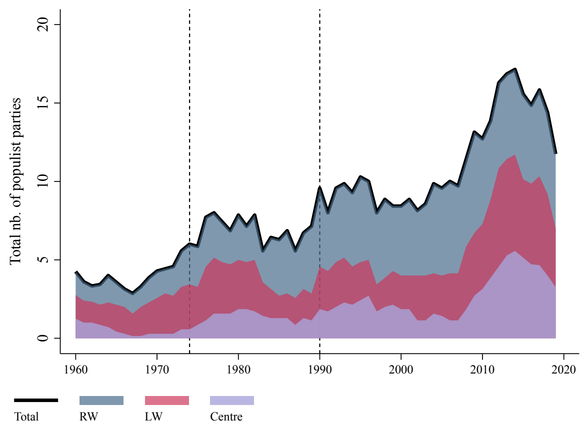
Trends in left-wing vs. right-wing populism. We finally decompose the trends along the right-left spectrum. Remember that we position parties over the right-left political scale using the *rile* index available in MPD (Budge and Laver, 2016), and we consider parties as left-wing, centrist or right-wing when their right-left index belongs to the first, second or third tercile of the distribution, respectively. We combine this with our dichotomous classification of populist parties and identify the extent of left-wing populism (often associated with radical left parties), right-wing populism (often associated with far-right parties), and the residual category of centrist populism. Stylized facts are depicted in Figure 5.

When aggregating all countries, Panel (a) shows that the recent rise in the number of populist parties (extensive margin) is driven by parties belonging to the centre and left-wing terciles of the distribution. This might be surprising at first glance, but it is worth reminding that the political success of parties (i.e., their vote share) is not taken into account at this stage. The number of right-wing populism increased drastically between the second half of the eighties and the early 2000s.

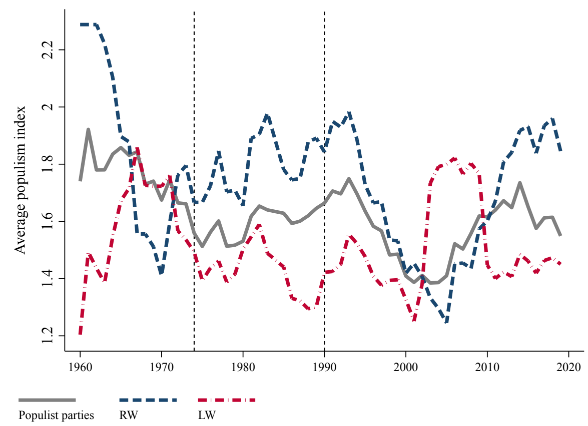
Panel (b) shows that the average populism score of left-wing populist parties has decreased since the financial crisis of 2008 (it reaches 1.4 – i.e., 1.8 standard deviations in 2019). On the contrary, the average populism score of right-wing populist parties has increased since 2005 (it reaches 1.8 – i.e., 2.3 standard deviations in 2019). This suggests that the financial crisis of 2008 and the resulting economic inequalities have probably allowed a return to more authoritarian positions towards established elites, open markets, and protection of minorities. For the first time since the sixties, radical-right populist leaders are more populist than the radical-left ones.

Panels (c) and (d) compare the trends observed in the European Union and in the rest of the world. On the one hand, after a sharp decline between the mid-seventies (oil crisis) and the early nineties, the share of elections with at least one left-wing populist party has steadily increased in all regions of the world (from 15 to 30 percent), as shown in Panel (c). On the other hand, Panel (d) shows that the share of elections with at least one right-wing populist party has increased from 5 to more than 50 percent in European Union member states. In the rest of the world, this share right-wing populist party has increased from 10 to 25 percent over the same period; with a sharp decline during the last wave of elections. Once more, this evidences an increased expression of right-wing populism in Europe over the last two decades. We show in the Appendix C.4 that these changes are even more pronounced in the core members of the European Union (EU15).

Figure 5: Stylized facts III – Left-wing and right-wing populism at the aggregate level

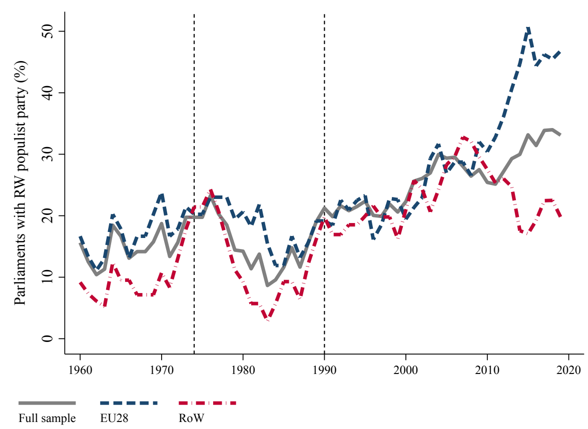


(a) Number of populist parties



(b) Average score of populist parties

(c) Parliaments with a LW populist party (%)



(d) Parliaments with a RW populist party (%)

Notes: Fig. (a) shows the total number of populist parties, dividing between left-wing and right wing. Fig. (b) presents the average populism score of populist parties, splitting between left-wing and right-wing parties. Fig. (c) and (d) give the percentage of parliaments with at least a left-wing and right-wing Populist party, respectively. Populist parties are defined as those with a score exceeding 1 standard deviation (0.808), while left-wing and right-wing parties are defined as those that belongs to the first and third tercile of the right-to-left index. Fig. (a), (b), (c) and (d) show moving averages including 3 years before and 3 years after each date. Vertical lines indicate shifts in our sample size: inclusion of Greece, Portugal and Spain in 1975, and inclusion of Latin American and former Soviet Union countries around 1990. Similar trends are obtained in the balanced sample (see Appendix B.8).

4 Links with Globalization

Previous literature has looked at the determinants of the volume margin of populism and has identified several important determinants to its recent rise. First, the perception of economic insecurity and increased inequality is one of the main drivers of the rising demand for populism (Inglehart and Norris, 2016; Guiso et al., 2017; Rodrik, 2018, 2021); economic fears are sometimes linked to automation and de-industrialization shocks (Frey et al., 2018; Anelli et al., 2018; Gallego et al., 2018), or to severe economic and financial crises (Funke et al., 2016; De Bromhead et al., 2013; Algan et al., 2017). Second, populism is also associated with the perception that the elites are neglecting the risk of social conflicts as well as with a perception of lost identity, or cultural dissolution (Norris and Inglehart, 2019; Mukand and Rodrik, 2018; Algan et al., 2018). In addition, the recent rise of populism also relates to the expansion of internet and new media (Zhuravskaya et al., 2020; Campante et al., 2018; Guriev et al., 2021).

While all the above mentioned studies somehow relate to globalization, other studies have focused explicitly on trade and migration, noting that the associated overall income gains may be distributed very unevenly. The "losers from globalization" (i.e., the socially and economically downgraded segments of the workforce) are then likely to join the ranks of the support base of populist parties (Autor et al., 2013, 2020; Helpman et al., 2017; Colantone and Stanig, 2018; Hays et al., 2019; Colantone et al., 2022). Theory suggests that the distributional consequences of globalization are governed by the skill structure of immigration and imports, whose roles have been investigated separately and in a handful of studies only (Edo et al., 2019; Moriconi et al., 2022, 2019; Autor et al., 2020; Mayda et al., 2022; Aksoy et al., 2024). The cultural dimensions of the backlash against globalization have also received empirical support, especially on the immigration side (Halla et al., 2017; Moriconi et al., 2022; Shehaj et al., 2019).

The next section focuses on the empirical relationship between populism and the size and structure of immigration and trade shocks. The fact that we look at trade and immigration shocks (and their skill-content) jointly presents a number of advantages in terms of exposition but also methodologically. In particular, this helps addressing potential omitted variable biases. And indeed, we show in Appendix E.1 that including migration shocks increases the magnitudes and statistical precision of the trade-related coefficients.

4.1 Empirical Strategy

Our empirical approach aims to quantify the effect of economic, cultural, communication, and globalization factors on the evolution of the volume of populism ($\Pi^V_{i,e,t}$ defined in Eq. (3)), as proxied by the share of votes for populist parties, and on the evolution of the mean margin of populism ($\Pi^M_{i,e,t}$ defined in Eq. (2)), as proxied by the weighted average populism score of all parties having obtained at least one seat in a given election (Gross and Sigelman, 1984).[20]

Baseline specification. We consider the following specification for both margins of populism:

$$\Pi^m_{i,e,t} = \mathbf{F}\left(\mathbf{X}_{i,e-2,t}, \mathbf{Mig}^S_{i,e,t}, \mathbf{Imp}^S_{i,e,t}\right), \tag{4}$$

where $m = (V, M)$ is the margin of populism for country i. $\mathbf{Mig}^S_{i,e,t}$ measures cumulative skill-specific inflows of immigrants in election an event e in election year t and in the previous year $t-1$ and expressed as percentage of the host country population (with $S = HS$ for the high-skill and $S = LS$ for the low-skill); and $\mathbf{Imp}^S_{i,e,t}$ measures cumulative skill-specific imports in election year t and $t-1$ expressed as percentage of GDP. We also include $\mathbf{X}_{i,e-2,t}$, a vector of controls expressed in logarithms, which includes human capital and the size of the population with a two-election lag, and the number of parties in election year t. The parsimonious and selected vectors of controls is therefore able to control for unobserved heterogeneity without incurring a simultaneity bias (Angrist and Pischke, 2008). Remember that we combine the two subscripts e and t because some countries had two elections during the same year. We remain parsimonious in our baseline specification but experiment with richer sets of covariates in our robustness checks, such as voter turnout,[21] skill-specific exports and emigration, or the electoral system, in Appendix E.

The specification of the $\mathbf{F}$-function differs according to the dependent variable. The mean margin is a continuous variable that, given our normalization procedure, can take both negative and positive values. For this reason, our baseline model assumes that $\Pi^M_{i,e,t}$ is a linear function of the globalization variables. On the contrary, the volume margin is a continuous variable that takes non-negative values only, exhibits a high level of heteroskedasticity, and includes a non-negligible share of zeroes (about 60% in the full sample). We estimate it with the Poisson pseudo maximum likelihood (hereafter PPML) estimator, which is found to perform better under various heteroskedasticity patterns, large number of zeroes and rounding errors for the dependent variable (Santos Silva and Tenreyro, 2006; Silva and Tenreyro, 2011).[22] Therefore, our baseline model assumes that $\Pi^V_{i,e,t}$ is an exponential function of the logged transformation of the globalization variables.

[20] In the Appendix E.3, we decompose the volume margin into its extensive and intensive margins (denoted by $\Pi^E_{i,e,t}$ and $\Pi^I_{i,e,t}$, respectively), and analyze their specific determinants.

[21] Guiso et al. (2017, 2024) show that economic insecurity depresses voting turnout in a selected manner, and increases the share of (participating) electors voting for a populist party. Leininger and Meijers (2020) find that the presence of populist parties (both left and right) in an election increases political participation of citizens. Therefore, the drivers of turnout can potentially influence the shares of populist vote, and the turnout of voters could respond to globalization shocks. As shown in the Appendix E.10, our results are robust to the inclusion of turnout as control; moreover, we show that turnout is not significantly impacted by our measures of globalization.

[22] Given that $\Pi^V_{i,e,t}$ is a bounded dependent variable, other estimators such as a fractional logit model could be implemented. Nonetheless, the PPML estimator is better suited in our context for two reasons. First, our volume margin is bounded between 0 and 100, but the only mass of observation at the available limits is at 0, where the PPML estimator is well behaved (Silva and Tenreyro, 2011). Second, as Papke and Wooldridge (2008) show, with panel data the fractional logit estimator produces similar marginal effects as linear models; therefore implementing this type of estimator is only moderately important.

Econometric issues. Three additional issues might lead the OLS/PPML standard models to generate inconsistent estimates. First, the margins of populism can be influenced by a large number of observable and unobservable determinants. Second, the relationship between populism and globalization is potentially influenced by mismeasurement problems and reverse causality, as populist parties tend to support anti-globalization policies. Hence, OLS/PPML estimates for the globalization terms can underestimate the causal impact of globalization on populism, thus calling for an instrumental approach. Third, the effect of globalization shocks can be amplified under adverse economic conditions, when social media networks are expanding, or when the cultural diversity embedded in foreign goods/people increases. We address these issues sequentially, within the limits of our cross-country setting.

We first mitigate *unobserved heterogeneity* concerns by saturating the model with a full set of country (θ_i^m) and year (θ_t^m) fixed effects, which allow to account for time-invariant unobservable factors and common trends. Assuming that all drivers of populism act in an additive way, our baseline specifications of Eq. (4) writes as:

$$\begin{cases} \Pi^M_{i,e,t} = \alpha^M + \beta^M \mathbf{X}_{i,e-2,t} + \sum_S \gamma^M_S \mathbf{Mig}^S_{i,e,t} + \sum_S \zeta^M_S \mathbf{Imp}^S_{i,e,t} \\ +\theta^M_i + \theta^M_t + \epsilon^M_{i,e,t}, \\ \\ \Pi^V_{i,e,t} = \exp[\alpha^V + \beta^V \mathbf{X}_{i,e-2,t} + \sum_S \gamma^V_S \log(\mathbf{Mig}^S_{i,e,t}) + \sum_S \zeta^V_S \log(\mathbf{Imp}^S_{i,e,t}) \\ +\theta^V_i + \theta^V_t + \epsilon^V_{i,e,t}]. \end{cases} \tag{5}$$

where β^m is a set of coefficients associated with the traditional determinants of populism included in our $\mathbf{X}_{i,e-2,t}$ vector already described in equation (4) above, γ^m_S is a pair of coefficients associated with skill-specific immigration shocks, ζ^m_S is a pair of coefficients associated with skill-specific import shocks, (θ^m_i, θ^m_t) is a set of country and year fixed effects; and $\epsilon^m_{i,e,t}$ is the error term. Coefficients of the mean margin model are simple incidence parameters, whereas coefficients of the volume margin model must be interpreted as elasticities.

Second, our baseline specification allows to identify an association between globalization shocks and populism, without necessarily capturing a causal relationship between them. Causation is hard to establish with aggregate data. As detailed in Section 4.3, we rely on *instrumental variables* and two-stage least squares (2SLS) techniques to mitigate endogeneity concerns. Starting from the linear OLS specification of the mean-margin model, we can use the standard 2SLS estimator and instrument all globalization terms jointly. In line with Frankel and Romer (1999), Munshi (2003) or Autor et al. (2020), our IV strategy relies on a "zero-stage" gravity model that predicts the bilateral and skill structure of imports and immigration using dyadic and origin-specific factors (destination-specific factors are excluded). We then aggregate these dyadic predicted flows for each destination and use these skill-specific sums (less prone to endogeneity concerns) as instruments for observed globalization variables in the linear equation explaining the mean margin of populism. With regard to the volume margin, implementing a standard IV approach can induce an additional bias due to the incidental parameter problem. This is due to the non-linear structure of the PPML model and to the presence of a large number of fixed effects (Lancaster, 2000). For the volume margin, we follow Angrist and Pischke (2008) and compare our PPML results with those of a reduced-form IV approach, which consists in replacing actual import and immigration flows with predicted ones.

Third, in Section 4.4, we conduct a series of *robustness checks* and analyze whether the baseline results hold when considering sub-samples of countries and years, alternative lag structures for measuring globalization shocks, and alternative thresholds used to define populist parties.

Finally, the estimation of Eq. (5) sheds light on the average effect of skill-specific globalization shocks on populism. In Section 4.5, we supplement Eq. (5) with *interaction terms* between globalization shocks and a subset of potential amplifiers of the magnitude of populist responses to skill-specific globalization shocks (denoted by $\underline{\mathbf{X}}_{i,e,t}$). Our extended specifications writes as:

$$\begin{cases} \Pi^M_{i,e,t} = \alpha^M + \beta^M \mathbf{X}_{i,e-2,t} + \sum_S \gamma^M_{S0} \mathbf{Mig}^S_{i,e,t} + \sum_S \gamma^M_{S1} \mathbf{Mig}^S_{i,e,t} \times \underline{\mathbf{X}}_{i,e,t} \\ + \sum_S \zeta^M_{S0} \mathbf{Imp}^S_{i,e,t} + \sum_S \zeta^M_{S1} \mathbf{Imp}^S_{i,e,t} \times \underline{\mathbf{X}}_{i,e,t} + \delta^M \underline{\mathbf{X}}_{i,e,t} + \theta^V_i + \theta^V_t + \epsilon^V_{i,e,t}, \\ \\ \Pi^V_{i,e,t} = \exp[\alpha^V + \beta^V \mathbf{X}_{i,e-2,t} + \sum_S \gamma^V_{S0} \log(\mathbf{Mig}^S_{i,e,t}) + \sum_S \gamma^V_{S1} \log(\mathbf{Mig}^S_{i,e,t}) \times \underline{\mathbf{X}}_{i,e,t} \\ + \sum_S \zeta^V_{S0} \log(\mathbf{Imp}^S_{i,e,t}) + \sum_S \zeta^V_{S1} \log(\mathbf{Imp}^S_{i,e,t}) \times \underline{\mathbf{X}}_{i,e,t} + \delta^V \underline{\mathbf{X}}_{i,e,t} + \theta^V_i + \theta^V_t + \epsilon^V_{i,e,t}]. \end{cases} \tag{6}$$

The set of amplifiers $\underline{\mathbf{X}}_{i,e,t}$ includes a dummy equal to one if the country experienced a year of negative real growth since the previous election as well as proxies for de-industrialization, and dummies capturing high levels of diversity in the origin mix of imported goods and of immigrants (proxies for cultural diversity embedded in goods or in people), and high levels of internet expansion. Additional interactions are considered in Appendix E.

Data. Annual trade data are obtained from Feenstra et al. (2005) for the years 1962-2000 and from the United Nations *Comtrade* database for the years 2001-2015. We extract the series of annual imports for each country, and we split them by type of goods using the Standard International Trade Classification (SITC) described in the Trade and Development Report (2002). Product categories at the 3-digit level are classified on the basis of their technological complexity, capital and skill intensities. While we acknowledge that the technological content and production processes of goods may evolve over time, time-varying classifications at this level of sectoral detail are unfortunately not available for the full 60-year period covered by our analysis. For the sake of consistency and comparability, we treat the classification as constant over time, as is common practice in related studies (e.g., Aksoy et al., 2024).

Five categories are distinguished, namely primary commodities, labor-intensive and resource-based manufacturing goods, and manufacturing goods with high intensities in low-, medium-, and high-skill labor and technology. In our baseline regressions, we only account for the divide between manufacturing goods that are intensive in low-skill and high-skill labor (in short: "low-skill goods"

Table 2: Summary Statistics - 55 Countries, 1960-2019

Variable	Mean	S.D.	Min.	Max.	Obs.	Pc(25)	Pc(50)	Pc(75)
PANEL A - Populism V.								
Volume Margin (All)	8.97	16.93	0.00	92.18	595	0.00	0.00	10.08
Volume Margin (RW)	4.79	12.45	0.00	84.73	595	0.00	0.00	0.00
Volume Margin (LW)	2.48	7.86	0.00	79.35	595	0.00	0.00	0.00
Mean Margin (All)	-0.07	0.45	-1.15	1.98	595	-0.35	-0.14	0.14
Volume Margin (RW)	0.03	0.29	-1.06	1.55	476	-0.12	-0.01	0.12
Volume Margin (LW)	-0.05	0.24	-0.85	1.65	478	-0.15	-0.03	0.04
PANEL B - Globalization V.								
log Imp (LS)	-3.40	0.97	-7.55	-1.28	581	-3.98	-3.23	-2.69
log Imp (HS)	-2.40	0.87	-5.71	-0.10	581	-2.86	-2.28	-1.83
log Mig (LS)	-4.15	1.34	-11.71	-1.54	586	-4.78	-3.86	-3.23
log Mig (HS)	-5.53	1.48	-15.10	-2.81	586	-6.26	-5.44	-4.61
Imp (LS)	0.05	0.04	0.00	0.28	581	0.02	0.04	0.07
Imp (HS)	0.13	0.11	0.00	0.91	581	0.06	0.10	0.16
Mig (LS)	0.03	0.03	0.00	0.21	589	0.01	0.02	0.04
Mig (HS)	0.01	0.01	0.00	0.06	589	0.00	0.00	0.01
PANEL C - Country Control V.								
log Pop	16.15	1.51	12.08	19.50	593	15.23	16.03	17.46
log HC	0.99	0.19	0.14	1.29	595	0.92	1.02	1.13
log Parties	1.72	0.45	0.00	2.89	595	1.39	1.79	2.08

and "high-skill goods"). We experiment with different treatment of labor-intensive and of medium-skill manufacturing in the robustness section.

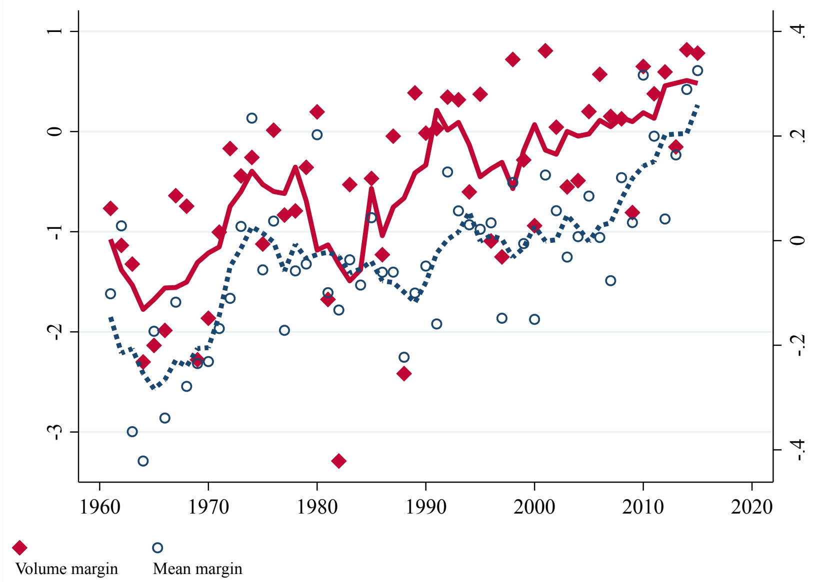
Data on 5-year migration inflows by country of destination for the same period are obtained from Abel (2018).[23] Flow data by education level are not directly observable but can imputed by using information about the skill level of the stock of migrant population from each origin in each destination country, available for a few census rounds (say, 1990, 2000 and 2010). We compute a dyadic skill-selection index, proxied by the ratio of college graduates in the migration stock to the one in the origin-country population. We use this ratio in the closest available census round to impute a skill level for the dyadic immigration flows, accounting for the evolution of the share of college graduates in the origin country (taken from Barro and Lee, 2013). This method proved to be relevant as the dyadic levels of skill selection are stable over time (see Burzynski et al., 2018).[24]

Table 2 provides descriptive statistics of our main outcomes, variables of interest and controls. In terms of our set of controls, the population and the human capital index are retrieved from the Penn World Table. The number of parties winning a seat in each election is available from the MPD.

[23] We interpolate the 5-year data to get annual migration flows over the time period.

[24] Some aggregate and country-specific stylized facts are provided in Appendix C.1.

Figure 6: Time fixed effects for the volume and mean margins of populism



Notes: Red diamonds (left scale) and blue circles (right scale) represent the year fixed estimated from Eq. (5) for the volume and the mean margin of populism, respectively. The red solid line and blue dashed line are the centered moving average computed over 5 years over the times fixed effects estimated for the volume margin and the mean margin, respectively.

4.2 Baseline Empirical Results

Tables 3 provides estimates of our baseline PPML and OLS models as depicted in Eq. (5), in which all potential drivers of populism act in an additive way, and skill-specific levels of imports and immigration are included jointly. The left panel of Table 3 focuses on the volume margin of populism,[25] while the right panel shows the results for the mean margin of populism.

To avoid simultaneity bias, we include human capital and population with a lag of two elections (i.e., 10 years on average). We confirm that in general, higher levels of human capital are associated with lower volume and mean margins of populism, mainly among right-wing parties. Figure 6 plots the year fixed effects estimated for the volume margin (diamonds) and for the mean margin (circles) of populism, as well as their moving average. We observe a positive trend for both margins, and even more so during the first half of the seventies, in the first half of the nineties, and in the years after 2008 (Funke et al., 2023; De Bromhead et al., 2013; Algan et al., 2017). Other control variables tend to be barely significant.

In line with the existing literature, imports of low-skill intensive goods are positively and significantly associated with total, right-wing, and left-wing populism. On the contrary, imports of

[25] In the Appendix E.3, we decompose these effects along the extensive and intensive margins.

Table 3: Baseline PPML and OLS results – Volume and Mean Margins

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log Imp$_{i,t}$ (LS)	0.81**	1.14**	1.05**			
	(0.33)	(0.56)	(0.50)			
log Imp$_{i,t}$ (HS)	-0.68	-1.23**	-0.72			
	(0.46)	(0.59)	(0.63)			
log Mig$_{i,t}$ (LS)	0.15	1.39**	-1.79***			
	(0.37)	(0.55)	(0.54)			
log Mig$_{i,t}$ (HS)	-0.25	-1.21**	0.99			
	(0.33)	(0.52)	(0.63)			
Imp$_{i,t}$ (LS)				3.65**	4.00**	-0.17
				(1.70)	(1.55)	(0.64)
Imp$_{i,t}$ (HS)				-0.25	-0.48	0.32
				(0.45)	(0.29)	(0.23)
Mig$_{i,t}$ (LS)				-0.47	1.58	-1.47
				(1.96)	(2.01)	(1.31)
Mig$_{i,t}$ (HS)				3.72	-0.34	4.26
				(4.95)	(4.12)	(3.31)
log Pop$_{it-2}$	1.27	1.58	2.22	0.29	0.43**	-0.00
	(0.94)	(1.49)	(1.72)	(0.21)	(0.19)	(0.13)
log Parties$_{it}$	0.51*	0.62	0.42	0.10	-0.03	0.07
	(0.29)	(0.48)	(0.33)	(0.07)	(0.07)	(0.05)
log HC$_{it-2}$	-4.22	-7.28**	4.45	-1.43**	-1.36**	0.17
	(2.58)	(3.09)	(5.49)	(0.55)	(0.54)	(0.31)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.40	0.33	0.53			
R^2				0.50	0.40	0.48

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe`, while coefficients in column (4) to (6) have been estimated with OLS using the Stata command `reghdfe`.

high-skill intensive goods are associated with lower volumes of right-wing populism.

The results for low-skill immigration are qualitatively different: they display a positive association with right-wing populism, as for low-skill imports, however this is now matched with a negative association with left-wing populism of a slightly larger magnitude, resulting in an overall insignificant effect on the total volume of populism (right-and left-wing combined). As for high-skill immigration, the results are similar to those for high-skill imports. They suggest a negative association between an increase in high-skill immigration and the level of right-wing populism, and conversely for left-wing populism (hence an insignificant result for the overall volume of populism.

Overall, these results are consistent with the findings of Autor et al. (2020), Edo et al. (2019), and Moriconi et al. (2019, 2022). However, these studies do not jointly consider trade and immigration. Appendix E.1 provides the results when including either trade or migration shocks separately. The results for immigration remain stable independently of whether trade shocks are included in the analysis. The direction of the coefficients related to trade shocks is also not sensitive to the inclusion or exclusion of immigration shocks, but the precision of the estimates is influenced by the inclusion of migration shocks, providing ground to the validity of an unified skill-specific approach of the implications of globalization for populism.

Nonetheless, the analysis of the volume margin does not capture the full effect of globalization shocks on the actual "extent" of populism which voters are exposed to during an election. The right panel of Table 3 focuses on the association between globalization and the mean margin of populism calculated, according to Eq. (2), as the weighted average of the populism scores with weights equal to the party's share in votes.[26] The mean margin accounts for the level of populism of all parties (classified as populist or non-populist) running for election at time t, as well as for their vote shares.[27] We find that imports of low-skill labor intensive goods are positively and significantly associated with the mean margin of total and right-wing populism. The coefficient is around 4, which means that a 1 percentage point change in the import rate of goods which are intensive in low-skill labor (corresponding to a 25% standard deviation change, see Table 2) is associated with a 0.04 increase in the mean margin of populism (corresponding to a 14% standard deviation change, see again Table 2). This is equivalent to the variation in the mean margin of right-wing populism in the U.S. between 2004 and 2008 (from -0.19 to -0.16) or in The Netherlands between 2003 and 2006 (from -0.07 to -0.02).[28] In contrast, imports of goods which are intensive in high-skill labor, as well as high-skill immigration, are not significantly correlated with the mean margin of populism. [29]

The combined analysis of the volume and mean margins allow us to better understand the mechanisms at work. In Appendix E.3, we decompose the volume margin into its extensive (number of populist parties) and intensive (vote share per populist party) components. In Appendix

[26] When we distinguish between left- and right-wing populism, the number of observations decreases. This is because our sample includes some elections without parties belonging to the first or latter tercile of the right-to-left index distribution.

[27] In MPD data, the cumulative vote share is less than 100% for many election-year pairs. This is because small parties and most independent candidates running for election failed to obtain a seat and are excluded from the sample. In the last three columns, we normalize the vote shares of parties represented in the parliament so that their sum is equal to 100%. In the Appendix E.5, we show that our results are robust to this normalization.

[28] Note that the Dutch 2006 election saw the first participation of the *Party for Freedom (PVV)* of Geert Wilders.

[29] It is difficult to compare our estimates with existing works because our sample includes many countries and years, hence including many zeroes, which requires using different estimators (PPLM and log-log transformation), and our measure of populism is new.

E.4 we estimate the links between globalization shocks and the volume margin of populism when considering a dichotomous time invariant definition. In Appendix E.5, we divide our parties into two groups – those who have never been classified as populist, and those who have been classified at least once as populist (including potential switchers) – and we estimate the links between globalization shocks and the mean populism score within these two groups.

Imports of low-skill goods are associated with an increase in the share of votes for centrist and right-wing populist parties (volume margin) and in the average post-election level of centrist and right-wing populism (mean margin). Our decomposition suggests that the volume-margin effect operates along the intensive margin, and the mean-margin effect is jointly governed by the rising vote share for populist parties, and by an increase in the populism score of centrist populist parties.

In contrast, low-skill immigration is associated with a reduction of votes for left-wing populist parties and an increase for right-wing populist parties, without impacting the total volume of populism or the average "extent" of populism (mean margin). This result could be seen as a shift of populist voters between the opposite ends of the left–right political spectrum. However, suggestive evidence based on individual-level data on political and voting preferences presented in Appendix C.5 do not support such explanation. The decomposition of the different margins suggests that these changes operate along the extensive margin of right- and left-wing populism, and are concomitant with a decrease in the mean level of populism of all types of parties. The most likely hypothesis is that low-skill immigration encourages new right-wing populist parties with moderate populism scores to run for election, or allows them to gain at least one seat in the election. Furthermore, it is worth emphasising that low-skill intensive imports and immigration never increase the mean populism score of traditional (i.e., never populist) parties.

4.3 Regressions with Instrumental Variables

The correlations presented in the previous section can be driven by unobserved common determinants of globalization and populism and suffer from reverse causation problems. In particular, we may expect that an increase in populism translates into greater restrictions on trade and immigration, which implies that the estimates in Tables 3 might underestimate the causal impact of globalization shocks on populism.

Identification strategy. To mitigate such endogeneity concerns, we use an instrumental variable approach (IV, hereafter) with instruments pertaining to the origin country and the structural break due to the collapse of the Soviet block (for both trade and migration flows). Following Autor et al. (2013, 2016), the "China shock" has been extensively exploited in the trade literature as a source of exogenous variations in imports and exports in partner countries. Similarly, following Munshi (2003), push factors of origin countries have been frequently used to instrument immigration shocks in the destination country (Boustan, 2010; Kleemans and Magruder, 2018; Monras, 2020). The exclusion restriction requires that push factors in origin countries will only affect populism in destinations through their impact on immigration or trade, but not through other channels.

We generalize this approach by predicting dyadic flows of goods and migrants between countries relying on origin countries' time-varying characteristics and time-invariant dyadic factors. We then aggregate these flows by destination, and use the aggregate predictions as instruments for skill-specific imports and immigration flows. Hence, our IV strategy relies on a "zero-stage" gravity-model for dyadic trade and migration (Frankel and Romer, 1999; Feyrer, 2019; Alesina et al., 2016; Docquier et al., 2020), which writes as:

$$Y_{ij,t} = \exp\left[\alpha + \theta_{ij} + \theta_{ij} * Post_{1990} + \theta_{j,t} + \epsilon_{ij,t}\right], \tag{7}$$

where $Y_{ij,t}$ is the dyadic skill-specific flow of either imported goods ($\text{Imp}^S_{i,t}$) or immigrants ($\text{Mig}^S_{i,t}$) from origin country j to destination country i at year t.[30] Given the large number of zeroes in dyadic flows, we estimate Eq. (7) using PPML, which explains the exp transformation of the right-hand-side term. We estimate Eq. (7) over the global matrix of destination-origin countries.

Our zero-stage regression in Eq. (7) includes a set of fixed effects. We have dyadic fixed effects (θ_{ij}) capturing bilateral determinants such as distance, colonial linkages, cultural and linguistic proximity, as well as time-invariant destination-specific characteristics. Remember that in our second stage, we control for country fixed effects and identify the effect of globalization shocks using the within-variation in imports and immigration. Dyadic fixed effects are also interacted with a post-1990 dummy ($Post_{1990}$), which proxies structural changes due to the fall of the Berlin Wall (including political transformations in Eastern European countries and greater intra-European labor mobility). We interpret this as a permanent shock on bilateral migration flows. For instance, the estimated bilateral fixed effects on migration flows are, on average, 50% higher in the post-1990 period, suggesting the enhanced mobility across countries due to the collapse of the Soviet block. We also have origin-year fixed effects ($\theta_{j,t}$) capturing time-varying shocks in the origin country (e.g., changes in trade policies, economic shocks, socio-demographic changes, conflicts, natural disasters, etc.). For instance, the estimated China origin-year fixed effects over low-skill imports are both positive and characterized by a positive trend after 2001 (i.e., the inclusion of China in the WTO), while they were mainly negative and without any specific trend in the pre 2001 period.

We predict skill-specific trade and migration flows $\widehat{Y}_{ij,t}$ using the estimated coefficients from Eq. (7), then aggregate them using $\widehat{Y}_{i,t} \equiv \sum_j \widehat{Y}_{ij,t}$, and use $\widehat{Y}_{i,t}$ as an external instrument for $Y_{i,t}$ in the model for the mean margin. Being estimated from the gravity model without time-varying destination-country characteristics, the predicted flows should be less prone to reverse causation and omitted variable biases.[31] When focusing on the volume margin, we use a reduced-form IV

[30] The dependent variable for trade is skill-specific, i.e., $Y_{ij,t}$ refers either to low- or high-skill import flows. For migration, we use total flows and we rely on the strategy used in the baseline to derive skill-specific immigration flows.

[31] In Appendix E.2 we apply a modified gravity model where destination-by-year fixed effects are included in the estimation but excluded from the prediction. The results available in Table E.3 confirm our main results, although the predicted skill-specific shocks have less predicting power as instrumental variables.

approach and replace the actual flows ($Y_{i,t}$) by the predicted ones ($\widehat{Y}_{i,t}$) in the PPML setting, as recommended by Angrist and Pischke (2008). The results of the first stage regression are provided in Table D.2, in Appendix D.4.[32]

Exogeneity and Exclusion Restrictions. This conceptual framework closely resembles a shift-share design, as pioneered by Bartik (1991) and Blanchard et al. (1992), where origin-year fixed effects capture quasi-exogenous shifts, while dyadic fixed effects account for the shares. The core idea is to exploit origin-specific shocks as a source of variation in globalization shocks (i.e., trade and migration) affecting destination countries. Our exclusion restriction requires that changes to supply shocks only affect populist votes in other countries through its impact on trade and migration, a plausible assumption in our view.

In Appendices D.1 and D.2, we analyze the underlying sources of variation captured by our origin-year fixed effects for imports and immigration flows, which captures origin-specific shocks. We compare zero-stage estimates with and without these fixed effects, and aggregate them by destination. In the imports case, China's accession to the WTO and Germany's labour market reforms in the early 2000s are explaining most of the variations. Using the same approach for migration, our approach identifies significant emigration episodes in the aftermath of major political events (in countries such as Mexico, the Philippines or Russia) or of refugee crises following the collapse of Yugoslavia or the Syrian civil war. As these variations are unlikely to be endogenous political and economic shocks in the destination countries, they support the validity of our approach.

In addition, building on recent advances in the shift-share literature (Borusyak et al., 2022), we also tested the robustness of our estimates using a destination-specific leave-one-out (LOO) approach. For each destination country, we re-estimated the origin-year fixed effects, excluding all bilateral trade or migration flows involving that country. This demanding robustness check yielded reassuring results presented in Appendix D.3: although the magnitude of the coefficients was slightly reduced and the estimates were less precise—an expected outcome given the reduction in identifying variation, as emphasized by (Borusyak et al., 2022)—the key findings remained stable with those of our benchmark regressions. These results further reinforce the credibility of our identification strategy.

Main results. The results for the globalization variables are presented in Table 4. The left panel provides reduced-form IV estimates for the volume margin of populism. The estimates align with the results of our baseline PPML regressions in terms of the direction of the effects, but less precisely estimated. Overall, the results confirm that the skill structure of globalisation shocks plays a key role. Imports of low-skill goods generally promote votes for right-wing populist parties. On the contrary, imports of high-skill goods reduce votes for right-wing populist parties. With

[32] The predicted levels are nicely correlated with the actual ones, and the coefficients of the instruments are highly significant close to unity. The adjusted R-squared is usually large despite the fact that our zero-stage dyadic regressions abstract from destination-time characteristics.

Table 4: Reduced-form IV PPML and 2SLS results – Volume and Mean Margins

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.81	1.49*	0.82			
	(0.55)	(0.84)	(0.81)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.98	-1.99**	-0.60			
	(0.68)	(0.87)	(0.83)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.61	1.97***	-1.63**			
	(0.46)	(0.62)	(0.78)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.16**	-2.32***	0.47			
	(0.55)	(0.89)	(1.08)			
$\text{Imp}_{i,t}$ (LS)				4.70*	3.21	1.28
				(2.61)	(2.12)	(1.39)
$\text{Imp}_{i,t}$ (HS)				-0.23	-0.57	0.43
				(0.56)	(0.41)	(0.38)
$\text{Mig}_{i,t}$ (LS)				0.33	0.58	-0.96
				(3.34)	(2.71)	(1.52)
$\text{Mig}_{i,t}$ (HS)				4.50	5.43	4.26
				(10.88)	(7.36)	(4.32)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.40	0.34	0.51			
R^2				0.05	0.07	-0.00
K-Paap F-stat				29.89	26.02	12.92

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

regard to immigration, for which the results are generally more stable, the IV results also confirm those of the baseline regressions. Low-skill immigration has coefficients of similar magnitude but in opposite directions for right-wing populism and left-wing populism, increasing the former and decreasing the latter. High-skill immigration, on the other hand, reduces the votes for populist parties, especially for right-wing parties.

The right panel provides the 2SLS estimates for the mean margin of populism. These estimates are also in line with the OLS results of Table 3, although with slightly less precision (p-value 0.08). Imports of low-skill intensive goods increase the mean margin of total and right-wing populism.

On the contrary, imports of high-skill goods and both types of immigration do not lead to such populist responses. The coefficients are in the same order of magnitude as in the OLS setting. As for the strength of the instrument, the Kleibergen-Paap F-stat is around 20 across the different specifications, which is a satisfactory value given the fact that we are instrumenting four different endogenous variables simultaneously. Reassuringly, our results are preserved and K-P F-stat are much larger when instrumenting one variable at a time or in pairs (see Appendix E.6).

Instrumental variable techniques are also used in the decomposition of the volume and mean margins of populism (see Appendix E.4 and E.5). The IV results tend to reinforce the mechanisms highlighted in the previous section. With regard to imports of low-skill intensive goods, their effect on the volume of (mostly right-wing) populism operates along the intensive margin, whereas their effect on the mean margin is partly governed by a greater populism score of centrist populist parties. Low-skill immigration, on the other hand, favors new right-wing populist parties with moderate populism scores to run for election or to gain a seat without influencing their mean populism score. Finally, globalization shocks have no effect on the populism score of traditional (i.e., "never populist") parties.

Further discussion about endogeneity. Although our IV strategy is specifically designed to mitigate concerns relating to reverse causality and omitted variable bias driven by destination country characteristics, we acknowledge that more subtle forms of endogeneity may persist. For example, geopolitical dynamics or ideological spillovers could generate correlations between the error term and our instruments that our current design does not fully address. While we do not claim that our instruments are flawless, we argue that they remain informative. In line with Nevo and Rosen (2012), we note that under plausible assumptions—such as a downward bias in OLS and a positive correlation between the instrument and the endogenous regressor—the true causal effect is likely to exceed the maximum of the OLS and IV estimates.

4.4 Robustness Tests

To investigate whether our results are sensitive to specification choices, party classification, or sub-samples of countries and years, we conduct a battery of robustness checks and tests using the IV estimators. We summarize below our main findings, mostly focusing on the populism responses to imports of low-skill intensive goods and low-skill immigration. Overall, the skill-specific effects of migration and imports are stable across various robustness tests, although the precision of the import-related estimates varies across specifications.

Lag structure for globalization shocks (see Appendix E.8.1). In our baseline results, the skill-specific migration and import variables are defined as the sum of import and immigration flows over two years, namely the election year and the year prior to the election. To assess whether our results are sensitive to the lag structure of our model, we provide results with skill-specific import and migration defined as (i) the flows observed in the election year (t), (ii) the flows observed in the year before the election ($t-1$), (iii) the flows observed two years before before the election ($t-2$), (iv) the sum of the flows between the election year and two years before, and (v) the sum of the flows between the last two elections. The number of lags used to compute import and immigration shocks influences the scale of these variables and the magnitude of the coefficients. Overall, results for immigration are highly robust to the lag structure. The sign of the results for imports is also preserved, while the significance is less stable.

Classification of populist parties (see Appendix E.8.2). In our baseline results on the volume margin, we define populist parties as those exhibiting a populism score above one standard deviation ($\eta = 1.0$). The choice of this threshold maximizes the partial correlation with most existing classifications, and defines a clear-cut bundle of parties when using unsupervised clustering algorithms. We provide results obtained when using less restrictive ($\eta = 0.9$) or more restrictive ($\eta = 1.1$) thresholds. The significance and magnitude of the effects associated to migration are preserved when using a lax (or more inclusive) or a stricter (or less inclusive) classification of populist parties, while we lose precision on imports-related estimates. It is worth emphasizing that many parties usually perceived as populist by political scientists exit the list when using the stricter definition.[33] Additionally, we find stable results by using alternative measurement of the populism score, based either on a more extensive definition, or by relying on the net autarky stance suggested by Burgoon (2009) rather than our CTP proxy.

Classification of political ideology (see Appendix E.8.3). The analysis for left- and right-wing populism relies on the time-varying index of left/right ideology available in the MPD and constructed by Budge and Laver (2016). Our results could potentially be driven by the (not so uncommon) fact that some parties can switch from the left to the right (or conversely) of the political spectrum. To account for this, we present results obtained after excluding such "switching" parties. Our results are robust to such exclusion.

Proxies for skill-specific immigration shocks. (Appendix E.8.4). We analyze the sensitivity of our results to the imputation of the skill structure of immigration flows, or to the inclusion of interactions with migrant stock variables. First, we impute the skill structure of migration inflows using the selection ratios observed in the year 2000 only, rather than relying on the closest year (1990, 2000, 2010). The results for low-skill immigration remain stable in both magnitude and significance, while the direction of the high-skill immigration coefficients is maintained, though with bigger standard errors. Second, we explore whether the populist responses to immigration flows are magnified when the preexisting stock of immigrants is either large or small. To capture these

[33]Some relevant examples of parties that are not classified as populist with the stricter definition are *Syriza* in Greece, *Movimento 5 Stelle* in Italy, and *La France Insoumise* in France.

nonlinear effects, we interact low-skill immigrant flows with dummy variables equal to unity if the ratio of immigrant stock to population in the destination country belongs either to the top or the bottom quartile of the distribution in 1960. These interaction terms are barely significant on share of votes for left-wing populist parties. The magnitude and significance of the direct coefficients of imports and immigration are well preserved.

Proxies for skill-specific import shocks (see Appendix E.8.5). We consider alternative ways to characterize the skill and technological content of imported goods. Following the classification of the Trade and Development Report (2002), we first extend our specification by adding imports of labour-intensive goods (both high- and low-skill labour-intensive goods) to the set of regressors, and second, we extend our specification by adding imports that are medium-skill labour-intensive. These variants eliminate the significance of the volume and margin responses to imports, probably due to collinearity problems, while preserving the mean margin responses.

Combining skill content with economic development at origin (see Appendix E.8.6). We explore a more demanding specification in which our main variables of interest are now divided according to the level of economic development of the country of origin. We create dummies for low-income (LI) and a high-income (HI) countries using the World Bank country classification (combining those defined as low-income and lower-middle income in the LI category, whereas those considered as upper-middle and high-income form the HI category). Replicating the baseline analysis with the above variables, the findings highlight that the positive and significant populism responses to globalization are mostly driven by imports and immigration flows of goods and people originating from low-income countries on the volume margin while high-skill immigration from high-income countries seems to drive the reduction of the volume margin for left-wing parties.

Robustness by sub-sample (see Appendix E.8.7). Since our analysis covers a long time period and a wide set of countries, we provide results exploring whether our baseline results are driven by specific time-periods or subsets of countries. We first investigate whether our results are governed by more recent years, when the pace of globalization increased. We first include interaction terms between our global determinants of populism (i.e., low-skill imports and immigration) with a post-1990 dummy. The results are highly robust to the inclusion of these additional terms, which tend to attenuate the right-wing populist response to imports along the volume and mean margins. We then explore the role of the entry of China in the WTO by including an interaction with a post-2001 dummy. The main results are confirmed, showing a stronger effect for low-skill imports on the volume margin after 2001, in line with previous literature. We then explore interactions with EU membership by including an EU28 dummy. Although the signs of the coefficients remain the same, their magnitude and significance change, suggesting that the effects of low-skill imports and immigration on the volume margin of populism are mostly driven by EU28 countries. In addition, when restricting the sample to EU28 countries, left-wing populism also appears to be (negatively) affected by low-skill imports, for both the volume and mean margins. To characterize this result further, we show triple interactions with dummies for high welfare spending (capturing whether a country's social expenditure in 2000 exceeded the median level).[34] The results reveal that a large welfare state significantly mitigates the decline in support for left-wing populism at both the volume and mean margins. In other words, the EU28 result is driven by low-welfare state countries. We investigate whether the degree of human capital might moderate the skill-specific effects of globalization by introducing an interaction term with the human capital index (one of the baseline controls) and the skill-specific globalization shocks. The results indicate that education levels dampen the effects of the globalization shocks, in line with prior research on both migration (e.g., Moriconi et al., 2022; Mayda et al., 2022) and trade (e.g., Aksoy et al., 2024). We also explore whether the results are driven by the Latin American countries present in our sample. Excluding them from the sample does not impact our estimates. Finally, we show that the results are confirmed when using a balanced sample of countries (for example, when excluding countries which entered the sample after 1970).

Inclusion of emigration and export (see Appendix E.9). Our results are robust to the inclusion of skill-specific export and emigration flows. We decided not to include emigration and exports in our benchmark regression for three reasons. First, the effects of exports and emigration are less significant and robust. Second, instrumenting eight skill-specific globalization shocks is a heroic task. Third, we already account for the direct impact of emigration on the skill structure of the labor force by controlling for human capital.

Additional robustness checks. We show that our results are not driven by an effect of globalization on voting turnout (see Appendix E.10) as they also hold when controlling for the electoral system. Still, it is worth noticing that stronger effects for low-skill imports on left-wing populism are obtained under proportional representation systems (see Appendix E.7). Then, replacing election-year fixed effects (which are unevenly distributed across countries) by 6-years fixed effects does not significantly affect the results (see Appendix E.8.8). Finally, we include economic controls such as the GDP per capita or the employment rate, which can capture changes in economic conditions (although suffering of simultaneity bias), and this does not significantly affect the direction of the results (see Appendix E.8.9).

[34]We rely on the Social Expenditure data provided by the OECD, which provides information on social expenditure for OECD countries. For non-OECD countries in our sample, we estimated their social expenditure to fall below the median of our subset of OECD countries.

4.5 Searching for Amplifiers

The results described above can be considered as average populist responses to globalization shocks in normal times. We now consider the extended specification depicted in Eq. (6), which includes other potential drivers of populism (direct impact) and their interactions with low-skill intensive globalization shocks (amplifiers).

We create five dummies to capture whether (i) the country experienced a year of negative real income growth in the last two years before the election (a proxy for *economic crises*), (ii) the country experienced a variation in the share of manufacturing value added in GDP in the last two years that belongs to the bottom quartile of the distribution (a proxy for *de-industrialization*), (iii) the share of internet users in population belongs to the top decile of the distribution (a proxy for a high *prevalence of social media*), (iv) the level of diversity in the origin mix of imports of low-skill labor intensive goods belongs to the top decile of the distribution (a proxy for diversification in imports), and (v) the weighted mean of genetic distance between the origin and destination countries of low-skill immigrants belongs to the top decile of the distribution (a proxy for a high level of *cultural distance* between natives and low-skill immigrants).[35]

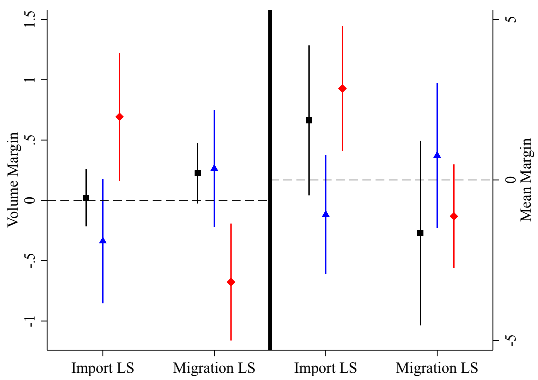
The first two amplifiers explore captures the role played by economic downturns in determining the upsurge of populist parties and leaders (Funke et al., 2016; Algan et al., 2017). The diffusion of internet, and subsequently of social media, has been also highlighted as one of the determinants of recent political polarization and populism (Levy, 2021; Manacorda et al., 2022). The diversity (or the lack thereof) of import basket or immigrant population could capture potential positive effects on consumers due to the availability of more product and skills on the market, potentially mitigating the pro-populism effect of low skill imports and immigration (Alesina et al., 2016; Docquier et al., 2020). Finally, the weighted genetic distance could proxy for potential cultural shocks due to immigration from distant countries (Norris and Inglehart, 2019).

Detailed IV regression results including the linear effect of the dummies are provided in the Appendix E.11. The linear terms are insignificant for the economic crisis and de-industrialization dummies, whose roles are likely to be captured by the year fixed effects. The internet dummy is positive and significant for the volume margin of populism (Zhuravskaya et al., 2020; Campante et al., 2018; Guriev et al., 2021), and virtually insignificant for the mean margin. Finally, a high level of diversity in imports increases the mean margin of populism, while we find insignificant direct impacts for cultural distance between natives and low-skill immigrants.

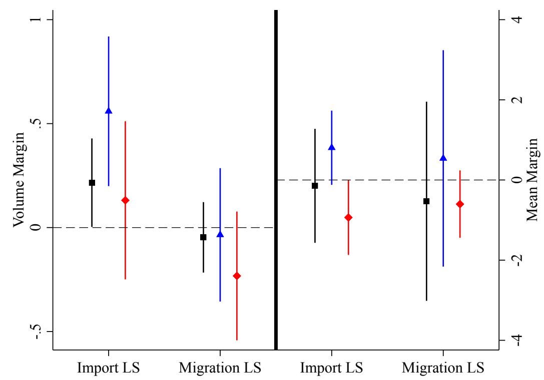
However, our main variables of interest are the interaction terms with globalization shocks,

[35] The data sources are the Penn World Tables for GDP growth rates, the UN National Accounts for the share of manufacturing output in GDP, Abel (2018) for dyadic immigration flow data, and the World Bank WDI for internet coverage (we assume zero coverage before 1990, since the World Wide Web was invented in 1989). Data on genetic distance are taken from Spolaore and Wacziarg (2009).
The top decile is defined over the whole period for the measure of diversity in imports and migration, while it is defined only from the 1990 for internet coverage, given the absence of internet coverage before 1990. In this way, we are able to capture amplifiers that are absolute throughout the period of analysis.

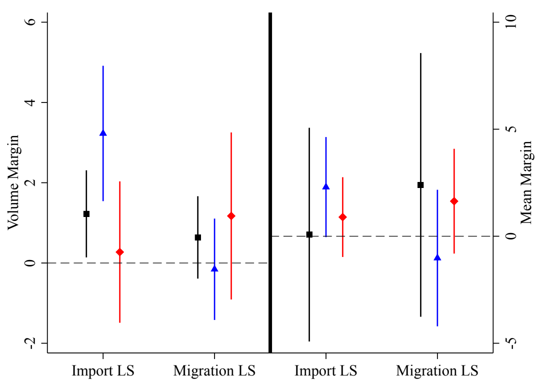
Figure 7: Interactions with amplifiers for volume and mean margins
Reduced-form IV PPML and 2SLS results



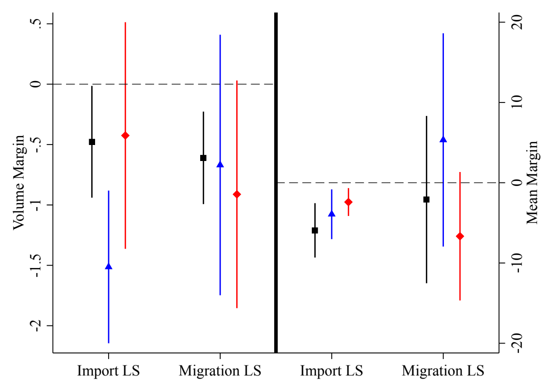
(a) Economic crisis



(b) De-industrialization



(c) Internet coverage



(d) Diversity (Imp) & genetic dist. (Mig)

Notes: Black (square), blue (triangle) and red (diamond) objects correspond to overall, right wing and left wing dimensions, respectively. Dependent variable is the volume margin on the left panels, while is the mean margin in the right panels. The estimates represent the coefficients of the interaction term between migration (LS) and imports (LS) with a dummy equal to one if the country experienced a year of negative real growth five years prior the election year (Figure (a)), as well as proxies for de-industrialization (Figure (b)), for internet coverage (Figure (c)), and trade diversity and genetic distance (Figure (d)). 90% confidence intervals are reported.

which reflect potential amplifiers of the populism responses to globalization. Figure 7 provides the estimated coefficients of the interaction terms and their confidence intervals at the 90% threshold. Each sub-figure focuses on one potential amplifier, and distinguishes between the volume margin of populism (left panel) and the mean margin (right panel), separated by a vertical line. Each panel includes two triplets of estimates, namely the effect of imports of low-skill labor intensive goods on the left, and the effect of low-skill immigration on the right. Finally, a triplet is made of three estimates for the effect of the interaction term on total (black squares), right-wing (blue triangle) and left-wing (red diamond) populism, respectively. We explain below how the inclusion of potential amplifiers affects the main findings of the previous sections.

Our first main result is that imports of low-skill intensive goods increase the volume of right-wing populism, without affecting the volume of total and left-wing populism. The estimates in Figure 7 show that these effects are reinforced in times of de-industrialization (Panel b) and when the internet coverage is high (Panel c). On the contrary, a high level of diversity in imported (low-skill labor intensive) goods reduces the right-wing populism response (Panel d). In addition, it cannot ruled out that imports increases the volume of left-wing populism in times of negative growth (Panel a).

Our second main result is that *imports of low-skill intensive goods increase the mean margin of total and right-wing populism, without affecting the mean margin of left-wing populism.* Figure 7 evidences that is smaller when imported goods are more diverse (Panel d), and that an effect on the mean margin of left-wing populism materializes during severe crises (Panel a).

Our third main result is that *low-skill and high-skill immigration have different effects on populism, with the former increasing the support for right-wing populism while decreasing support for left-wing populism, and the latter decreasing support for right-wing populism.* Focusing on low-skill migration, the results in Figure 7 show that the decline in left-wing populism is stronger in times of negative growth (Panel a). Interactions with the de-industrialization and internet coverage dummies are never significant. With regard to cultural distance, it does not amplify the right-wing populist response to low-skill immigration. Similar findings are obtained when we replace our proxy for cultural distance by an augmented diversity index *a la* Greenberg (1956) computed on low-skill immigrants, that combines diversity, cultural and economic distance in a single variable.[36] If anything, a high level of cultural distance reduces the centrist and left-wing populist responses to low-skill immigration (Panel d).

Finally, our fourth result is that *low-skill immigration has no meaningful impact on the mean margin of populism.* This result is fairly robust and unaffected when interactions terms with potential amplifiers are added.

4.6 Discussion

Our findings can be interpreted through the lens of distributional conflicts, identity politics, and perceived cultural and economic threats. Low-skill immigration can trigger perceptions of economic and cultural threats among native workers (especially of the low-skill type). Economically, it can

[36] In the Appendix E.12 we show that, once accounting for both economic and cultural distance, diversity has no amplifying effect on populism. If any, economic distance, rather than cultural distance, can enhance the effect of low-skill immigration on the volume of populism.

increase perceived competition for jobs, housing, and access to public services. Culturally, it can be seen as a challenge to existing social norms, raising concerns about national identity and social cohesion. Right-wing populist parties often mobilize these fears by framing immigration as a zero-sum game, invoking nationalist narratives, and linking immigration to concerns about unemployment, crime, social disorder, and welfare dependency. As immigration becomes more salient and reduces the perceived homogeneity of the host-country population, identity may shift from being based on economic class to ethnic or national identity, reinforcing nationalist and anti-immigrant attitudes (Shayo, 2009, 2020). This, in turn, can reduce support for redistribution (Moriconi et al., 2019; Alesina et al., 2021, 2023). Left-wing populist parties—which typically promote inclusiveness, redistribution, and support for immigrants—may be perceived as disconnected from the economic and cultural grievances of the native working class. As a result, these voters may increasingly turn to more nationalist and anti-immigrant alternatives, eroding the left's traditional base.

Similarly, exposure to imports of low-skilled labor-intensive goods can be perceived as exerting a downward pressure on wages and job security, particularly in traditional manufacturing sectors. This form of economic displacement disproportionately affects low-skill workers. When these workers attribute their insecurity to globalization—rather than to domestic policies or technological change—they may gravitate towards right-wing populist parties that offer protectionist platforms, promise to restore lost jobs, and blame external actors (Grossman and Helpman, 2021). These dynamics are consistent with the "China shock" literature, which highlights how exposure to that trade shock undermined support for mainstream parties seen as unresponsive to the adverse effects of globalization.

In contrast, highly-skilled immigration and trade in high-skill labor-intensive goods tend to generate complementarities with low-skilled labor, and promote innovation and productivity in knowledge-intensive sectors. These sectors are often urban, cosmopolitan, and highly dependent on highly-skilled labor. Workers in these settings tend to be embedded in networks and regions less exposed to economic downgrading, and are more likely to express inclusive values, institutional trust, and support for global engagement—all factors that mitigate support for populist movements. Moreover, high-skill immigration is often framed positively in public discourse, and rarely triggers the same economic or cultural threat perceptions as is the case for low-skill immigration (Shayo, 2009).

5 Conclusion

Populism is on the rise everywhere, and more so in Europe and for right-wing populism. This is a danger for democracy and for the economy (Funke et al., 2023; Bellodi et al., 2024). To be countered, its complexity (and multidimensionality) as well as its determinants need to be better understood. This paper contributes to a better understanding of populism in two ways. First descriptively, we construct new measures of populism capturing the vote shares of populist parties (the volume margin) and the average populist scores of all parties (the mean margin), as populist ideas are not restricted to populist parties. Both measures rely on the two dimensions identified in the political science literature as the main markers of populism – namely, the anti-establishment and commitment-to-protect stances. Our measures are consistent over time and allow to characterize the evolution of populism over a 60-year period, from 1960 to 2019. Equipped with these measures, we are able to characterize the long-run trends in the levels of total, left-wing, and right-wing populism. We show that both margins of populism (volume and mean) have fluctuated since the 1960s, with peaks after each major economic crisis, and have reached an all-time high during the last decade, at least as far as right-wing populism is concerned. The latter trend is largely driven by Europe.

Second, we empirically assess how globalization shocks have impacted populism in the past six decades. We propose a unified analysis of the effects of trade and immigration shocks on populism and disentangle their respective impacts according to their skill structure. We find that the skill structure of globalization shocks is key to explaining populist trends. Imports of high-skill labor intensive goods as well as high-skill immigration tend to reduce the volume of right-wing populism. This is not the case for low-skill globalization, as i) imports of low-skill intensive goods increase right-wing populism along the volume and mean margins alike while leaving left-wing populism mostly unchanged, and ii) low-skill immigration induces a shift of votes to the right, with less votes for left-wing populist parties and more support for right-wing populist parties, without affecting the total volume nor the mean margin of populism. These effects are magnified in times of economic crises and de-industrialization or when the internet coverage is high, and mitigated when the origin-mix of immigrants and of imports is more diverse.

Future trends in globalization are likely to shape the political landscape in profound ways. In particular, the demographic growth of low-income countries is expected to increase immigration pressures on high-income countries. Low- and lower-middle-income countries currently account for about 55% of the world's population aged 15 to 44, and this share is projected to rise to 80% by 2100. Such demographic shifts are likely to reduce the average skill level of immigrants, potentially fueling populist sentiment (Docquier and Rapoport, 2025). The future of trade is more uncertain, as evidenced by newly announced protectionist measures by the Trump administration, retaliatory responses from trading partners, and growing anti-globalization pressures linked to climate change, pandemic risks and other global crises.

Taken together, our findings suggest that the blame for the rise of populism cannot be laid on globalization as a whole. It is essential to acknowledge the differentiated effects of trade and migration on various margins of populism and to account for the sometimes opposing effects of high-skill v. low-skill globalization shocks. Neglecting these aspects is likely to lead to ill-informed recommendations for trade and immigration policy.

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Online Appendix

Populism and the Skill-Content of Globalization

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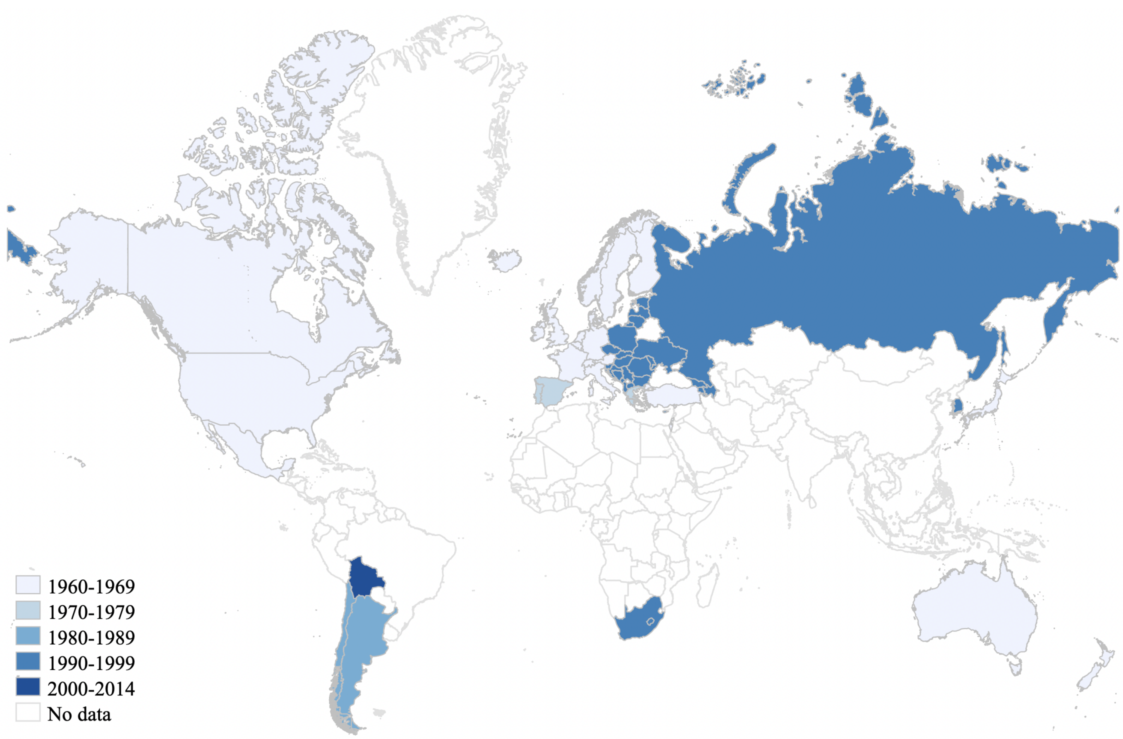
A List of Countries Included in MPD

Figure A.1 illustrates the set of countries available in our data set. We cover both economically developing and developed countries, not all of them being available from the beginning of our period of analysis.

Figure A.1: Countries Available in MPD data



Note: The figure plots the countries that have at least one electoral and the different colors show the year of the first election available in the sample.
Source: Authors' elaboration on MPD.

This project is based on the 2024(a) version of the Manifesto Project Database (Lehmann et al., 2024). In order to analyze the evolution of populism and the impact of skill-specific globalization shocks across countries, we start our sample in 1960, as no dataset provides bilateral immigration stocks before that year for a wide range of countries. We exclude the COVID-19 crisis and its aftermath due to its structural effects on electoral outcomes (e.g., Noury et al., 2021; Miller et al., 2022), trade (Evenett et al., 2022), and migration patterns (Guadagno et al., 2020). We retain all elections for which the MPD reports vote shares and exclude countries with only a single recorded election, as our analysis requires temporal variation. In effect, we cover the period 1960 to 2019.

Table A.1 provides the list of countries, the year of the first (third column) and last (fourth column) electoral event available, the number of elections (fifth column) and the total number of unique parties that won at least one seat in an electoral event (sixth column). Our sample collects information over 55 countries, 657 elections and 1,277 parties. The total number of observations in our dataset (hence party-election) is 4,140. As expected, several former Soviet Union countries enter the sample after the fall of the Berlin Wall (1989). At this stage, if a party A changes its name to become party B between elections, we count them as two different parties. The MPD provides the results and the percentage votes for the 1990 results for the German Democratic Republic (East Germany), the Uruguayan election in 2014, and the Belarusian election in 1995, but we exclude these countries due to the lack of time variation.

Table A.1: Manifesto Project Database – Sample

	i	1^{st} E.	Last E.	# E.	# P.		i	1^{st} E.	Last E.	# E.	# P.
Denmark	1	1960	2019	22	21	Bulgaria	30	1990	2017	10	28
Japan	2	1960	2017	20	30	Croatia	31	1990	2016	9	35
New Zealand	3	1960	2017	20	14	Czech Rep.	32	1990	2017	9	25
Sweden	4	1960	2018	18	16	Georgia	33	1990	2016	9	42
USA	5	1960	2016	15	2	Hungary	34	1990	2018	8	17
Australia	6	1961	2019	23	14	Montenegro	35	1990	2016	10	23
Belgium	7	1961	2019	18	36	Nth Mac.	36	1990	2016	9	29
Germany	8	1961	2017	16	11	Romania	37	1990	2016	8	31
Ireland	9	1961	2016	16	16	Serbia	38	1990	2016	11	38
Israel	10	1961	2019	18	64	Slovakia	39	1990	2016	9	27
Mexico	11	1961	2018	20	26	Slovenia	40	1990	2018	9	26
Norway	12	1961	2017	15	13	Albania	41	1991	2001	5	12
Turkey	13	1961	2018	16	22	Poland	42	1991	2019	9	37
Austria	14	1962	2019	18	13	Estonia	43	1992	2019	8	26
Canada	15	1962	2019	19	9	Lithuania	44	1992	2016	7	27
Finland	16	1962	2019	16	20	Sth Korea	45	1992	2016	7	16
France	17	1962	2017	14	35	Latvia	46	1993	2018	9	36
Iceland	18	1963	2017	17	19	Russia	47	1993	2011	6	25
Italy	19	1963	2018	15	58	Moldova	48	1994	2019	8	18
Netherlands	20	1963	2017	17	28	Sth Africa	49	1994	2019	6	13
Switzerland	21	1963	2019	15	25	Ukraine	50	1994	2019	8	41
Luxembourg	22	1964	2013	11	11	Armenia	51	1995	2018	7	20
UK	23	1964	2019	16	14	Azerbaijan	52	1995	2000	2	6
Greece	24	1974	2019	18	21	Cyprus	53	1996	2016	5	12
Portugal	25	1975	2019	16	22	Malta	54	1996	1998	2	2
Spain	26	1977	2019	15	46	Bolivia	55	2009	2014	2	8
Argentina	27	1989	2013	6	14						
Chile	28	1989	2017	6	15						
Bosnia-Herz.	29	1990	2018	9	22	**Total**				**657**	**1277**

Note: Countries are sorted by the year of the first election available and alphabetically when having the same first year in the data. Variables: i = country number; 1^{st}E. = first year of election; Last E. = last year of election; # E. = number of elections; # P. = number of parties.
Source: Authors' elaboration on MPD.

B Construction of New Populism Score

B.1 Definitions and Correlation with MPD Components

Table B.1 presents the name, description and source of the variables used in the construction of the Populism score. Panel A presents the two proxies used to capture parties' anti-establishment stance, while Panel B shows the four proxies selected to capture the commitment-to-protection stance by focusing on external/foreign threats. When both positive and negative stances towards a specific issue are reported in the Manifesto Project Database (e.g. Internationalism), we constructed a measure of net favorable position, which is the difference between favorable and negative references. Concerning the proxy on EU institutions (CTP_3), for parties outside the EU, and so less interested on the topic, we replace the value of that variable equal to zero.

Table B.2 provides the level, direction and significance of the correlation between the above mentioned political preferences within each domain. Even though the pairwise correlations are small, going from a value of 0.04 to 0.16 in absolute terms, they are highly statistically significant. Moreover, the direction of the correlations supports our previous set of intuitions. Parties that are particularly against political corruption are also more prone to claim themselves better than the others, as the positive correlation in Col. (1) suggests. Cols. (2) to (4) show that internationalization is positively related with positive statements towards the European Union, while these aspects are negatively correlated with positive views towards protectionism and nationalization.

Table B.3 describes the results related to the Polychoric Principal Component Analysis used to construct synthetic indexes for parties' anti-establishment and commitment-to-protection stances. For both set of variables, only the first component has an eigenvalue above one, hence following the Kaiser-Guttman criterion we retain only the first components as our synthetic indexes. Looking at the coefficients/loadings associated to the anti-establishment stance, we can see that the first component gives positive and equal weights to both variables, AES_1 and AES_2, indicating that parties against political corruption and pluralism will have an higher first component. We then define this first component as our index of anti-establishment stance (I_{AES}). With regard to commitment to protection, the first component give high weights to all the analyzed variables, and provides negative weights on parties' positive stance towards protectionism (CTP_1) and nationalization (CTP_4), positive weights on support for internationalism (CTP_2) and EU institutions (CTO_3). Hence, parties with a more political openness agenda will score high on the first component. To facilitate the interpretation, we multiply the first component by minus one, and we define such flipped first component as our commitment-to-protection index (I_{CTP}).

Table B.1: Selection of Political Dimensions in MPD

Variables	Description	MPD Label
Panel A: Anti-establishment Stance		
Pol. corruption (AES_1)	Need to eliminate political corruption and associated abuses of political and/or bureaucratic power. Need to abolish clientelist structures and practices.	per304
Anti-pluralism (AES_2)	References to the manifesto party's competence to govern and/or other party's lack of such competence. Also includes favourable mentions of the desirability of a strong and/or stable government in general.	per305
Panel B: Commitment-to-protection stance		
Protectionism (CTP_1)	Net favorable position. (per406) Favourable mentions of extending or maintaining the protection of internal markets. Measures may include: tariffs, quota restrictions and export subsidies. (per407) Support for the concept of free trade and open markets. Call for abolishing all means of market protection.	per406-per407
Internationalism (CTP_2)	Net favorable position. (per107) Need for international co-operation, including co-operation with specific countries. May also include references to: the need for aid to developing countries; need for world planning of resources; support for global governance; need for international courts; support for UN and international organisations. (per109) Negative references to international co-operation. Favourable mentions of national independence and sovereignty with regard to the manifesto country's foreign policy, isolation and/or unilateralism as opposed to internationalism.	per107-per109
EU Institutions (CTP_3)	Net favorable position. (per108) Favourable mentions of European Community/Union in general. May include the: desirability of the manifesto country joining (or remaining a member); desirability of expanding the European Community/Union; desirability of increasing the ECs/EUs competences; desirability of expanding the competences of the European Parliament. (per110) Negative references to the European Community/Union. May include: opposition to specific European policies which are preferred by European authorities; opposition to the net-contribution of the manifesto country to the EU budget.	per108-per110
Nationalization (CTP_4)	Favourable mentions of government ownership of industries, either partial or complete; calls for keeping nationalised industries in state hand or nationalising currently private industries. May also include favourable mentions of government ownership of land.	per413

Table B.2: Correlations Across Political Dimensions

	AES_2	CTP_2	CTP_3	CTP_4
Panel A				
AES_1	$.070^{\dagger}$			
Panel B				
CTP_1		$-.045^{**}$	$-.102^{\ddagger}$	$.085^{\ddagger}$
CTP_2			$.113^{\ddagger}$	$-.073^{\dagger}$
CTP_3				$-.161^{\ddagger}$

Notes: The table shows the pairwise correlation and the precision associated to the political preferences related to: anti-establishment stance (Panel A) and commitment-to-protection stance (Panel B). Level of significance: * p<0.05, ** p<0.01, *** p<0.001, † p<0.0001, ‡ p<0.00001.
Source: Authors' elaboration on MPD.

Table B.3: PPCA - Anti-Establishment & Commitment-to-Protection Stances

Anti-Establishment (AES)

Comp.	(1) Eigenv.	(2) Explained	(3) Cumulative
Comp. 1	1.068	0.534	0.534
Comp. 2	0.931	0.466	1

Scoring Coefficients/Loadings

Variable	Comp 1	Comp 2
AES_1	0.707	0.707
AES_2	0.707	-0.707

Commitment to Protection (CTP)

Comp.	(1) Eigenv.	(2) Explained	(3) Cumulative
Comp. 1	1.299	0.325	0.325
Comp. 2	0.958	0.239	0.564
Comp. 3	0.909	0.229	0.793
Comp. 4	0.830	0.207	1

Scoring Coefficients/Loadings

Variable	Comp 1	Comp 2	Comp 3
CTP_1	-0.420	0.666	-0.604
CTP_2	0.419	0.736	0.473
CTP_3	0.594	0.048	-0.210
CTP_4	-0.541	0.106	0.605

B.2 Correlation with Alternative Database

The six databases used to provide checks to our populism score are described here below. Table B.4 provides the results of our validation analysis.

- *Van Kessel.* Van Kessel (2015) identifies populist parties based on their manifesto and political discourses in 31 countries over the 2000-2013 period. A party is defined as populist if it portrays people as virtuous and homogeneous, if it claims popular sovereignty and positions itself against the political elite. This data set identifies 57 populist parties. It has been used as a relevant reference point for alternative populism measures (e.g., Guiso et al., 2017).

- *Swank.* Based on the definition of right-wing populism provided by Betz (1994), Swank (2018) identifies about 30 right-wing populist parties in 21 countries over the 1950-2015 period. Betz (1994) defines right-wing populist parties as those providing a mixed political stance based on economic liberalism, questioning of the legitimacy of democracy, and fueling xenophobic views.[1] Left-wing populist parties are not included.

- *PopuList.* The PopuList dataset developed by Rooduijn et al. (2019) identifies a list of populist parties over the 1989-2020 period for 31 developed countries. Validated by more than 80 academic scholars, it includes parties that have won at least one seat or at least 2% of the votes in an election. The information for the 212 parties available in the PopuList data set has been frequently used in recent studies of populism (e.g., Guiso et al., 2024; Morelli et al., 2021).[2]

- *GPop 1.* The Global Populism data (Grzymala-Busse and McFaul, 2020) from the Freeman Spogli Institute for International Studies provides information on populist parties (only) for 40 developed and developing countries over a long period (1916-2019).[3] This data set is particularly relevant for our analysis, since it allows us to cross-validate our time-variant measure over a time-invariant definition of populist parties for the whole 1960-2019 period.

- *GPop 2.* The Global Populism Data (Hawkins et al., 2019) provides a continuous measure of populism based on textual analysis of the political discourses of parties' leaders who won the national election. The analysis is limited to presidents or prime ministers (depending on the institutional context). The measure is based on four types of speeches – campaign speeches

[1] A few parties identified by Swank (2018) as right-wing populist are not available in our sample due to the low percentage of votes received during their national elections (e.g., *Démocratie Nationale* in Belgium or the *National Renovator Party* in Portugal).

[2] The sample of countries includes: Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom.

[3] The sample of countries includes: Albania, Argentina, Austria, Belgium, Bolivia, Bulgaria, Chile, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Mexico, Moldova, Netherlands, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom.

(usually closing or announcement speech), ribbon-cutting speeches, international speeches and famous speeches. Speeches are categorized between 0 (containing few populist elements) and 2 (extremely populist). The sample includes 31 countries over the 1998-2017 period.[4]

- *CHES.* The Chapel Hill Expert Survey (Bakker et al., 2015) provides a continuous index of populism, based on expert surveys and following the definition of Mudde (2004). By asking whether parties believe that the people should have the final say on political issues against the elite, CHES provides a continuous measure of populism (from 0 for pro-elite views, to 10 for pro-people views). However, this index is available in the last wave of the survey (2019) only, and for a reduced number of parties (247). To have a proper comparison with our dataset, we match CHES observations with parties participating in the last electoral event available in the MPD. Since MPD includes parties that won at least a seat during the elections, the matched sample includes 183 parties over 28 countries over the 1998-2019 period.[5]

[4] It includes Austria, Bulgaria, Canada, Croatia, Czech Republic, Estonia, Georgia, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Moldova, Montenegro, Netherlands, North Macedonia, Norway, Poland, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Turkey, Ukraine and UK.

[5] The list of countries includes Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and United Kingdom.

Table B.4: Correlation with existing classifications of populist parties

	I. Van Kessel (2000-2013) Populist party (PRB)			II. Swank (1960-2015) RW Populist party (PRB)			III. PopuList (1989-2019) Populist party (PRB)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$S^p_{i,e,t}$	0.699***			0.463***			0.573***		
	(0.157)			(0.110)			(0.090)		
AES		0.263***			0.248**			0.164***	
		(0.090)			(0.096)			(0.050)	
CTP			0.473***			0.239***			0.445***
			(0.090)			(0.045)			(0.067)
Obs.	653	653	653	1670	1670	1670	1772	1772	1772
Countries	25	25	25	16	16	16	28	28	28
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.18	0.08	0.18	0.16	0.12	0.14	0.17	0.09	0.19
RAF (%)	82.4	81.3	82.5	91.3	91.6	91.4	86.3	86.3	86.7

	IV. GPop 1 (1960-2019) Populist party (PRB)			V. GPop 2 (1998-2019) Average Populism Speeches (OLS)			VI. CHES (1998-2019) People vs. Elite (OLS)		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
$S^p_{i,e,t}$	0.393***			0.134**			1.401***		
	(0.079)			(0.055)			(0.250)		
AES		0.095**			0.066*			0.935***	
		(0.049)			(0.035)			(0.262)	
CTP			0.292***			0.096*			0.763***
			(0.051)			(0.050)			(0.172)
Obs.	3101	3101	3101	100	100	100	183	183	183
Countries	37	37	37	31	31	31	28	28	28
Country FE	✓	✓	✓	✗	✗	✗	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.16	0.12	0.16						
RAF (%)	88.8	88.8	88.8						
R^2				0.22	0.18	0.22	0.34	0.16	0.30

Notes: In Cols. (1) to (12), we provide partial correlations between parties' political induces and the probability of being coded as populist party or right wing populist party following the definition of Van Kessel (2015), Swank (2018), Rooduijn et al. (2019) and Grzymala-Busse and McFaul (2020) and adopting a probit model. Each regression controls for country and year fixed effects. We also provides the ratio of accurate forecasts (RAF) between our estimated model and actual data, using a predicted probability of 0.5 as threshold to define a party as populist. In Cols. (13) to (15), we provide partial correlations between political indices and party leader's speeches (Hawkins et al., 2019) after controlling for year fixed-effects. In Cols. (16) to (18), we provide partial correlations between political indices and expert evaluations of parties degree of populism (Bakker et al., 2015). Standard errors are clustered at country level. Level of significance: * p<0.1, ** p<0.05, *** p<0.01.

B.3 Correlation Between Populism Score, Party Families, Preferences for Immigration, Cultural Identity and Interventionism

Relying on the party family classification provided by the Chapel Hill Expert Survey (CHES), Table B.5 presents the results of linear probability models (LPM) using dummy variables to classify parties across various political families and our novel populism score. Based on the classification by Hix and Lord (1997), CHES categorizes parties into eleven families: radical right, conservative, liberal, Christian-democratic, socialist, radical left, green, regionalist, confessional, agrarian/center, and no family. Since the last three categories contain only a handful of cases, we focus on the partial correlation between our populism score and classification within the remaining eight families. In Table B.5 we show that our populism scores are positively related to the parties' likelihood to belong either to the radical right or the radical left – using the classification provided in the Chapel Hill Expert Survey for the 1994-2014 period. In contrast, we find a negative association with the likelihood to belong to other political families (i.e., liberal, Christian-democratic and socialists). Taking the estimates at face value, a one standard deviation increase in the populism score (i.e., being classified as populist) is associated with a 9.7 percentage point higher probability of being categorized as radical right-wing and an 8.9 percentage point higher probability of being categorized as radical left-wing.

Table B.5: Populism Score and Ideology

	Rad. Right	Rad. Left	Liberal	Chris.-Dem.	Socialist	Conserv.	Green	Regionalist
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Populism index	0.12***	0.11***	-0.07***	-0.04***	-0.06***	-0.05***	0.01	-0.02
	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Observations	1810	1810	1810	1810	1810	1810	1810	1810
R^2	0.175	0.190	0.128	0.127	0.041	0.100	0.062	0.320

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses. The table show the estimates of linear probability models (LPM) using parities as unit of observation and dummy as outcomes variable, which classifies parties belonging to a specific political family following Hix and Lord (1997) classification.

In Table B.6, we compute partial correlations between our populism score $S^p_{i,e,t}$ and four MPD proxies capturing preferences for immigration and multiculturalism. We standardized the proxies with mean zero and standard deviation equal to one. We use four variables available in the MPD database: (i) immigration is negative for country's national way of life, (ii) immigration is positive for country's national way of life, (iii) immigration positively contributes to multiculturalism, and (iv) immigrant should assimilate to the country culture. Note that these variables are not available for the years prior to 2006. In line with intuition, we find that the populism score of centrist and right-wing parties is negatively and significantly correlated with positive stances towards immigration and its contribution to multiculturalism. This is not the case among left-wing parties, where the populism score is negatively correlated with the pressure of assimilating the migrant to country's culture. Nonetheless, the small magnitude of the partial correlation and the within R^2 indicate that while the direction of the relationship is consistent, caution is advised in focusing solely on migration-related stances to derive parties' populism stances.

Table B.6: Populism Score and Migration-Related Political Preferences

	All Parties				No Left-Wing Parties				Left-Wing Parties			
	Immi. (−) (1)	Immi. (+) (2)	Immi. (+) Multicul. (3)	Immi. Assimi-lation (4)	Immi. (−) (5)	Immi. (+) (6)	Immi. (+) Multicul. (7)	Immi. Assimi-lation (8)	Immi. (−) (9)	Immi. (+) (10)	Immi. (+) Multicul. (11)	Immi. Assimi-lation (12)
Populism index	0.18	-0.07**	-0.09**	0.09*	0.24	-0.10**	-0.10**	0.14*	-0.02	0.08	-0.03	-0.10*
	(0.13)	(0.04)	(0.04)	(0.05)	(0.19)	(0.04)	(0.04)	(0.07)	(0.03)	(0.19)	(0.11)	(0.05)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	772	772	772	772	445	445	445	445	327	327	327	327
R^2	0.169	0.285	0.215	0.288	0.253	0.345	0.227	0.426	0.235	0.340	0.334	0.229
Within R^2	0.023	0.004	0.006	0.007	0.034	0.022	0.019	0.016	0.001	0.002	0.000	0.018

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses. Analysis available from 2006 on, given the availability of the measures only from that election-year.

Table B.7: Populism Score and Preferences for Culture and Interventionism

	All Parties			No Left-Wing Parties			Left-Wing Parties		
	Cultural Conser-vatism (1)	Govern-ment Inter. & Econ. Planning (2)	Lab. Group Positive (3)	Cultural Conser-vatism (4)	Govern-ment Inter. & Econ. Planning (5)	Lab. Group Positive (6)	Cultural Conser-vatism (7)	Govern-ment Inter. & Econ. Planning (8)	Lab. Group Positive (9)
Populism index	0.14***	0.15***	0.04	0.18***	0.08***	-0.00	-0.01	0.36***	0.15
	(0.04)	(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.02)	(0.06)	(0.10)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4098	4098	4098	2733	2733	2733	1365	1365	1365
R^2	0.142	0.194	0.136	0.193	0.215	0.164	0.215	0.271	0.189
Within R^2	0.013	0.015	0.001	0.018	0.006	0.000	0.000	0.044	0.008

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses.

In Table B.7, we compute pairwise partial correlations between our populism score and proxies for (i) cultural conservatism, (ii) preferences for government intervention and economic planning, and (iii) stances towards labor groups. As for the previous proxies, we standardize them with mean zero and standard deviation equal to one to facilitate the interpretation of the magnitude. We find that the populism score of centrist and right-wing parties is positively and significantly correlated with cultural conservatism; this is not the case among left-wing parties. Interventionism and populism are positively and significantly correlated on both sides of the right-to-left spectrum, with a stronger partial correlation among left-wing parties. We do not find any statistically significant partial correlation between our populism score and parties' stances towards labor groups, although the magnitude of the partial correlation is almost zero among right-wing and centrist parties, while positive among left-wing ones.

B.4 Does Populism Require a More Extensive Definition?

We consider two *extended populism scores* that exploit additional potential characteristics of populist parties, and check whether these extended scores better correlate with existing measures. Our first extended score accounts for the fact that populist parties are sometimes characterized by their *shortsighted and opportunistic research agenda*, which guides their political strategy (Guiso et al., 2017). Populists rely on narrow/thin ideological references, which can cohabit with other ideological framework, like the usual right-left divide (Mudde, 2004; Rooduijn et al., 2014). However, a frequent denominator is that their main objective is to increase parties political support and consensus in the short-run (Weyland, 2001; Betz, 2002), without addressing the long-run challenges faced by the society. Populist parties tend to focus on more actual and immediately salient issues, implying the concealment of long run costs and issues. Building on our *Standard Populism Score*, we construct an extended index that includes a third component. We refer to it as the **3C Populism Score**, which accounts for shortsighted opportunistic strategy (OPP). To do so, we combine two additional MPD variables covering aspects which are primarily influenced by policies with a long-term perspective, i.e., the salience of and position towards (*i*) education expansion, which involves mentions towards expansion of educational provision and the reduction of educational fees, and (*ii*) environmental protection, capturing parties' favorable positions towards green economy and the need for fighting climate change.

Our second extended score accounts for the whole set of information available in MPD. We construct synthetic indices of political preferences using the remaining set of 44 variables available from the MPD. We only consider variables that are available for all political parties included in our sample over the whole period. In line with our PPCA approach, we first perform a PPCA over the variables belonging to the different domains covered by MPD and then retain components with an eigenvalue above one, in line with Kaiser's criterion. We end up with 12 synthetic indices capturing new political dimensions. We then combine them with the three dimensions of populism used to construct the 3*C Populism Score* (i.e., AES, CTP and OPP).[6] We use the same dimensionality reduction technique (PPCA) as in the previous section to construct our populism score, referred to as the **15C Populism Score**.

Table B.8 provides the eigenvectors associated with the variables within each component. The first component, which explains the majority of the variance in the data, is positively correlated with our three highlighted indices. In addition, the size of their coefficient is intuitive, suggesting that the three indices play a relevant role in the definition of the first component. We then define this first

[6] These new dimensions are: (1) promotion of peaceful external relationship; (2) support towards freedom, democracy and constitution; (3) support for political decentralization and public administration efficiency; (4) support for free markets and incentives; (5) economic growth and investments as main tool for country development; (6) support for government intervention in the economy and economic planning; (7) welfare state expansion and support for equality; (8) support for cultural activities likes museums; (9) support for cultural conservatism; (10) support for tradition-based national cohesion rather then public enforcement; (11) focus on non-economic groups of the society; (12) focus on economic groups of the society.

component as our $15C$. Such an index not only has at its core the main features which characterized the $3C$ Populism Score (positive correlation with parties' stance towards anti-establishment issues, commitment to protection, and concealment of long term issues), but it also account for parties' position towards the whole spectrum of political issues.

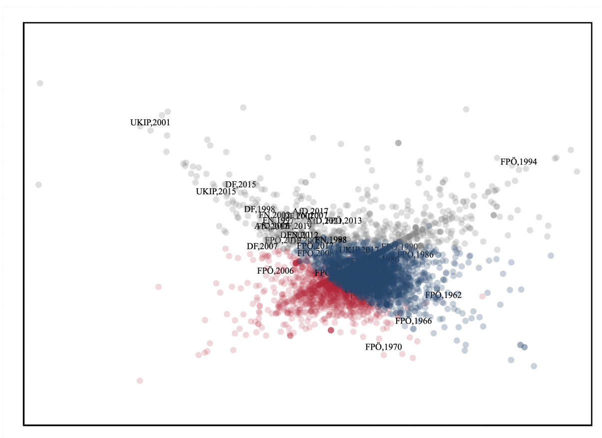
Table B.8: PPCA - Eigenvectors

	Cpt 1	Cpt 2	Cpt 3	Cpt 4	Cpt 5	Cpt 6
Index						
Anti-establishment	.3236	.0866649	.168615	-.4454157	-.0070795	.1631254
Protectionism	.2414376	-.1090295	.4825606	.107923	.0506964	.272777
LT costs	.3980992	.2775066	-.0097265	-.0239581	.2909856	.1054792
Peaceful ext. relations	.2999157	-.2900902	-.1610873	.0790423	.2258213	.2281799
Freedom & democracy	.2705419	-.12289	-.4324478	-.2010165	.0435092	-.2480756
Political decentralization	-.2260661	.2012557	-.1394121	-.4809725	.3243406	.2335047
Free market	-.117958	.5102452	-.016111	.0533955	.0761923	-.2485923
Economic growth	-.3392872	-.0547227	.3183679	.0588738	.3867792	-.0973993
Economic planning	.2493642	.0174169	.2054276	.3777058	.435326	-.0453066
Welfare state expansion	-.1317248	-.5033992	.2564979	-.0221428	-.0108146	-.2160816
Cultural conservatism	.0927254	.2718799	.2536932	.0987465	-.5952069	.2741062
Tradition-based cohesion	.2679219	-.0072693	-.2368088	.328697	-.1593724	-.3657313
Non-econ. groups focus	-.0918706	-.0277832	-.3814928	.386488	.0814273	.5797808
Econ. groups focus	-.0701798	.4091336	.0679143	.2627503	.1485585	-.1469304
Support cultural activities	-.4024305	-.0681258	-.1612969	.1603779	-.0349574	.1818469

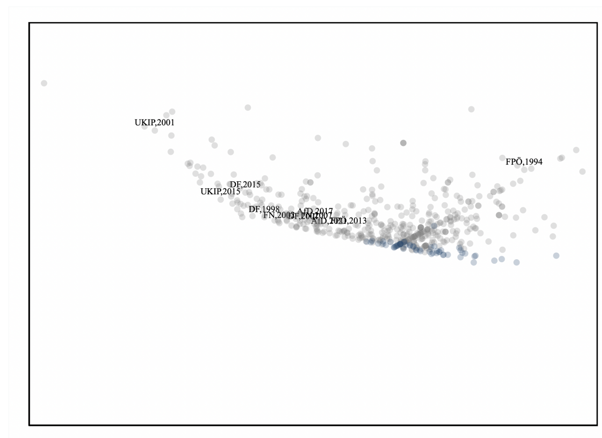
Table B.9 presents the correlation between the standard populism index and the six components from our last PPCA. The first component (the one we defined as Extended Populism Index) has the highest positive correlation with the standard Populism Index. Second, it is also able to explain the highest amount of variance of the standard populism index, as it is reported by the R^2 value. Hence, the first component looks a suitable candidate as alternative and extended populism index.

Finally, we analyze whether the extended scores better identify populist parties and better correlate with existing measures. First, for illustrative purpose, we rely on the same unsupervised machine-learning algorithm to cluster political parties. Figure B.1 provides the result of the cluster analysis. The top panel shows the results obtained when accounting for 3 dimensions of populism ($3C$). The left panel considers all election-party pairs and identifies three clusters of parties colored in gray, blue and red. The top-right panel isolates election-party pairs with standard populism scores above the one standard deviation threshold. It shows that populist parties tend to cluster in a specific upper part of the artificial space, just as in Figure 2 when we account for two dimensions only. The bottom panel shows the results obtained with fifteen dimensions of populism ($15C$). The bottom-right panel shows that populist parties tend to cluster in a specific upper part of the artificial space, even if this pattern is less clear-cut as with 2 or 3 dimensions.

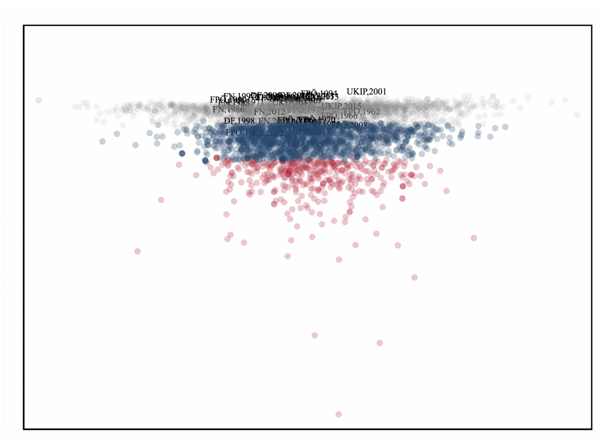
Figure B.1: Unsupervised Clustering Analysis on Three and Fifteen Selected Dimensions of Populism



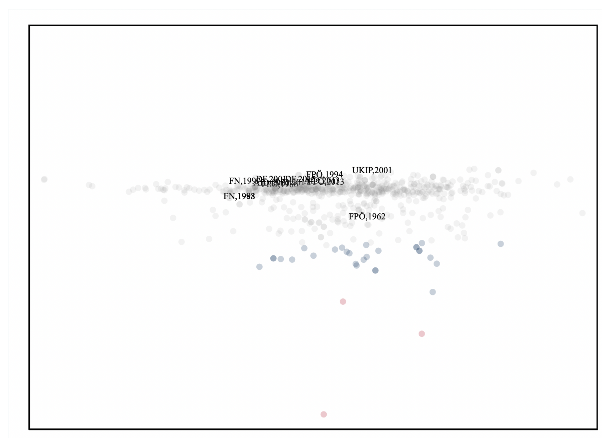
(a) All parties – 3 dimensions



(b) Populist parties only – 3 dimensions



(c) All parties – 15 dimensions



(d) Populist parties only – 15 dimensions

Note: We perform a clustering analysis using the fifteen political indicators built from the MPD. The left panel presents the space including all parties, while the right panel shows the space once we focus on populist parties only (populism index above one standard deviation). Source: Authors' elaboration on MPD.

Table B.9: Correlations Between Standard Populism Index and Political Dimensions

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
	Dependent variable: standard populism index						
Cpt 1	.30***						.30***
Populism^{ext}	(.01)						(.00)
Cpt 2		-.02*					-.02***
		(.01)					(.01)
Cpt 3			.36***				.36***
			(.01)				(.01)
Cpt 4				-.17***			-.17***
				(.01)			(.01)
Cpt 5					.03**		.03***
					(.01)		(.01)
Cpt 6						.24***	.24***
						(.01)	(.01)
Obs.	4098	4098	4098	4098	4098	4098	4098
R^2	0.28	0.00	0.28	0.05	0.00	0.09	0.70

Second, we apply a second-stage PPCA of the 3 or 15 indices computed from the MPD and retain components with eigenvalues above one. We then define this first component of these PPCA as our $3C$ vs. $15C$ Populism Scores. These alternative scores not only have at their core the main features of the standard populism score (positively correlated with AES, CTP), but they also account for the OPP component ($3C$) or for political parties' position towards the whole spectrum of political issues covered in MPD ($15C$).

Although the extended populism scores account for a larger number of political characteristics, they do not provide better proxies for populism. Adding more information to the populism score can create additional noise. In Table B.10, we compare the partial correlations between the standard and extended populism scores and the alternative classifications and measures available in existing literature. These partial correlations are the outcomes of Probit regressions when the dependent is a dichotomous classification variables, and of OLS regressions when the dependent is a continuous variable. In both case, the regression includes country and year fixed effects.

Whatever the alternative source, our *standard populism score* exhibits a greater correlation with existing measures and experts' views than the $3C$ and $15C$ *extended scores*. Adding the OPP component usually reduces the partial correlation estimates, while roughly preserving the ratio of accurate forecasts and pseudo-R^2. It is worth noticing that parties considered as populist by many experts (such as the *Movimento 5 Stelle* in Italy, the *Front National* in France, or *Podemos* in Spain) exit the list when OPP is included.[7] Moreover, adding the whole set of information available in MPD strongly deteriorates the correlation with existing classifications our measures. These regressions suggest that our standard populism score is a relevant – and perhaps better – proxy for populism, and that there is not need to exploit the whole amount of information available in MPD for approximating populism.

[7]This is driven by the fact that in more recent years several parties took a strong pro-environment stance, which generates a lower $3C$ score to parties like the *Movimento 5 Stelle*.

Table B.10: Standard vs. Extended Populism Scores – Correlation

	I. Van Kessel (2000-2013) Populist party (PRB)			II. Swank (1960-2015) RW Populist party (PRB)			III. PopuList (1989-2019) Populist party (PRB)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Standard	0.699***			0.463***			0.573***		
	(0.157)			(0.110)			(0.090)		
3*C*		0.468***			0.405***			0.426***	
		(0.099)			(0.089)			(0.072)	
15*C*			0.280***			0.239***			0.269***
			(0.062)			(0.079)			(0.058)
Obs.	653	653	653	1670	1670	1670	1772	1772	1772
Countries	25	25	25	16	16	16	28	28	28
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.18	0.17	0.11	0.16	0.19	0.13	0.17	0.17	0.13
RAF (%)	82.39	81.93	81.78	91.32	91.50	91.56	86.34	86.06	86.51

	IV. GPop 1 (1960-2019) Populist party (PRB)			V. GPop 2 (1998-2019) Average Populism Speeches (OLS)			VI. CHES (1998-2019) People vs. Elite (OLS)		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Standard	0.393***		0.134**				1.401***		
	(0.079)			(0.055)			(0.250)		
3*C*		0.296***			0.111***			0.661***	
		(0.055)			(0.033)			(0.188)	
15*C*			0.178***			0.032			0.590***
			(0.046)			(0.031)			(0.185)
Obs.	3101	3101	3101	100	100	100	183	183	183
Countries	37	37	37	31	31	31	28	28	28
Country FE	✓	✓	✓	✗	✗	✗	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo-R^2	0.16	0.16	0.14						
RAF (%)	88.84	88.75	88.78						
R^2				0.22	0.24	0.17	0.34	0.18	0.19

Note: In Cols. (1) to (12), we provide partial correlations between parties' political induces and the probability of being coded as populist party or right wing populist party following the definition of Van Kessel (2015), Swank (2018), Rooduijn et al. (2019) and Grzymala-Busse and McFaul (2020) and adopting a probit model. Each regression controls for country and year fixed-effects. We also provides the ratio of accurate forecasts (RAF) between our estimated model and actual data, using a predicted probability of 0.5 as threshold to define a party as populist. In Cols. (13) to (15), we provide partial correlations between political indices and party leader's speeches (Hawkins et al., 2019) after controlling for year fixed-effects. In Cols. (16) to (18), we provide partial correlations between political indices and expert evaluations of parties degree of populism (Bakker et al., 2015). Standard errors are clustered at country level. Level of significance: * p<0.1, ** p<0.05, *** p<0.01. Source: Authors' elaboration on data from MDP.

B.5 Commitment to Protect and Net Autarky Score

The literature exalining on the potential implications of globalization on the political preferences of parties/countries regarding international trade has explored variations in a *net autarky score*, constructed from data available in the MPD (Burgoon, 2009; Colantone et al., 2022). While sharing similarities with our "commitment to protect index," these two measures also exhibit distinct differences.

Firstly, the construction of the scores differs. The net autarky score, based on proxies derived from the MPD, does not take into account parties' positions on nationalization. Additionally, it is formulated by aggregating parties' preferences following the methodology outlined by by Lowe et al. (2011):

$$Net\ Autarky^{p}_{i,e,t} = log(0.5 + z^{+}_{p,i,e,t}) - log(0.5 + z^{-}_{p,i,e,t}). \tag{8}$$

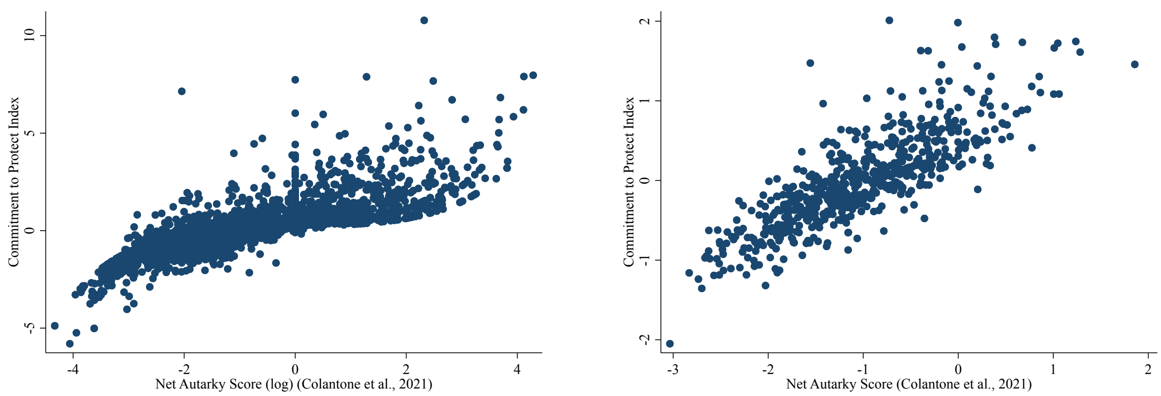
where z^{+} represents the sum of mentions with a positive stance towards autarky (supporting protectionism and opposing the EU and internationalism), and z^{-} represents the sum of mentions with a negative stance towards autarky (opposing protectionism and favoring the EU and internationalism) for party p in country i during election e in year t.

While this measure effectively captures non-linear changes based on manifesto content, it assumes two key elements: (i) the existence of a relationship between the variables and the net autarky score, and (ii) equal relevance of each political preference in shaping the net autarky score. In contrast, our approach first considers the net stance (when both positive and negative stances exist), and subsequently employs unsupervised machine learning (PPCA) to minimize the role of aggregation choices. By doing so, we determine the relationship (i.e., the sign) and relevance (i.e., the weight) of each political preference in constructing the commitment to protect index, with the goal of synthesizing the authentic data generating process underlying parties' political preferences.

Another distinction lies in the ambition of our index. Although the political preferences articulated in parties' manifestos reflect their willingness or commitment to implement autarky measures and decrease exposure to international institutions, it is unclear whether parties have the capacity to carry out such policies once in power. Parties with a pronounced anti-globalization stance often face challenges in executing extensive autarky policies, given the intricate rights and obligations linked to participation in international organizations and trade agreements. Consequently, characterizing these measures as a "commitment" appears more plausible than implying genuinely robust policy stances.

Subsequent to delineating the distinctions between the two metrics, Figure B.2 elucidates the correlation between the net autarky score and the commitment to protect index at both party and country levels. In the case of the latter, the computation entails deriving the average of the two measures without applying weightings to parties proportionate to their share of votes. As anticipated, a positive correlation is evident between the two metrics, manifesting as a correlation coefficient of 0.793 at the party level and 0.818 at the country level.

Figure B.2: Correlation Between Commitment to Protect Index and Net Autarky Score



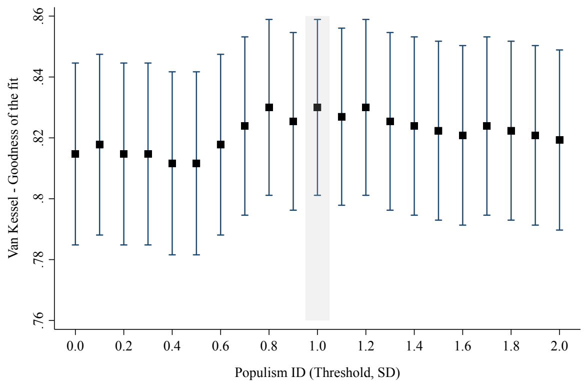
(a) Party level

(b) Country level

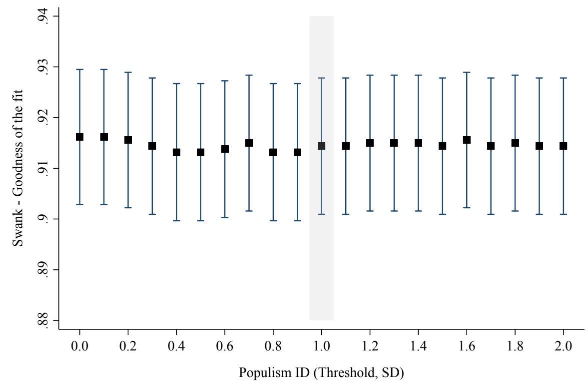
Fig. (a) and (b) show the correlation between the Commitment to Protect Index and the Net Autarky Score (Colantone et al., 2022) at party and country level, respectively.

B.6 Selection of the Threshold Used to Define Populist Parties

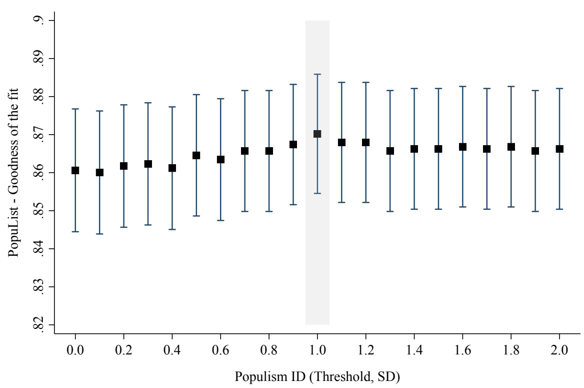
Figure B.3: Threshold Definition - Share of Correct Predictions



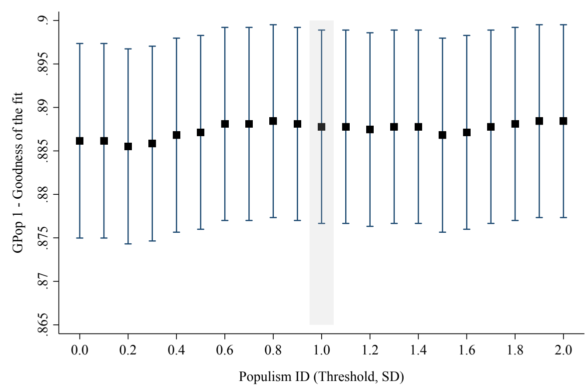
(a) Van Kessel - All Parties



(b) Swank - All Parties



(c) PopuList - All Parties



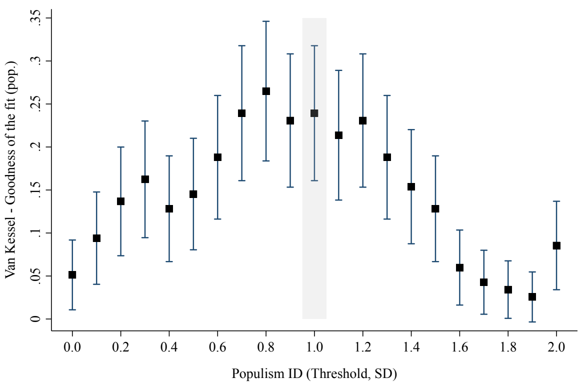
(d) GPop 1 - All Parties

Notes: The figure shows the proportion of good matches among all parties after predicting a populist party identifier based on the estimated models presented in Figure 1 and comparing it with the following populist identifier based on: Van Kessel (2015) (Panel a), Swank (2018) (Panel b), Rooduijn et al. (2019) (Panel c) and Grzymala-Busse and McFaul (2020) (Panel d). A party is classified as populist if the predicted probability to be populist is above 0.5.
Source: Authors' elaboration on MPD.

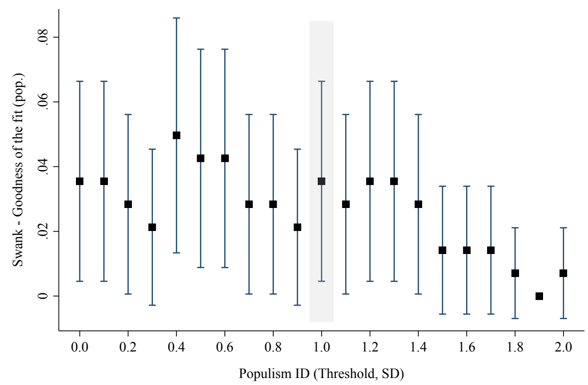
Most of existing studies provide a dichotomous classification of populist parties. Based on our continuous and centered (i.e., zero-mean) score of populism, we classify a party as populist ($\mathbf{1}(SD)$) when its score exceeds a certain threshold, which can be expressed as a multiplying factor SD of the standard deviation. In the core of the text, Figure 1 shows that $SD = 1$ is a relevant threshold, maximizing the partial correlation with three existing classifications. Figure B.3 below shows that

$SD = 1$ also maximizes the rate of accurate forecasts for the overall set of parties and for populist parties only, whatever the classification used as a reference (even the GPop 1 classification).

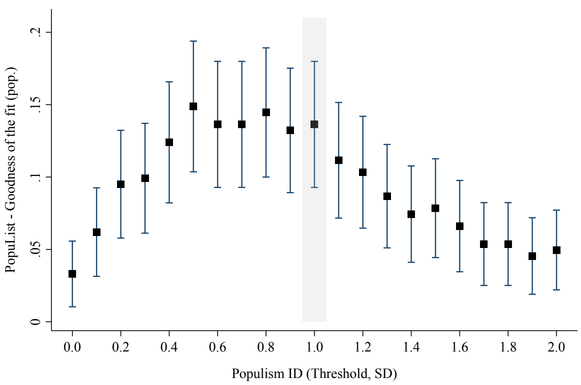
Figure B.3: Threshold Definition - Share of Correct Predictions (Cont'd)



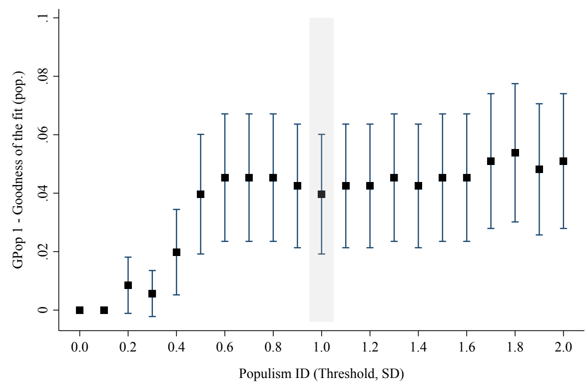
(e) Van Kessel - Populist Parties



(f) Swank - Populist Parties



(g) PopuList - Populist Parties

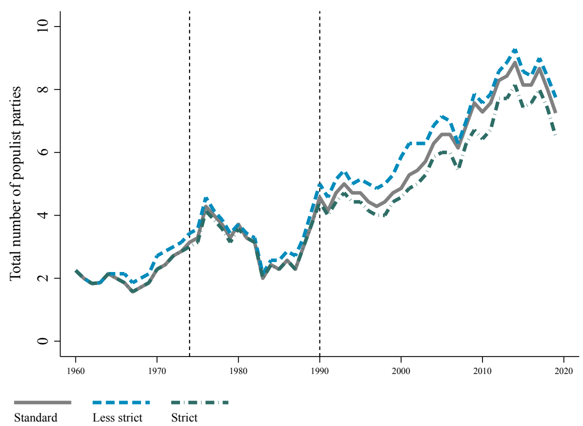


(h) GPop 1 - Populist Parties

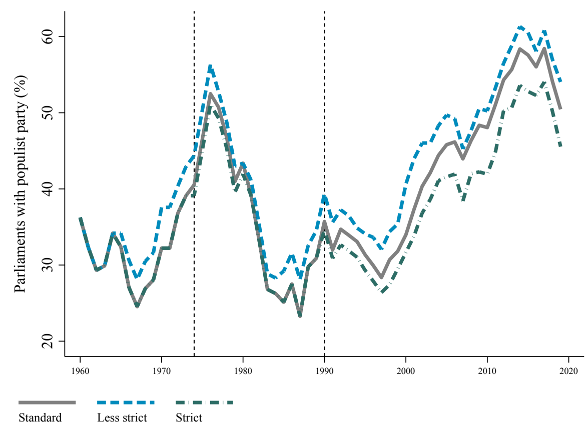
Notes: The figure shows the proportion of good matches among populist parties after predicting a populist party identifier based on the estimated models presented in Figure 1 and comparing it with the following populist identifier based on: Van Kessel (2015) (Panel e), Swank (2018) (Panel f), Rooduijn et al. (2019) (Panel g) and Grzymala-Busse and McFaul (2020) (Panel h). A party is classified as populist if the predicted probability to be populist is above 0.5.
Source: Authors' elaboration on MPD.

B.7 Stylized Facts: Robustness to Threshold Selection

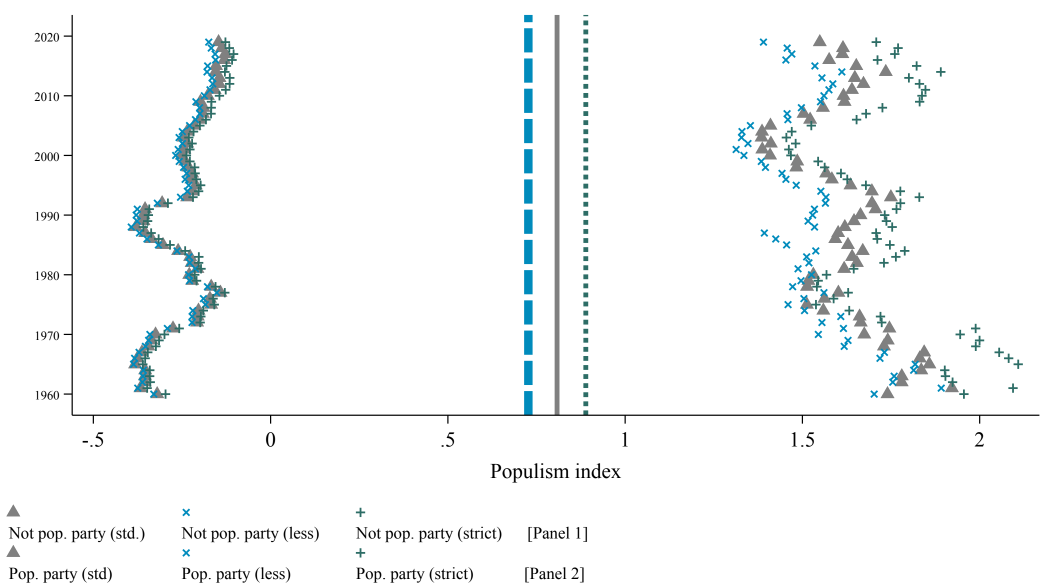
Figure B.4: Populist Parties - Different Threshold



(a) Number of Populist Parties



(b) Parliaments with a populist party (%)

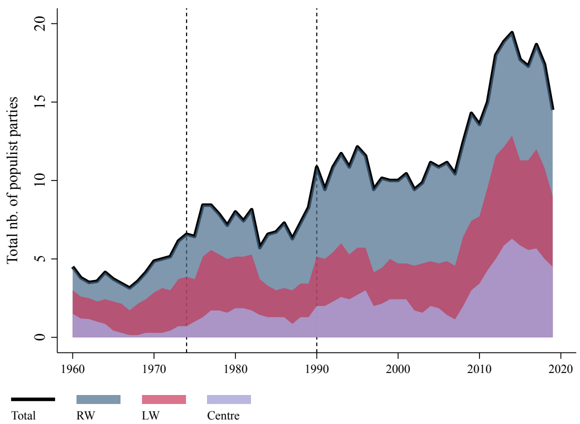


(c) Score of populist vs. non populist

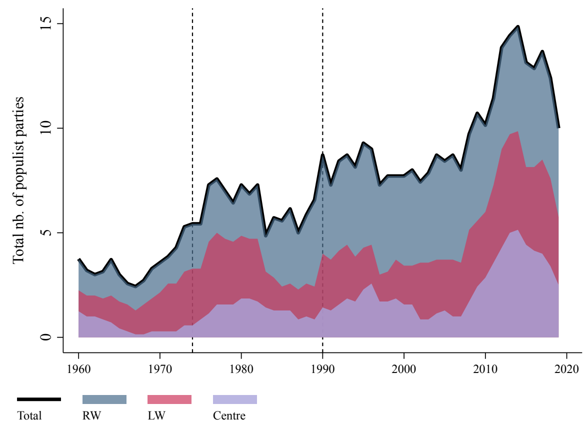
Notes: Fig. (a) shows the total number of populist parties. Fig. (b) gives the percentage of parliaments with at least a Populist party. Fig. (c) presents the average populism score of populist and non populist parties. Populist parties are defined as those with a score exceeding 1 standard deviation (standard), exceeding 0.9 standard deviation (lax) or exceeding 1.1 standard deviation (strict). Figures (a), (b) and (c) show moving averages including 3 years before and 3 years after each date.
Source: Authors' elaboration on MPD.

Figures B.4, B.5 and B.6 illustrate the robustness of the stylized fact described in Section 2 to the selection of the threshold used to classify parties. All stylized facts are preserved when using a lax or restrictive classification of populist parties.

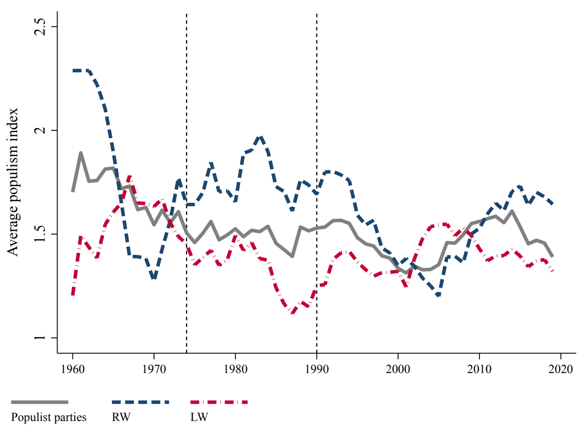
Figure B.5: Populist Parties and the Left vs. Right-Wing Divide – Different Threshold



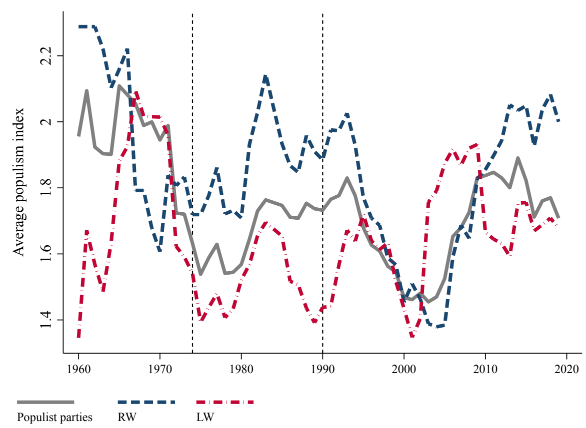
(a) Number of Populist Parties - Lax



(b) Number of Populist Parties - Strict



(c) Average Score Populist Parties - Lax

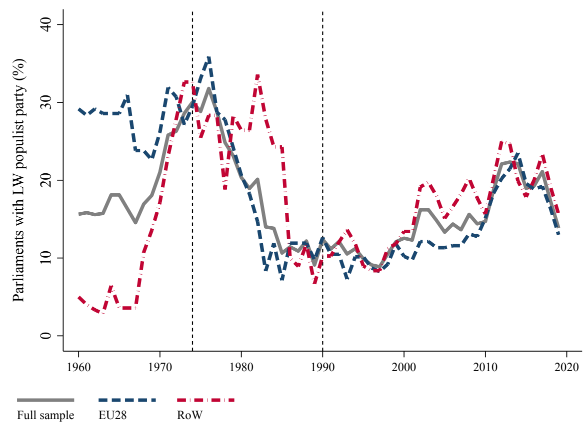


(d) Average Score Populist Parties - Strict

Note: Fig. (a)-(b) shows the total number of populist parties, dividing between left-wing and right wing. Fig. (c)-(d) presents the average populism score of populist parties, splitting between left-wing and right-wing parties. Populist parties are defined as those with a score exceeding 0.9 standard deviation (Fig. (a)-(c)) and 1.1 standard deviation (Fig. (b)-(d)), while left-wing and right-wing parties are defined as those that belongs to the first and third tercile of the right-to-left index. Figures (a), (b), (c) and (d) show moving averages including 3 years before and 3 years after each date.
Source: Authors' elaboration on MPD.

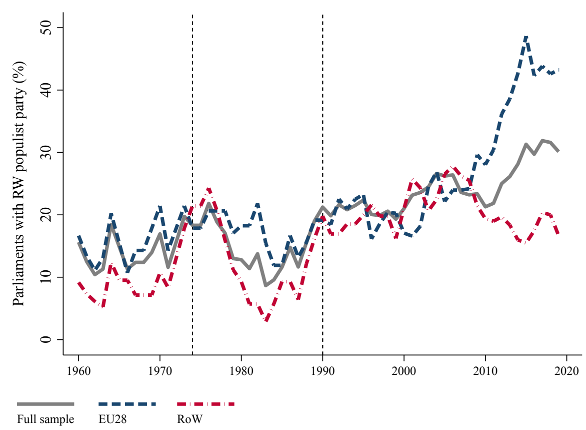
Figure B.6: Populist Parties and the Left vs. Right-Wing Divide - Different Threshold (Cont'd)

(a) Parliaments with LW populist party (%) - Lax



(b) Parliaments with LW populist party (%) - Strict

(c) Parliaments with RW populist party (%) - Lax

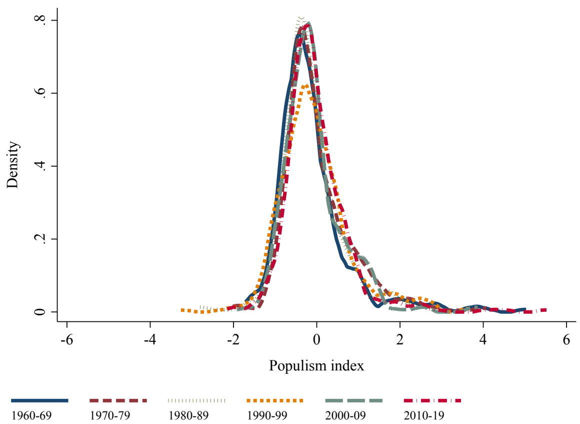


(d) Parliaments with RW populist party (%) - Strict

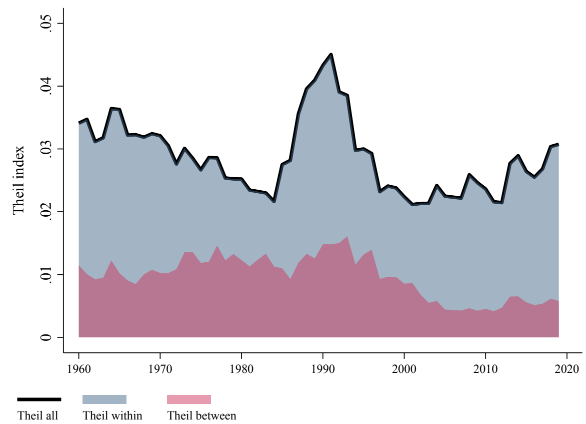
Note: Fig. (a)-(b) shows the percentage of parliaments with a left-wing party. Fig. (c) - (d) presents the percentage of parliaments with a right-wing party. Populist parties are defined as those with a score exceeding 0.9 standard deviation (Fig. (a)-(c)) and 1.1 standard deviation (Fig. (b)-(d)), while left-wing and right-wing parties are defined as those that belongs to the first and third tercile of the right-to-left index. Figures (a), (b), (c) and (d) show moving averages including 3 years before and 3 years after each date.
Source: Authors' elaboration on MPD.

B.8 Stylized Facts - Robustness to Balanced Sample

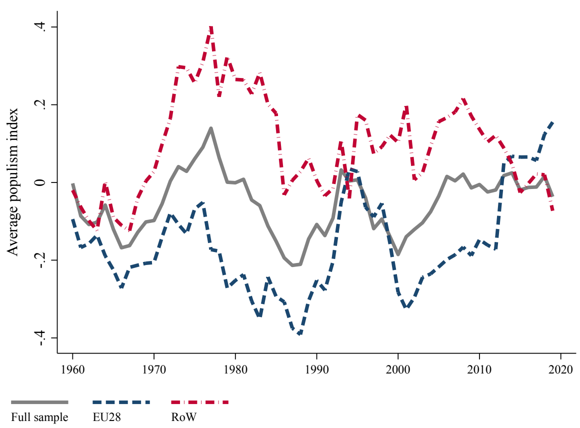
Figure B.7: Stylized facts I – Distribution of Populism Scores and Mean Margin of Populism in the Balanced Sample (1960-2019)



(a) Density of populism score by period



(b) Inequality across parties (Theil)



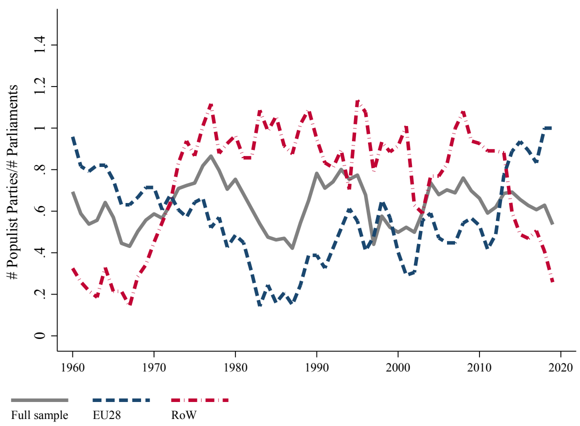
(c) Mean populism score of all parties (unweighted)

(d) Mean margin of populism ($\Pi^M_{i,e,t}$)

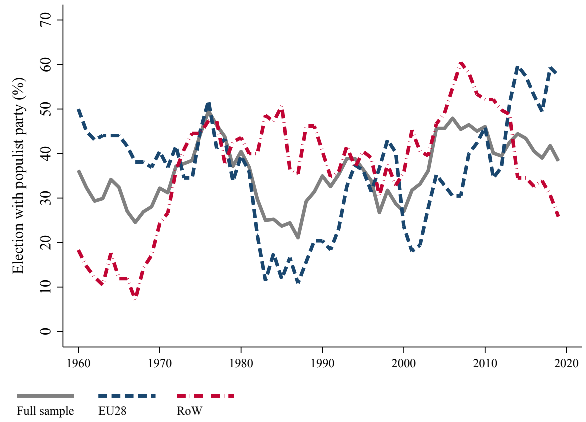
Notes: Fig. (a) shows the kernel-density of the populism score by decade. Fig. (b) depicts the Theil index of inequality in populism across parties, and gives its between-countries component and the within-countries components (Cadot et al., 2011). Fig. (c) plots the average populism score of all parties running for election in a given year. Fig. (d) plots the *mean margin of populism*, a weighted average of the populism scores with weights equal to the party's share in votes. Fig. (c) and (d) show moving averages including 3 years before and 3 years after each date. The balanced sample excludes Greece, Portugal and Spain, Latin American and former Soviet Union countries.

Figures B.7, B.8 and B.9 illustrate the robustness of the stylized facts described in Section 2 to the composition of the sample. In this section, the stylized facts are presented considering the set of countries that appear in the MPD database starting from the first decade of 1960s. The balanced sample exclude Greece, Portugal, Spain as well as Latin American and former Soviet Union countries.

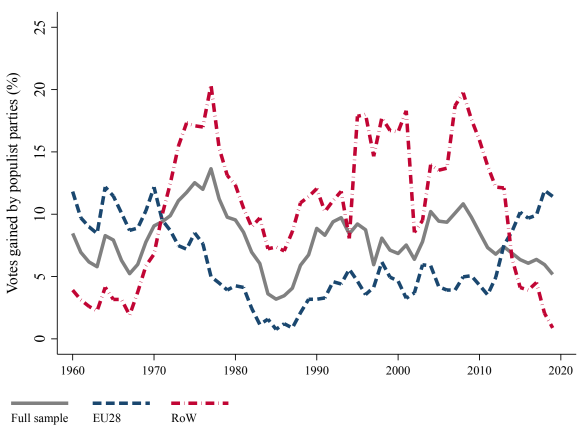
Figure B.8: Stylized facts II – Presence, Electoral Success and Score of Populist Parties in the Balanced Sample (1960-2019)



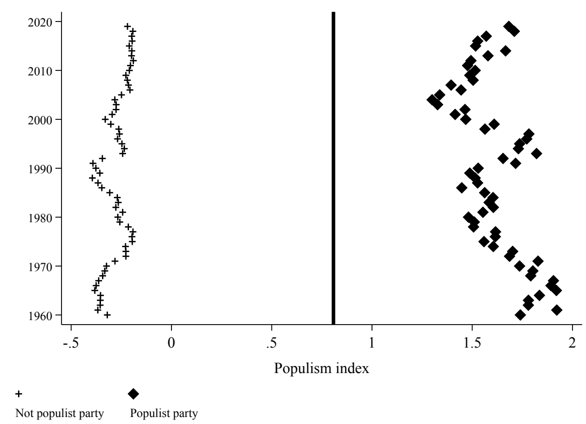
(a) Number of populist parties per parliaments



(b) Parliaments with a populist party (%)



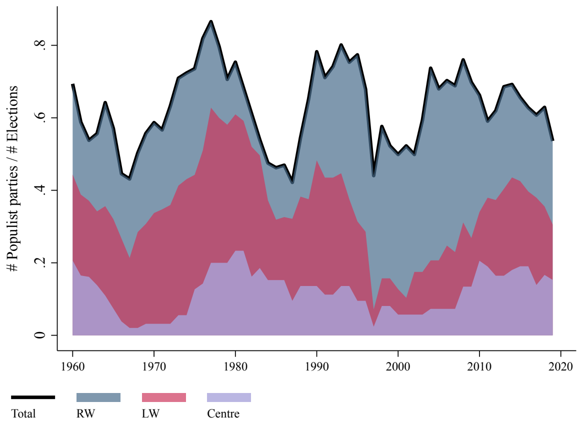
(c) Volume margin of populism ($\Pi^V_{i,e,t}$)



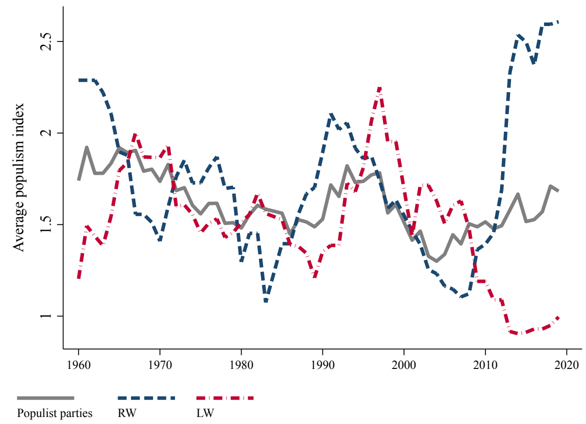
(d) Mean score of populist vs. non populist

Notes: Fig. (a) shows the total number of populist parties. Fig. (b) gives the percentage of parliaments with at least a Populist party. Fig. (c) depicts the average share of votes for populist parties (the volume margin). Fig. (d) presents the average populism score of populist and non populist parties. Populist parties are defined as those with a score exceeding 1 standard deviation (0.81). Fig. (a), (d), (e) and (f) show moving averages including 3 years before and 3 years after each date. The balanced sample excludes Greece, Portugal and Spain, Latin American and former Soviet Union countries.

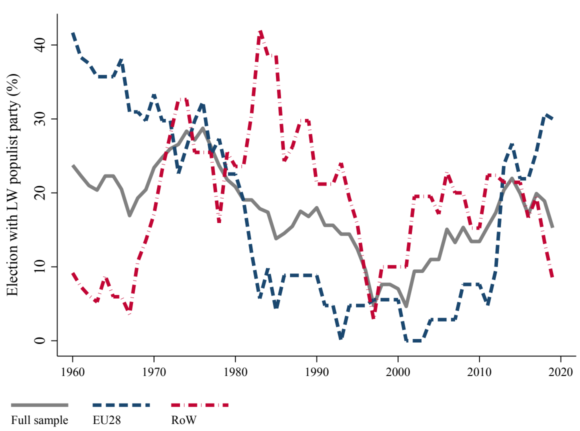
Figure B.9: Stylized facts III – Left-Wing and Right-Wing Populism at the Aggregate Level in the Balanced Sample (1960-2019)



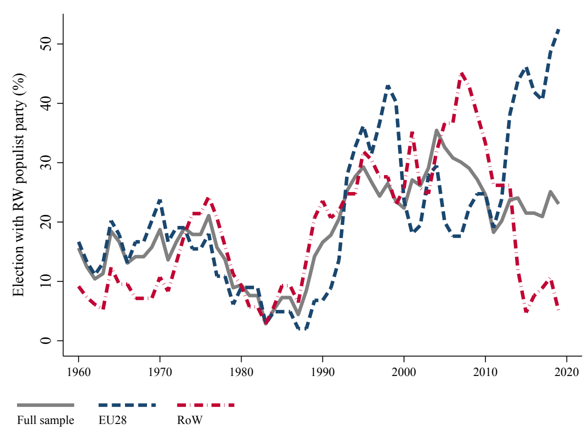
(a) Number of populist parties



(b) Average score of populist parties



(c) Elections with a LW populist party (%)



(d) Elections with a RW populist party (%)

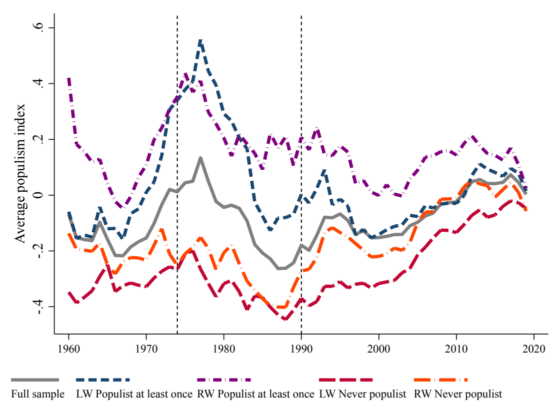
Notes: Fig. (a) shows the total number of populist parties, dividing between left-wing and right wing. Fig. (b) presents the average populism score of populist parties, splitting between left-wing and right-wing parties. Fig. (c) and (d) give the percentage of elections with at least a left-wing and right-wing Populist party, respectively. Populist parties are defined as those with a score exceeding 1 standard deviation (0.808), while left-wing and right-wing parties are defined as those that belongs to the first and third tercile of the right-to-left index. Fig. (a), (b), (c) and (d) show moving averages including 3 years before and 3 years after each date. The balanced sample excludes Greece, Portugal and Spain, Latin American and former Soviet Union countries.

B.9 Stylized Facts - Dissecting Mean Margin Trends

Figure B.10 depicts the overall trend in the mean margin of populism by distinguishing between traditional parties that have never been categorized as populist, and those that have been classified as populist at least once, based on our measurement framework. This decomposition yields two salient observations. First, the ups and downs in populism can be ascribed to these two groups during distinct time periods. As shown in Figure B.10(a), the rise and fall of populism from the 1960s to the late 1980s is primarily driven by the political stance of populist parties. Nevertheless, starting from the early 1990s, traditional parties (never classified as populist) also contribute to the trend in the mean margin, manifesting a discernible propensity towards populism and accruing a substantive portion of votes. Second, the fluctuations in the mean margin until the late 1980s are predominantly associated with left-wing populist parties, in part attributable to the pervasive influence of Communist ideology. In contrast, contemporary years have witnessed right-wing parties (both populist and non-populist) playing a role in the recent upswing of the mean margin.

Figure B.10: Trends in the Mean Margin of Populism: Populist vs. Non-Populist Parties

(a) Populist vs Never Populist Parties



(b) Populist vs Never Populist Parties: LW/RW

Notes: Fig. (a) plots the evolution of the *mean margin of populism* for the entire sample (bold gray line), with a breakdown between parties that have been classified at least once as populist (dashed blue line) and those that have never been classified as populist (dash-dotted red line). Fig. (b) illustrates the evolution of the *mean margin of populism* for the entire sample (bold gray line) and its decomposition among left-wing parties classified as populist at least once (dashed blue line), right-wing parties classified as populist at least once (dash-dotted purple line), left-wing parties never classified as populist (long dashed red line), and right-wing parties never classified as populist (long dash-dotted orange line). Populist parties are categorized as left-wing or right-wing based on their position in the first or third tercile of the right-to-left index, respectively. Vertical lines indicate shifts in our sample size: inclusion of Greece, Portugal and Spain around 1975, and inclusion of Latin American and former Soviet Union countries around 1990. Both Fig. (a) and (b) display moving averages, encompassing data from 3 years before and 3 years after each date.

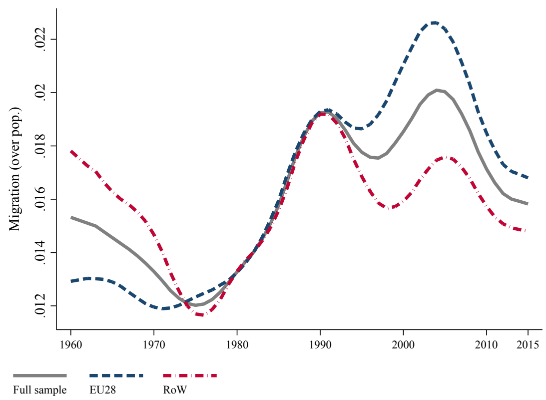
C Stylized Facts by Country Group

C.1 Long-run Trends in Globalization

Figure C.11 describes globalization trends at the aggregate level. The top panel compares European countries with the rest of the world. Both immigration and import trends are very similar across regions, although their intensity varies. Panel (a) shows that the share of immigrants has gradually increased since the mid-seventies, slightly decreased in the first half of the nineties, before increasing again until the financial crisis of 2008. Post-1990 changes are more pronounced in the Europe as a result of the enlargement of the European Union to Eastern Europe. With regard to imports, their share in GDP remained stable from 1960 to 1990. A slight decrease is observed after the second oil crisis. Trade growth has been more pronounced since the mid-nineties. Technological changes and policy reforms (multilateral and bilateral negotiations at the WTO) have given the first impetus, followed by the entry of China in WTO after 2000. Due to the financial economic crisis, this pace has slowed down in recent years. Again, the recent increase in trade is more pronounced in European Union countries. In the bottom panel, we split immigration and import flows by education level or by level of development of the origin countries. Panel (c) evidences a gradual increase in low-skill immigration between the early seventies and the financial crisis. The enlargement of the European Union also materializes in rising immigration rates from middle-income countries to Europe after the nineties. Panel (d) evidences a marked rise in imports of medium- and high-skill labor intensive goods after the mid-nineties. To a lesser extent, imports of low-skill labor intensive goods have almost doubled as well over the same period.

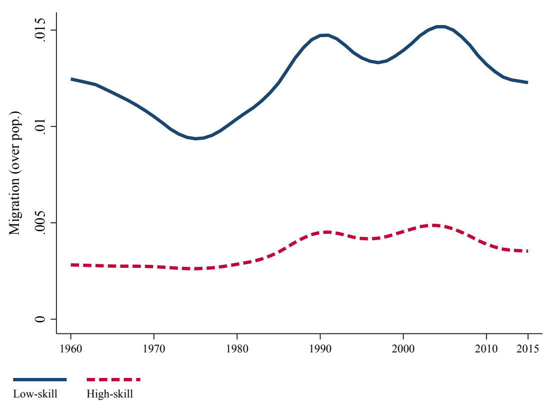
As low-skill immigration and imports of low-skill labor intensive goods are shown to translate into populist pressures. In Figure C.12, we focus on these two indicators and compare the trends observed in the four groups of countries, namely Western European countries (France, Germany and the UK), Eastern European countries (Czech Republic, Hungary and Poland), traditional settlement countries (Australia, Canada and the U.S.), and Latin American countries (Argentina, Chile and Mexico). With regard to low-skill immigration, it has gradually increased in virtually all countries since the early eighties. The highest levels are observed in settlement countries (Australia, Canada and the U.S.), in the UK, Germany, and Chile. The Czech Republic shows a peak between 1995 and the financial crisis. The evolution of imports of low-skill labor intensive goods follows even more homogeneous patterns. The share of imports in GDP has increased in all countries since the early nineties. The most pronounced changes are observed in Eastern European countries, Latin America, Austria, Canada and Australia. Our panel data analysis takes advantage of these huge variations to identify the effect of globalization shocks on the margins of populism.

Figure C.11: Stylized Facts IV – Trade and Immigration Trends at the Aggregate Level

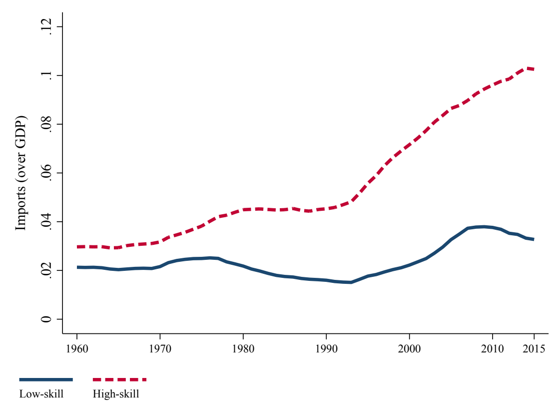


(a) Immigration by broad destination

(b) Imports by broad destination



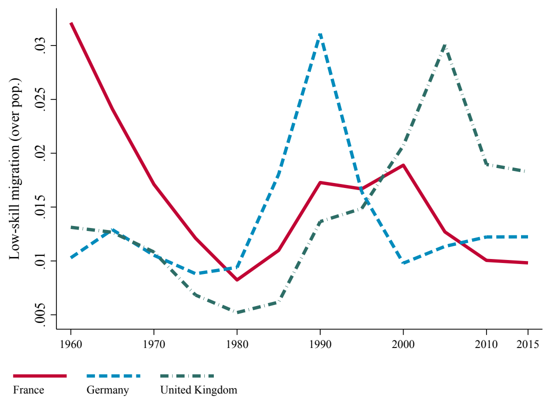
(c) Immigration by skill level



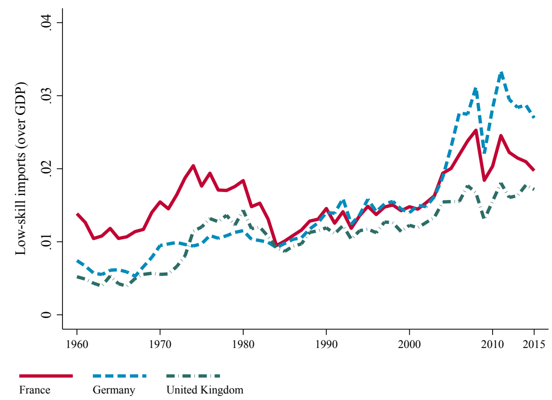
(d) Imports by skill level

Note: Figures (a), (b), (c) and (d) show moving averages including 3 years before and 3 years after each date. Source: Authors' calculations on Abel (2018), Feenstra et al. (2005) and UN Comtrade.

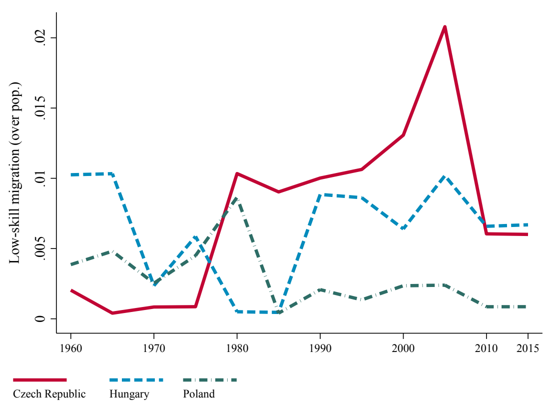
Figure C.12: Stylized Facts IV – Low-Skill Immigration and Imports in Selected Countries



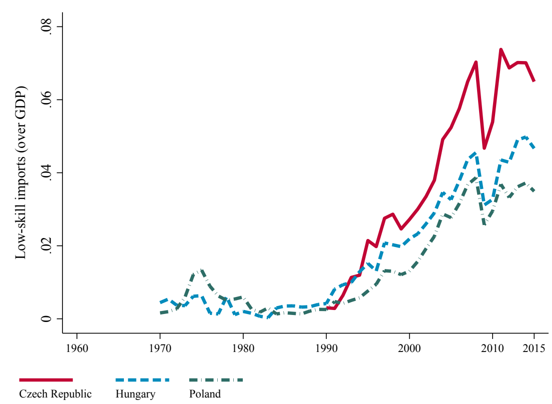
(a) Immigration in Western Europe



(b) Imports in Western Europe



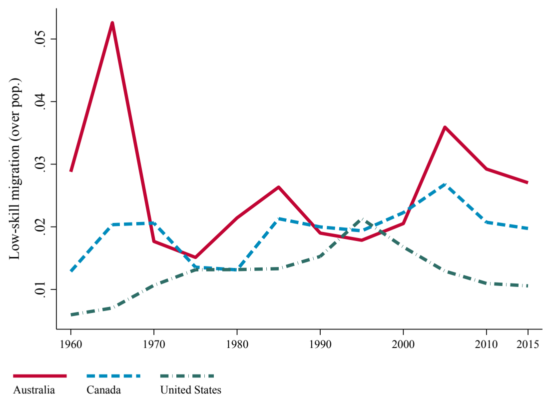
(c) Immigration in Eastern Europe



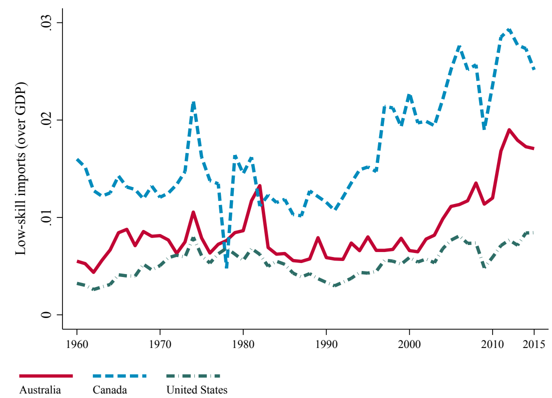
(d) Imports in Eastern Europe

Note: Figures (a), (b), (c), and (d) show moving averages including 3 years before and 3 years after each date. Source: Authors' calculations on Abel (2018), Feenstra et al. (2005) and UN Comtrade.

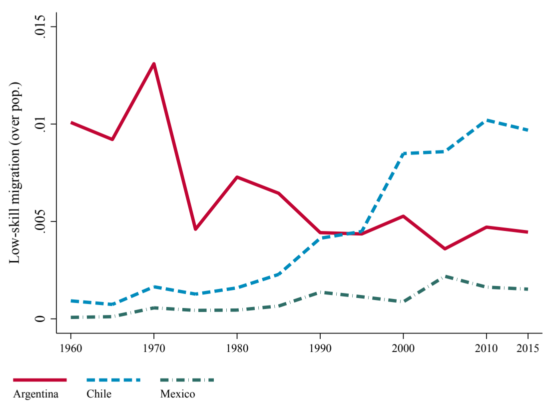
Figure C.12: Stylized Facts IV – Low-Skill Immigration and Imports in Selected Countries (Cont'd)



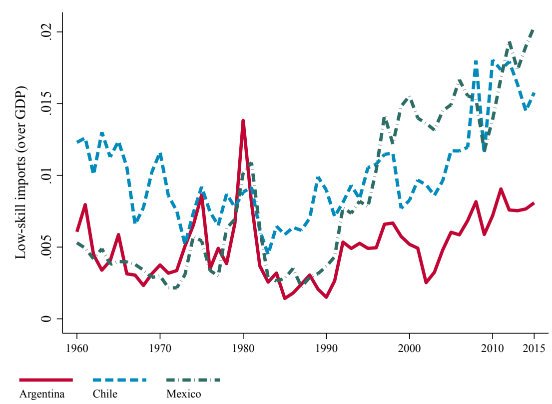
(e) Immigration in settlement countries



(f) Imports in settlement countries



(g) Immigration in Latin America



(h) Imports in Latin America

Note: Figures (e), (f), (g) and (h) show moving averages including 3 years before and 3 years after each date. Source: Authors' calculations on Abel (2018), Feenstra et al. (2005) and UN Comtrade.

C.2 Populism at Party Level in Selected Countries

To elucidate the variations in our populism score across countries, Table C.11 presents summary statistics characterizing the broad distribution of populism scores across parties in selected countries: France, Greece, Hungary, Italy, the United Kingdom, and the United States. The provided summary statistics unveil the diverse levels of populism observed during the respective national elections in these nations. On average, Greece and Italy stand out for hosting the highest degrees of populism among their political parties, alongside a noteworthy prevalence of competing parties in each election. Conversely, the United States displays both the lowest degree of populism and an average number of participating parties. Except for the United States, the populism scores exhibit considerable variability across different parties, with Greece displaying the most pronounced standard deviations.

Table C.11: Average Populism Score in Selected Countries: Descriptive Statistics

	Avg.	SD	Min.	Max	Elections	Avg. N. of Parties	Time Coverage
France	-0.179	0.856	-1.999	1.894	14	6.846	1962-2017
Greece	0.739	1.290	-2.870	4.864	18	5.835	1974-2019
Hungary	-0.056	0.663	-1.532	1.708	8	6.333	1990-2018
Italy	0.057	0.834	-1.892	3.031	15	10.269	1963-2018
UK	-0.194	0.832	-1.908	3.751	16	6.687	1964-2019
US	-0.378	0.321	-0.913	0.320	15	2	1960-2016

To provide additional evidence regarding the party-level evolution in these countries, Figure C.13 offers a country-specific depiction of the party-level evolution of populism scores across national elections.

France. – Figure C.13(a) illustrates the prevalence of populism as articulated in the manifestos of French political parties spanning the years 1962 to 2017. Notably, two parties, the *Parti Communiste Français* (PCF) and the *Front National* (FN), consistently demonstrated a substantial degree of populism across multiple elections. However, in alignment with our broader macro-level evidence, these two parties – representing distinct ideological spectra (left-wing and right-wing, respectively) – manifested heightened levels of populism during different chronological epochs. Throughout the 1960s and 1970s, the PCF prominently conveyed a pronounced degree of populism through its manifestos, a trend that markedly declined with the dissolution of the Soviet bloc. Conversely, the FN's notable populism score became particularly accentuated in the 1990s, subsequent to its divergence from the more moderate faction led by Bruno Mégret, who established a new political entity known as the *Mouvement National Républicain*. This faction failed to secure substantial support from national voters. The 2012 national elections marked a pivotal juncture, coinciding with Marine Le Pen assuming leadership within the FN. This transition resulted in a reduction in the party's populism score, attributed to Le Pen's efforts to reposition the FN as a mainstream political entity. This strategic shift involved distancing the party from the overtly antisemitic and xenophobic positions of its prior leader. In the most recent national election covered by our dataset (2017), a new left-wing party led by Jean-Luc Mélenchon, *La France Insoumise* (LFI), exhibited a populism score comparable to that of the FN. Furthermore, LFI's score marginally surpassed that of the PCF.

Greece. – Figure C.13(b) delineates the progression of parties' populism scores from the 1974 national elections to 2015 in Greek politics. As previously noted, Greek politics is marked by a notably high and widespread degree of populism, reaching its peaks in the early 1990s and in more recent years (Pappas and Aslanidis, 2015). The Communist Party of Greece (KKE) exhibited a substantial populism score following the collapse of the Soviet bloc, grounded in a robust anti-international stance (Marantzidis, 2008). The Coalition of Radical Left (SYRIZA), which entered the parliament for the first time in 2004, has consistently maintained a high populism score, aligning with a staunch anti-neoliberalism stance and opposition to the prevailing establishment (Van Kessel, 2015). Furthermore, parties espousing a more right-wing agenda, such as the Independent Greeks (ANEL) and the Golden Dawn (XA), also feature high populism scores, albeit lower in comparison to SYRIZA and KKE.

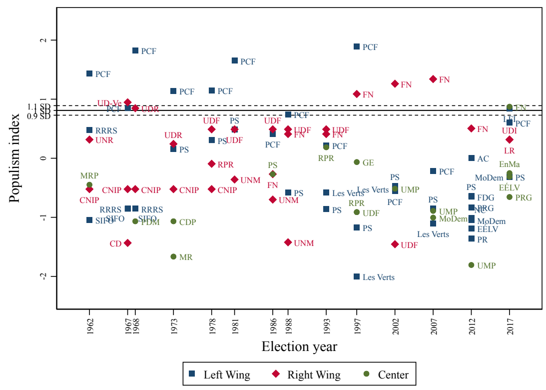
Hungary. – The Hungarian case is illustrated in Figure C.13(c). Across the seven electoral events documented in our data set, two distinct periods are marked by a notable populist stance among political parties in the parliament. In 1998, the right-wing Justice and Life Party (MIÉP), established in 1993, prominently espoused a populist stance at the core of its agenda, encapsulated by a statement from one of its political leaders, Istvàn Csurak, asserting that MIÉP stood for "the defence of the Hungarian people from foreign, oppressing powers and its own political elite" (Bartory, 2008). In the 1998 elections, securing a 5.57 percent share of votes enabled MIÉP to secure 14 seats in the Hungarian parliament. Additionally, the Independent Smallholder's Party (FKgP) manifested a noteworthy populism score, driven in part by its robust critique against Hungary's accession to NATO and the EU. Subsequently, in the latest available elections (2010 and 2014), the emergence of the Movement for a Better Hungary (Jobbik), positioning itself as a champion of "the people" and firmly opposing EU integration, alongside the transformation of the Alliance of Young Democrats (FiDeSz) under Viktor Orbán, ushered in a renewed wave of populism discernible from their respective political manifestos.

Italy. – Figure C.13(d) shows two distinct waves of populism scores in the annals of Italian political history. The initial wave reached its zenith at the conclusion of the "first republic" during the 1992 elections, coinciding with the onset of investigations that would later precipitate the "Mani Pulite" scandal. Small and liberal parties, such as the *Partito Radicale Italiano* (PRI) and the *Lista Pannella* (LP), along with the right-wing *Movimento Sociale Italiano* (MSI), exhibited a pronounced anti-establishment stance. Simultaneously, the *Partito Rifondazione Comunista* (PRC) propagated significant skepticism towards international institutions and the EU integration process, particularly directed against the Maastricht Treaty signed in the same year. The second wave of populism commenced with the 2006 elections, marked by the establishment of the *Popolo delle libertà* (PDL), a coalition party comprising major right-wing political factions. The *Lega Nord* (LN/League) displayed a substantial populism score in the 2008 and 2018 elections, notably the first national elections wherein Matteo Salvini assumed the role of party federal leader following Roberto Maroni, who obtained only 4 percent of votes in the 2013 elections (Albertazzi et al., 2018). The *Movimento 5 Stelle* (M5S) exhibited a high populism score in both the 2013 and 2018 national elections, while the *Fratelli d'Italia* (FDI) party distinguished itself with the highest populism score in the 2018 elections.

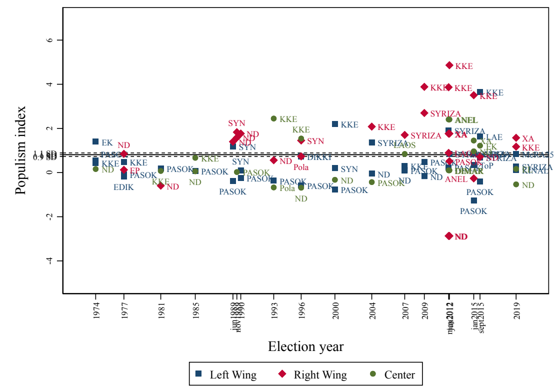
United Kingdom. – The populism scores of British parties remain relatively low across national elections, with two notable exceptions tied to pivotal events in UK politics, particularly concerning the relationship with the European Union. The initial surge of populism is discernible from the 1974 to the early 1980s' elections, primarily emanating from the Labour party. The contentious matter propelling the Labour party towards a pronounced populist stance pertains to the entry into the European Common Market, extensively documented by Lazer (1976). Characterized as a "capitalist club," the European Common Market was perceived by a faction within the Labour party as a direct threat to workers and the masses. Labour leader, Harold Wilson, following an intense debate on the UK's entry into the common market, notably encapsulated the prevailing political sentiment of his party at the time: "What we have seen (the debate) has been a classic confrontation - the Establishment against the common sense of the British people" (Lazer, 1976). Subsequent to the UK's entry into the European Common Market, the Labour party endorsed a radical program in 1973 centered on nationalism and the safeguarding of workers and the population. In more contemporary times, the UK Independence Party (UKIP) assumed the role of the principal antagonist to EU integration, espousing a robust populist manifesto in both 2001 and 2015. However, following the advocacy for the Brexit referendum in 2016, the degree of populism associated with UKIP witnessed a decline in the 2017 national elections.

United States. – Figure C.13 delineates the trajectory of the populism scores for the Democratic and Republican parties in the United States spanning the 1960 to the 2016 elections. Notably, both parties exhibit a relatively low degree of populism based on their political manifestos. This observation underscores the nuanced nature of populism, emphasizing that our methodology gauges the extent of populism discernible from their manifestos, without purporting to quantify the populism expressed in candidates' communication styles. Furthermore, over various elections, the Republican party consistently maintains, on average, a higher populism score compared to the Democratic party, with exceptions noted in the 1972, 1976, and 1980 elections.

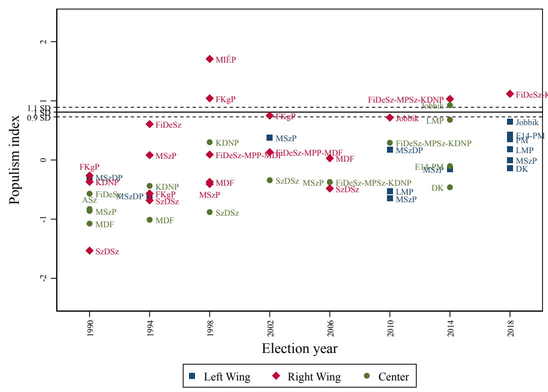
Figure C.13: Evolution of Populism at Party Level in Selected Countries



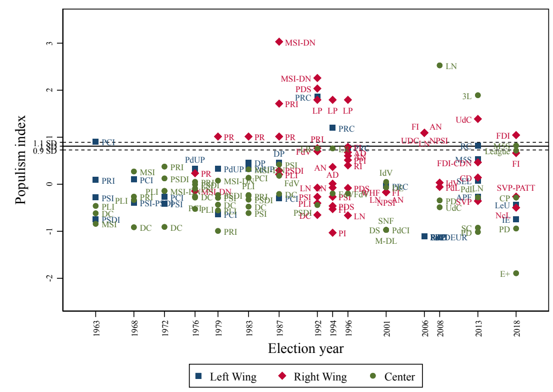
(a) France



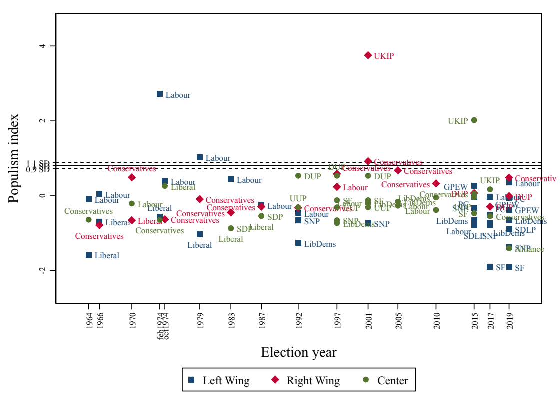
(b) Greece



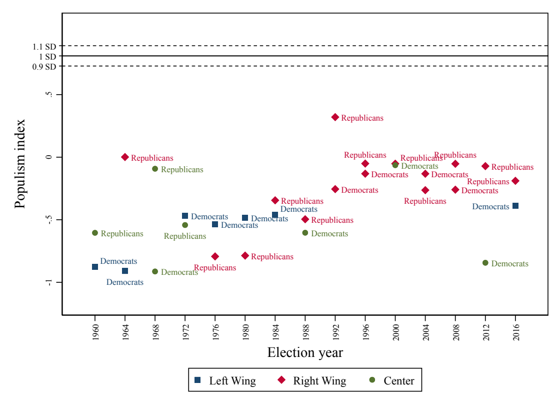
(c) Hungary



(d) Italy



(e) UK



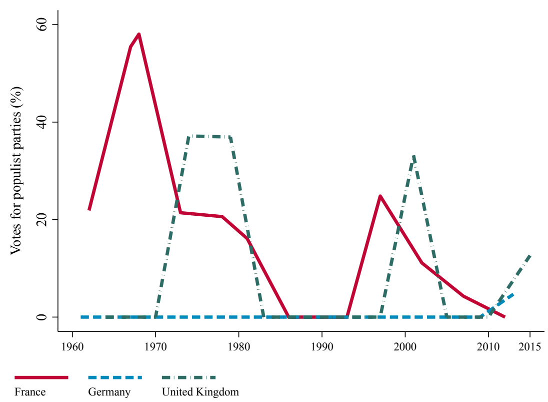
(f) USA

Note: Figures (a), (b), (c), (d), (e) and (f) show the populism index at party level for France, Greece, Hungary, Italy, UK and USA, respectively. Horizontal lines denote the levels of the populism index corresponding to 1 standard deviation (standard), 0.9 standard deviation (lax) or 1.1 standard deviation (strict). Left-wing, center, and right-wing parties are defined as those that belongs to the first, second or third tercile of the *rile* index.

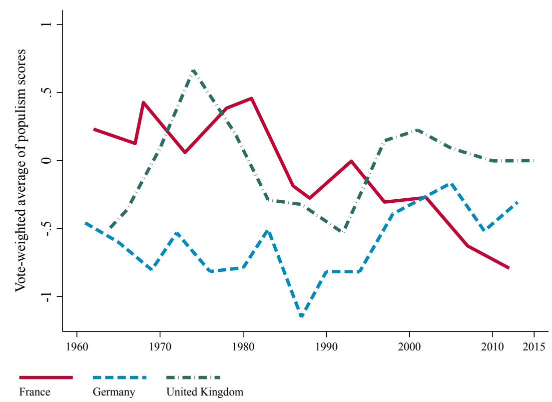
C.3 Volume and Mean Margins of Populism

These aggregate trends mask significant disparities across countries. In Figure C.14, we distinguish five types of countries, namely Western European countries (France, Germany and the UK), Eastern European countries (Czech Republic, Hungary and Poland), traditional settlement countries (Australia, Canada and the U.S.), and Latin American countries (Argentina, Chile and Mexico). For each group of countries, we plot the evolution of the volume and the mean margin of populism in the left and right panels, respectively.

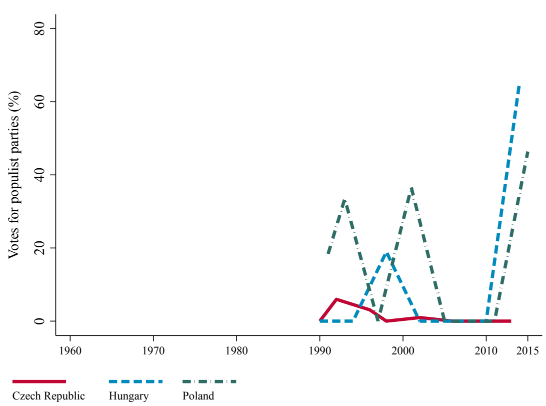
Figure C.14: Stylized Facts III – Volume and Margins of Populism for Selected Countries



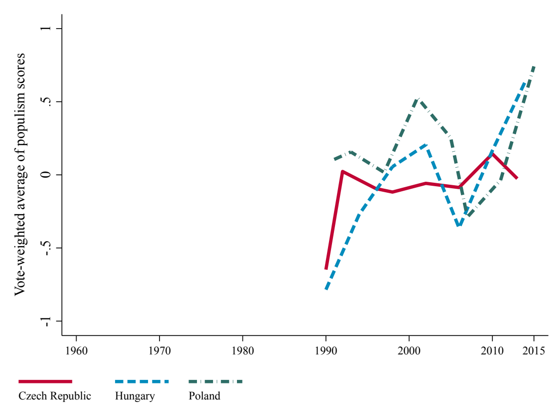
(a) Volume marg. in Western Europe



(b) Mean marg. in Western Europe



(c) Volume marg. in Eastern Europe

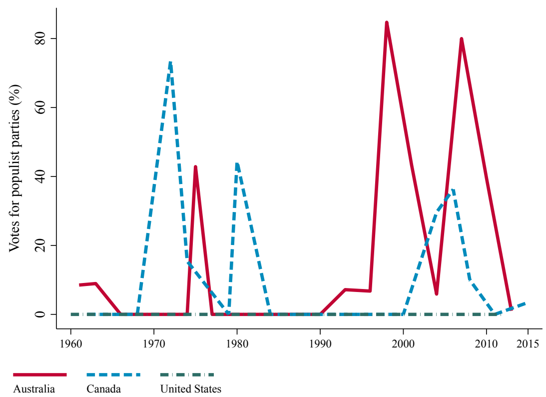


(d) Mean marg. in Eastern Europe

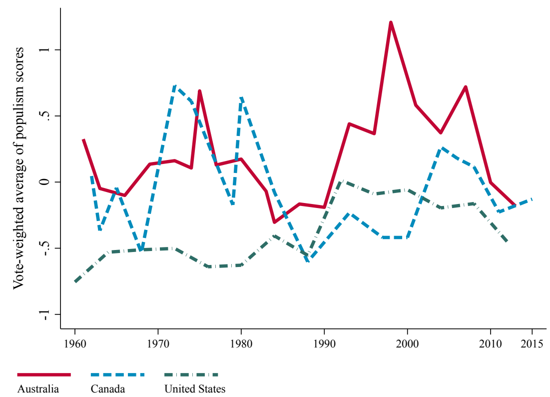
The left panel shows large ups and downs in the volume of populism across elections in virtually all countries. This is due to the fact that some populist parties appear and disappear, either because they enter and exit our sample (remember that our sample only includes parties with at least one seat in the Parliament), or because they moderate their anti-establishment and anti-corruption discourses once they come to power or reach a certain level of popularity. This means that some parties classified as populist in an election can be classified as non populist in a different election.

Using a time-invariant definition or score of populism would avoid such fluctuations, but it would also prevent us from exploiting variations in populism attitudes over a long time span.

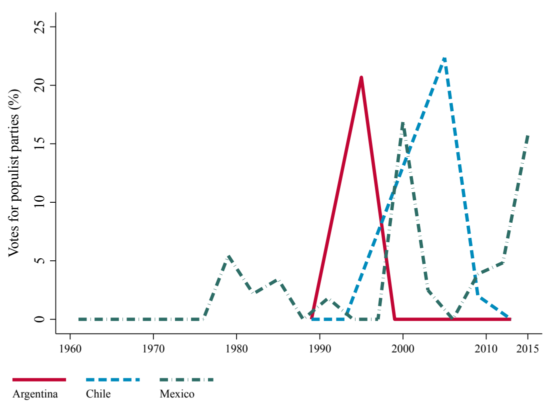
Figure C.14: Stylized Facts III – Volume and Margins of Populism for Selected Countries (Cont'd)



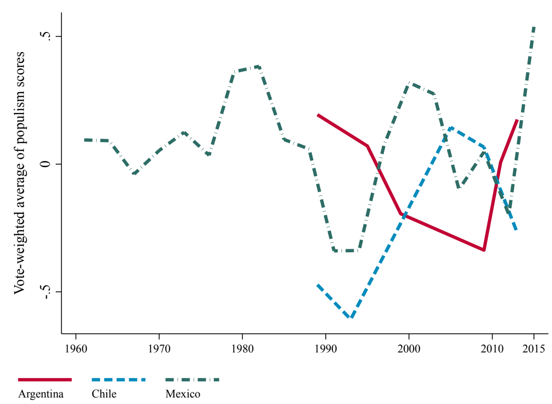
(e) Volume marg. in settlement countries



(f) Mean marg. in settlement countries



(g) Volume marg. in Latin America



(h) Mean marg. in Latin America

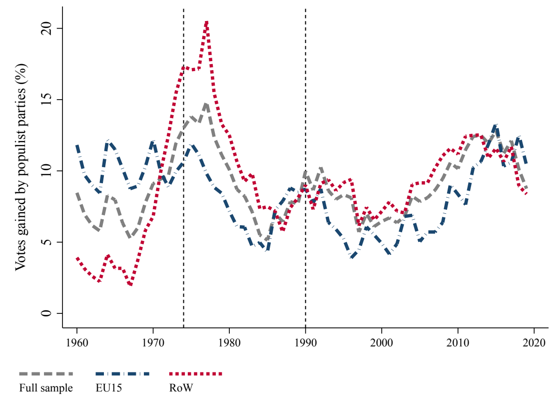
Note: The figures present the two margins (volume and mean) for a subset of countries from the rest of the world. Source: Authors' elaboration on MPD.

The mean margin does not rely on a dichotomous classification of parties and use the continuous populism score. The right panel of Figure C.14 shows that the evolution of the mean margin is smoother, but large variations are observed in many countries.

C.4 Right and Left Wing Populism: EU15 vs. Rest of the World

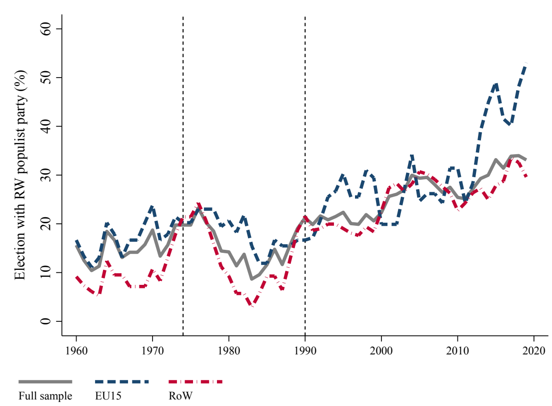
Figure C.15: Evolution of Populism: EU15 vs. RoW

(a) Mean margin of populism ($\Pi^M_{i,e,t}$)



(b) Volume margin of populism ($\Pi^V_{i,e,t}$)

(c) Elections with a LW populist party (%)

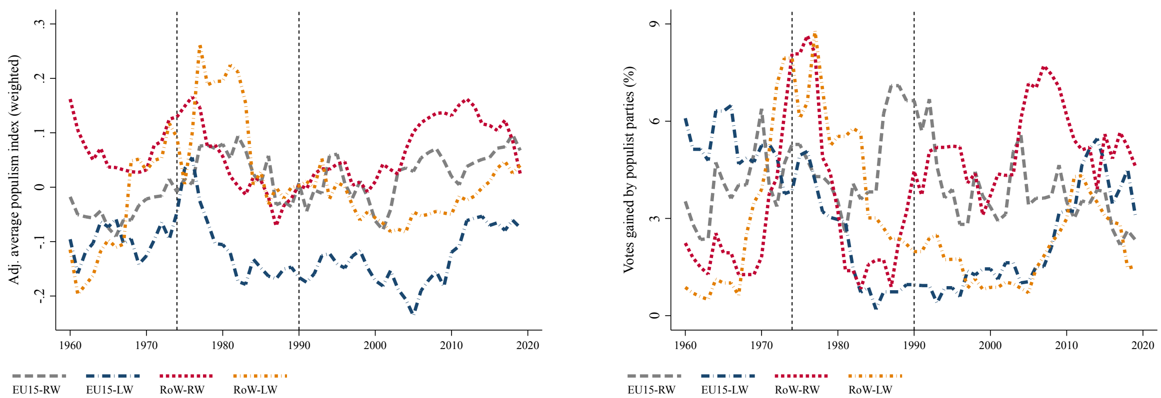


(d) Elections with a RW populist party (%)

Fig. (a) plots the *mean margin of populism*, a weighted average of the populism scores with weights equal to the party's share in votes. Fig. (b) depicts the average share of votes for populist parties (the volume margin). Fig. (c) and (d) give the percentage of elections with at least a left-wing and right-wing Populist party, respectively. Populist parties are defined as those with a score exceeding 1 standard deviation (0.81), while left-wing and right-wing parties are defined as those that belongs to the first and third tercile of the right-to-left index. Fig. (a), (b), (c) and (d) show moving averages including 3 years before and 3 years after each date.

Compared with the core of the text, we plot the evolution of the margins of populism and number of election with populist parties in the EU15 countries and in non-European countries. The EU15 countries are the member states of the European Union prior to the accession of ten candidate countries on 1 May 2004: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, United Kingdom.

Figure C.16: Evolution of Populism: RW and LW Populist Parties Across Broad Regions



(a) Mean margin of populism ($\Pi^{M}_{i,e,t}$)

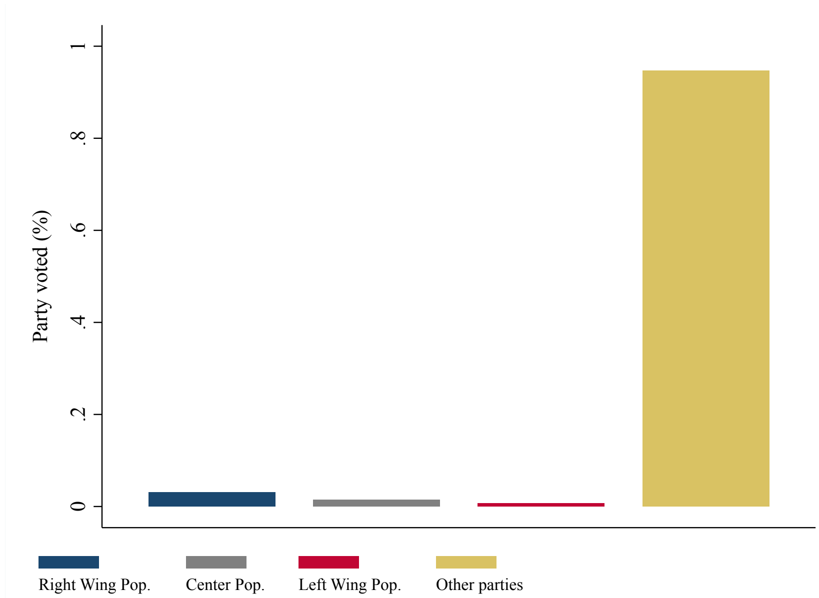
(b) Volume margin of populism ($\Pi^{V}_{i,e,t}$)

Fig. (a) plots the *mean margin of populism*, a weighted average of the populism scores with weights equal to the party's share in votes. Fig. (b) depicts the average share of votes for populist parties (the volume margin). Populist parties are defined as those with a score exceeding 1 standard deviation (0.81), while left-wing and right-wing parties are defined as those that belongs to the first and third tercile of the right-to-left index. Fig. (a) and (b) show moving averages including 3 years before and 3 years after each date.

C.5 European Social Survey - Individual-Level Political Preferences

To delve into the potential dynamics underpinning changes in electoral support for populist parties, we leverage individual-level information from the European Social Survey (ESS). The European Social Survey, conducted biennially since 2002, comprises a multi-country individual-level survey. Each country-wave involves the selection of a representative sample of approximately 1,500 individuals aged 18 and above. Within this extensive dataset, we specifically focus on two questions directly linked to voting and political preferences: (i) *which party did you vote for in the last national election?* (PVT); and (ii) *which political party do you feel closest to?* (PCL). Following the approach of Moriconi et al. (2022), we harmonize the provided party names to facilitate merging with our newly constructed populism measures derived from the Manifesto Project Database.

Figure C.17: Individual Level Political Preferences in ESS – Party Voted

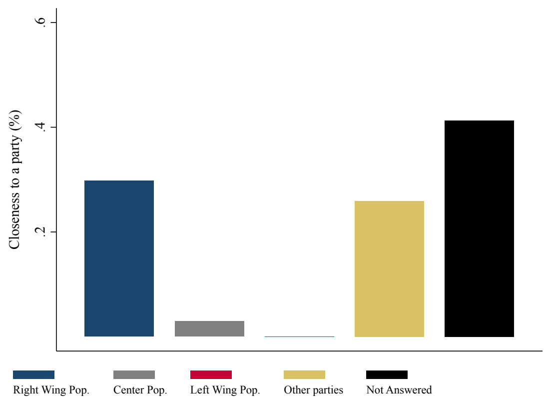


Note: Figure show the percentage of voters from ESS decomposed in four groups: right-wing populist voters, left-wing populist voters, centrist populist voters and not populist voters.

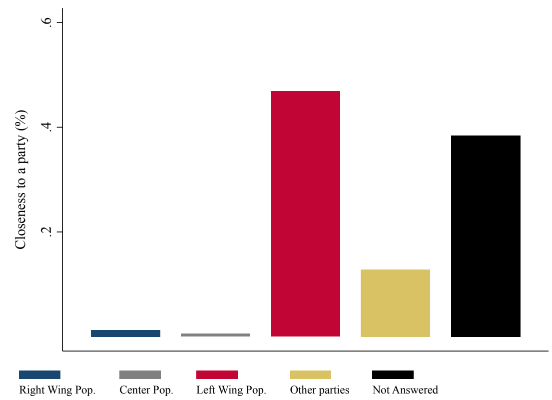
We combine the data from the party voted (PVT) with the corresponding populism measure, aligning it with the year and month of the election in which the respondent cast their vote. Conversely, information about a party's political platform from the first electoral event occurring *after* the date of the interview is integrated for the party closeness (PCT) measure. Our merged dataset encompasses data from 32 countries spanning 120 electoral events, spanning from 2001 to 2019. It provides populism measures for the party voted during the most recent national elections for 206,801 individuals and party closeness measures for 125,298 individuals. The difference between these two measures primarily stems from 82,296 individuals being unsure about which party they feel closest to at the time of the survey.

Figure C.17 depicts the distribution of voters among four groups: those who voted for non-populist parties following our dichotomous classification, and those who voted for either right-wing, left-wing, or centrist populist parties. On average, the vast majority of voters in the ESS cast their votes for parties not classified as populist. Regarding populist voters (constituting 0.5% of the sample), those who voted for right-wing populist parties form the predominant group (0.3% of the sample).

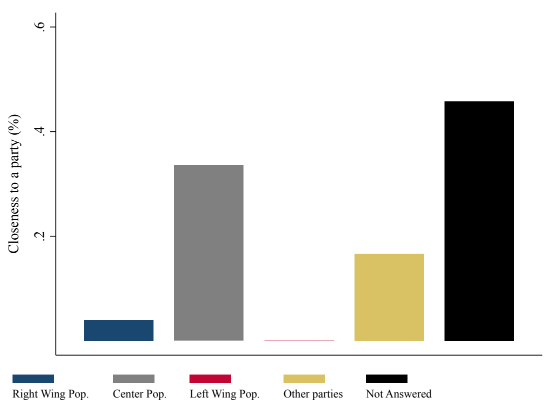
Figure C.18: Individual Level Political Preferences in ESS – Party Closeness



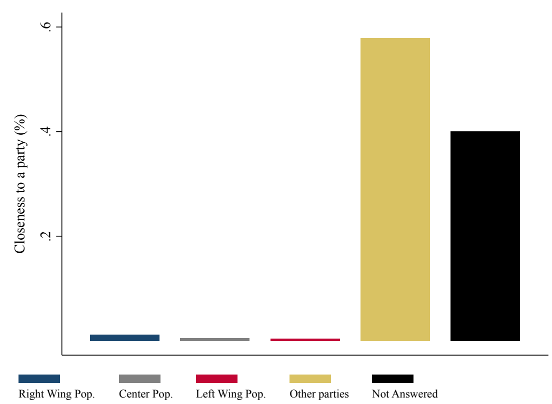
(a) Voters: Populist Right-Wing



(b) Voters: Populist Left-Wing



(c) Voters: Populist Center



(d) Voters: Not Populist

Note: Figures provides the percentage of individuals that feels close to a specific political party from the following population of voters: (a) right wing populist voters, (b) left wing populist voters, (c) centrist populist voters, and (d) not populist voters.

To capture potential changes in the political preferences of voters over time, Figure C.18 depicts, for each group of voters (populist right-wing, populist left-wing, populist centrist, and non-populist), the distribution of responses regarding party closeness (PCL). The categorization encompasses the four aforementioned groups, along with a category for respondents who did not provide an answer. On average, across the various voter groups, 40% choose not to disclose any information regarding their party closeness at the time of the interview. This phenomenon may be attributed to either the absence of a party that adequately reflects the respondent's political preferences at the interview date or the formulation of individual party preferences during an electoral campaign.

Turning attention to ideology-specific populist voters, they demonstrate a higher propensity to feel a sense of closeness to either a populist party within the same ideological spectrum (right-wing, left-wing, or centrist) or to a non-populist party. This suggests that the likelihood of populist voters shifting their allegiance to a populist party from a different ideological background (e.g., from left to right or vice versa) appears relatively low. Notably, non-populist voters are, on average, more inclined to feel close to non-populist parties. However, among those expressing affinity for populist parties, it is noteworthy that right-wing populist parties attract approximately three times as much support as their left-wing or centrist counterparts.

D More Details on the Identification Strategy

Our identification strategy aims to generalise the China-shock approach within a dyadic setting. It is also conceptually related to the shift-share literature pioneered by Bartik (1991) and Blanchard et al. (1992). In that literature, national industry growth in the U.S. is treated as exogenous from the perspective of individual regions, and local shocks are proxied by a weighted average of national shocks, with weights reflecting regional specialisation. Similarly, in our paper, we treat the growth of total exports from an exporter as exogenous from the perspective of individual importers, mapping these shocks according to the size of bilateral trade links. The idea is to use origin-specific shocks as a quasi-exogenous source of variation in trade openness for destination countries. Countries that import more from rapidly growing exporters should experience greater increases in openness that are plausibly exogenous to their own political and economic conditions. In the paper, we clarify that our approach mirrors the identifying assumptions of shift-share designs, relying on the exogeneity of origin-specific shocks (Borusyak et al., 2025). However, claiming exogeneity based on such a broad intuition is far from straightforward. In the next sections, therefore, we will provide additional tests for imports (Section D.1) and immigration (Section D.2), as well as the leave-one-out (LOO) approach (Section D.3), to support our intuition and clarify the type of bias we intend to address.

D.1 Sources of Variation in $\theta_{j,t}$ for Imports

To analyse the variation captured by our origin-year fixed effects, we first predict bilateral skill-specific flows using the fully specified "zero-stage" model presented in Eq. (7) of the manuscript. We denote these predicted values as $\widehat{Y}^1_{ij,t}$. Using the same model, we then construct an alternative prediction of bilateral flows, this time excluding origin-year-specific shocks $\theta_{j,t}$. Focusing on the predicted flows for the subset of 55 destinations included in our sample, we aggregate the bilateral flows by origin j and compute:

$$\Delta\widehat{Y}^{OR}_{j,t} = \sum_{i=1}^{I}\widehat{Y}^1_{ij,t} - \sum_{i=1}^{I}\widehat{Y}^2_{ij,t}. \tag{9}$$

The variation captured by Eq. (9) reflects the component driven by origin-year fixed effects. We interpret these as origin-specific shocks that are less likely to be influenced by destination-country-specific developments, such as electoral outcomes or support for populism. It is important to emphasise that this variation should be understood as a deviation from the average bilateral flows, which are themselves captured by the bilateral fixed effects (θ_{ij}).

Figure D.1 presents the results. Panels (a) and (b) show that most of the variation in our push factors originates from a limited number of origin-year pairs, while most others contribute only marginally. Panels (c) and (d) display the top 10 country-years in terms of positive and negative variation in our estimated origin-specific push factors. As expected, post-1990 China emerges as the most significant source of push factors, with a substantial increase in predicted exports from

1990 to the early 2010s (e.g., Autor et al., 2013).[8] Germany also stands out as a key source of variation, with a notable export surge following changes to its labour market institutions in the early 2000s (Dustmann et al., 2014). The set of countries and years is broadly similar for low- and high-skill intensive products, although the magnitude of the shocks is generally greater for high-skill products.

Taking the analysis one step further, we reproduce the figures in panels (e) and (f) after normalising the predicted flows by the destination country's GDP. Specifically, both $\widehat{Y}^1_{ij,t}$ and $\widehat{Y}^2_{ij,t}$ are divided by destination country i's import prices and GDP prior to aggregation. This normalisation aligns with our empirical specification, which uses import-to-GDP ratios as right-hand-side variables. The adjusted figures then more accurately reflect the variation actually exploited in the estimation, yielding two key insights.

First, although China remains a major source of variation in the early 2010s, Germany now emerges as the dominant contributor. This shift occurs because China's export surge during this period was disproportionately directed towards the U.S. Given the size of the U.S. economy, normalising by GDP reduces the relative magnitude of the shock. In contrast, Germany's export growth was primarily targeted towards smaller European neighbours, for whom the same export volume represents a larger share of GDP. Consequently, Germany's post-2005 export growth becomes a significant source of variation in European imports.

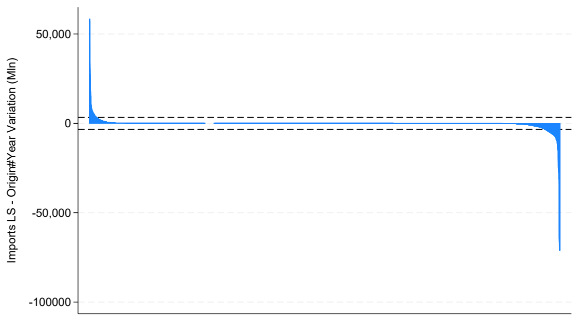
Second, Germany, the United States, and Japan exhibit negative push factors in the 1960s. This reflects their high export growth of these countries during the late 1960s and 1970s, making their earlier export levels appear relatively low when compared to their post-1990 average. Normalising by GDP makes predicted flows more comparable over time and prevents early variations from being discounted purely due to nominal differences.

This descriptive analysis reveals that China and Germany were two major contributors to variation in the 2010s. China's contribution aligns with the well-documented "China shock," which is oftent used as a plausible exogenous source of variation for both economic and political outcomes across our sample of countries. Germany's contribution follows a period of wage moderation in Germany, driven by political reforms in the early 2000s—reforms that appear exogenous to the political dynamics of other countries.

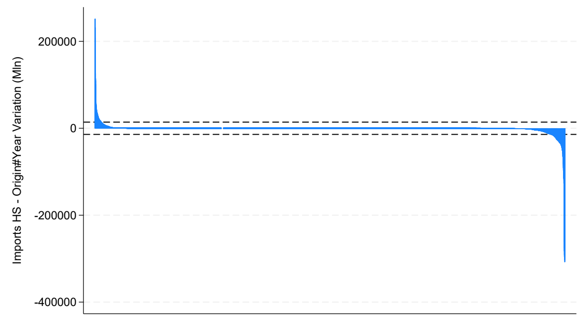
One caveat, however, is that Germany's export boom peaked during the eurozone crisis—a period of financial stress in debt markets that may have fuelled populist sentiment in the countries most affected (e.g., Greece). While this could be seen as a potential violation of the exclusion restriction, two points are worth noting. First, we conduct robustness checks that control for variations in the logarithm of real GDP per capita and the employment rate in destination countries, which would absorb crisis-related effects (see Appendix E.8.9), as well as a heterogeneity analysis focusing specifically on crisis episodes (see Figure 7). Secondly, Germany's export surge itself

[8] Note that the values are highly negative in the early 1990s, as the average post-1990s trade is captured through other fixed effects. The negative push factor in the early 1990s simply reflects lower exports during that period relative to subsequent decades.

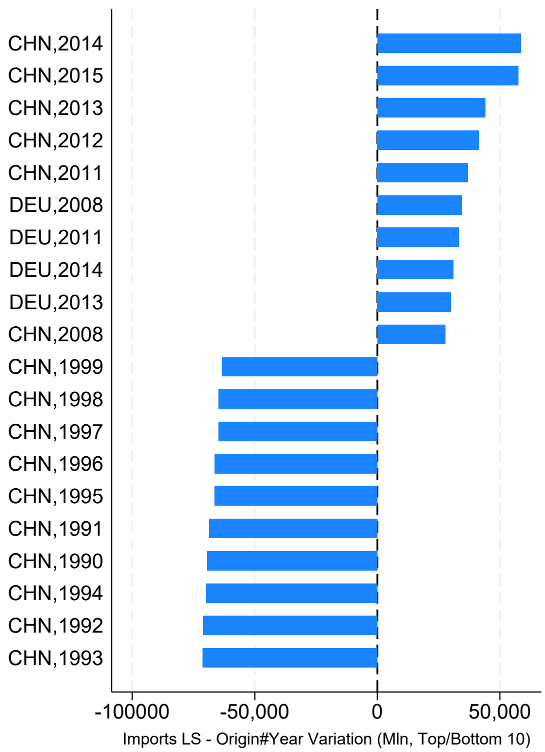
Figure D.1: Source of Variation IV Imports – Origin-Year Specific Variation



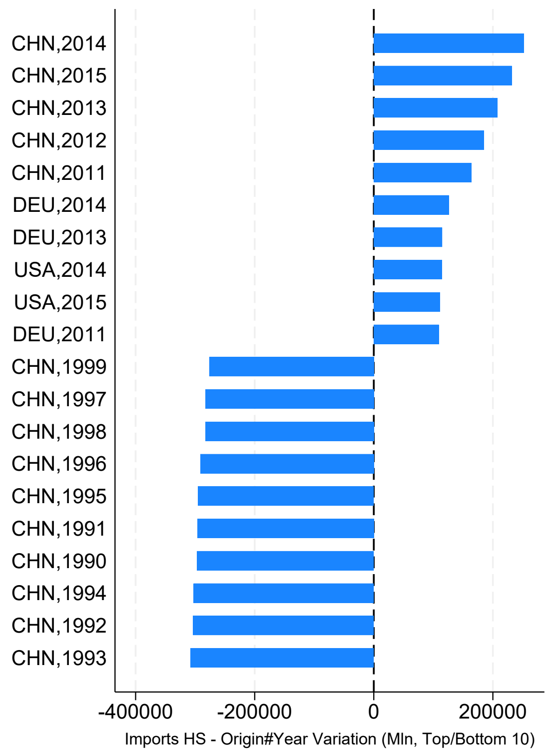
(a) Import LS - Origin-year Variation (All)



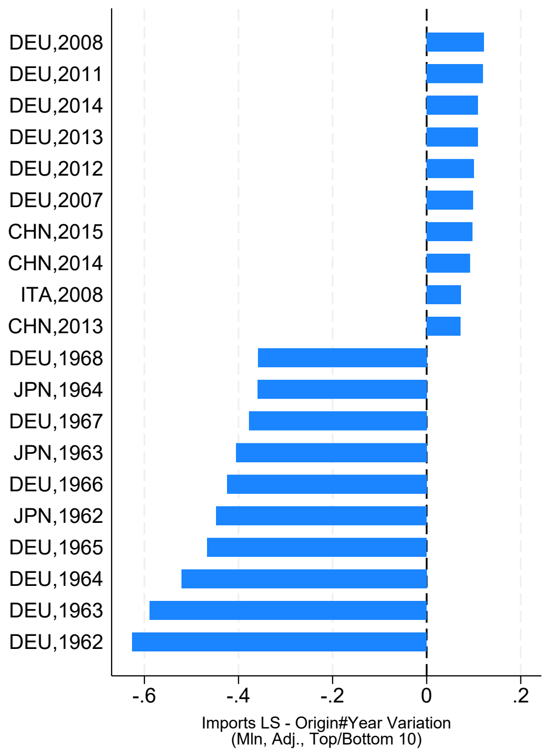
(b) Import HS - Origin-year Variation (All)



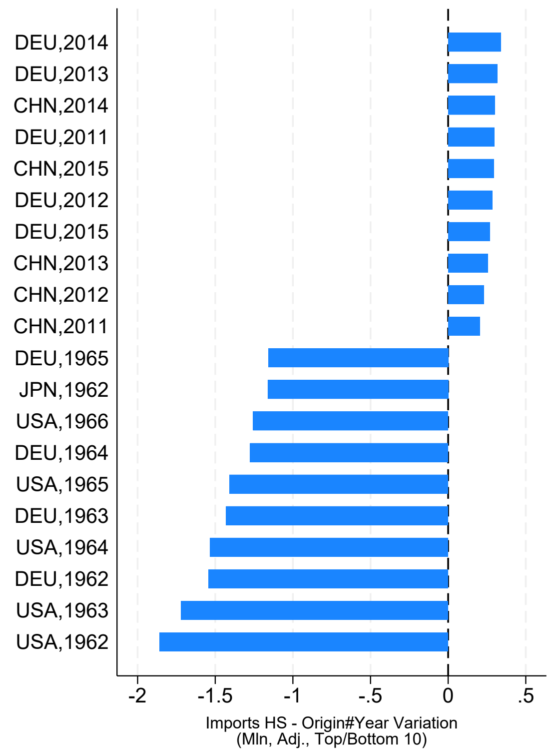
(c) Import LS - Origin-year Variation (Top/Bottom 10)



(d) Import HS - Origin-year Variation (Top/Bottom 10)



(e) Import LS - Origin-year Variation (Top/Bottom 10, Adjusted)



(f) Import HS - Origin-year Variation (Top/Bottom 10, Adjusted)

Notes: Panels (a) and (b) display the overall distribution of origin-specific changes in predicted imports, as computed in Eq. (9), for low-skill (LS) and high-skill (HS) imports, respectively. Panels (c) and (d) show the top and bottom 10 origin-year variations in skill-specific import values, driven by the origin-year shocks. Panels (e) and (f) present the same top and bottom 10 origin-year variations, but expressed as a share of destination-country GDP and adjusted for price levels. The dashed lines indicate one standard deviation of the skill-specific source of variation.

contributed to growing imbalances within the eurozone, suggesting that the eurozone crisis may have been one channel through which the German push factor influenced populism—thus reinforcing rather than undermining the relevance of our instrument.

The variation generated by the rapid growth in U.S. exports during the late 1960s also merits discussion. This period coincides with increased U.S. economic and political engagement abroad, particularly in Latin America, largely driven by Cold War dynamics. In this context, the concern with OLS estimation is that U.S.-backed political interventions may have coincided with economic benefits, implying that trade links were not politically neutral. Nonetheless, it is important to recall that the majority of Latin American destination countries are available from MPD, and therefore are present in our sample, only from the 1990, with the exclusion of Mexico. While our IV strategy should mitigate this concern, it is important to acknowledge that rapid U.S. export growth occurred during a time when U.S. foreign policy directly impacted the political landscape of partner countries.

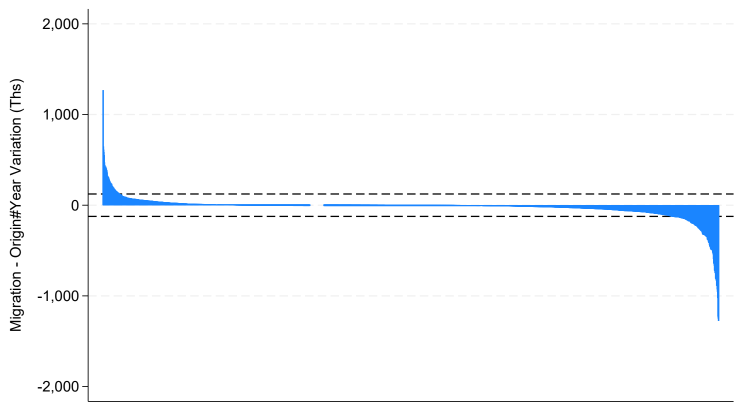
D.2 Sources of Variation in $\theta_{j,t}$ for Immigration

As with the approach used for trade, our identification strategy for immigration relies primarily on origin-year-specific shocks as a source of variation.[9] To address general concerns about the exogeneity of our instrumental variables for migration, we apply the same battery of tests, robustness checks, and descriptive analyses used in the trade section. It is important to recall that we first calculate total migration flows, and then we impute a skill level for dyadic immigration following the share of college graduates in the origin country. Therefore, the discussion that follows focuses on the variation derived from total flows. We compute the variation in migration flows driven by the origin-year component using the same approach as Eq. (9). The results are displayed in Figure D.2.

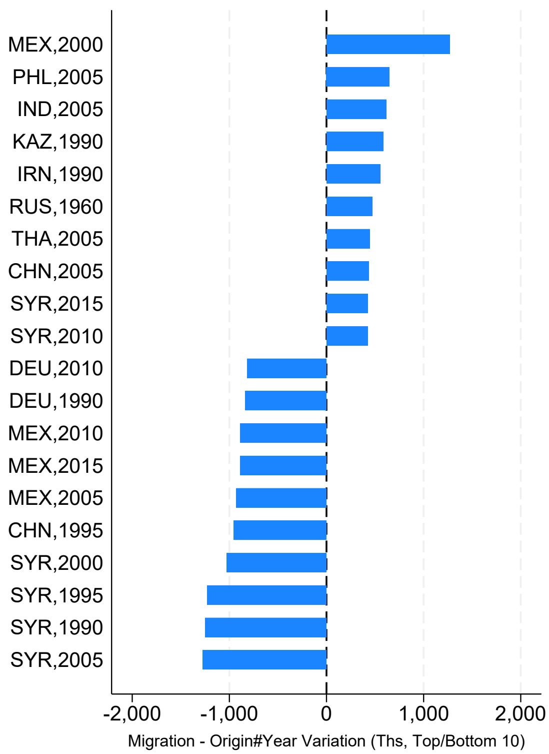
Regarding origin-year-specific variation, Figure D.2(a) shows that, similarly to the trade case, most of the variation in our origin-year push factors stems from a limited number of origin-year pairs. These variations should be interpreted as deviations from average bilateral migration flows, which are captured by the bilateral fixed effects (θ_{ij}). Panel (b) illustrates the top ten positive and negative country-year variations driven by origin-year fixed effects. Among the most significant positive shocks, we observe Mexico in 2000 and the Philippines in 2005. Our approach also captures other exceptional outflows, such as the Syrian exodus during the period around 2015, which was triggered by the outbreak and escalation of the civil war, and the large-scale emigration of ethnic Russians and Germans from Kazakhstan following the collapse of the Soviet Union and the formation of the Republic of Kazakhstan (Tishkov et al., 2005).

[9] To account for the lasting impact of geopolitical transformations, we also include an interaction between bilateral fixed effects and a post-1990 dummy. This allows us to capture the long-term effects of the fall of the Berlin Wall and the collapse of the Soviet bloc on international mobility. We interpret this as a permanent shock on bilateral migration flows.

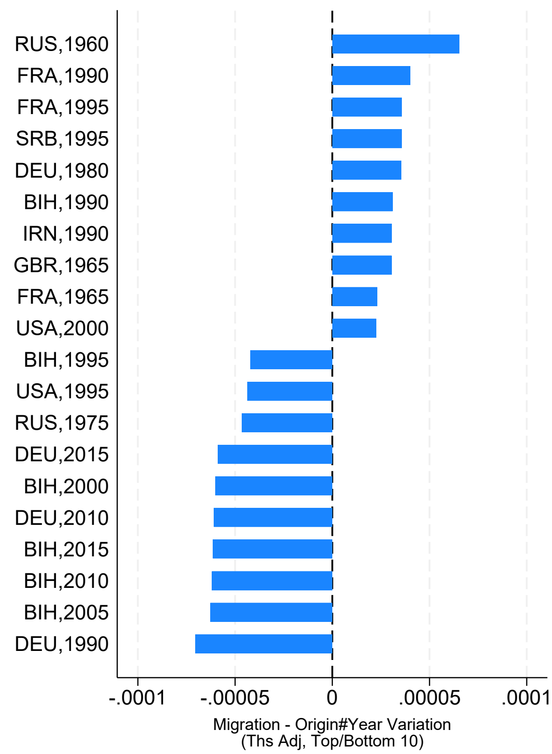
Figure D.2: Source of Variation IV Migration – Origin-Year Variation



(a) Migration - Origin-year Variation (All)



(b) Migration - Origin-year Variation (Top/Bottom 10)



(c) Migration - Origin-year Variation (Top/Bottom 10, Adjusted)

Notes: Panel (a) shows the overall distribution of origin-specific changes in predicted migration, as computed from equation (9). The dashed lines indicate one standard deviation of the underlying source of variation. Panel (b) displays the top and bottom 10 origin-year flows driven by the origin-year fixed effects, while panel (c) presents the results after adjusting these flows by the destination country's population.

To better align the analysis with the shocks used in our benchmark specification, Panel (c) presents results adjusted for destination-country population. Notably, Russia emerges as a major source country at the beginning of the sample period, likely reflecting the so-called Third Soviet Emigration (Heitman, 1988). Additional positive shocks include European countries and nations affected by the disintegration of Yugoslavia—such as Serbia and Bosnia and Herzegovina—where large outflows were recorded. Some high-profile shocks, such as those from Mexico or Syria, are not among the top-ranked cases in the normalised chart, as their flows are distributed across large destination populations—primarily in the U.S. and Germany.

Compared to the trade case, the origin-year-specific sources of variation in migration appear more dispersed across both countries and years. Nevertheless, as discussed above, our strategy successfully identifies origin-specific immigration shocks as meaningful departures from average bilateral migration patterns.

D.3 A Leave-One-Out IV Variant (LOO)

The estimated origin-year fixed effects $\theta_{j,t}$, which we use to capture push factors, may be mechanically biased because bilateral trade flows involving each destination country i contribute to their estimation. For example, if the variation we estimate for China in 2014 is largely driven by trade between China and the U.S., it becomes unclear whether we are capturing an origin-specific shock or a U.S.-specific shock that could be correlated with political developments in the U.S. This would undermine the core logic of our instrumental variable strategy.

To address this concern, we follow the recommendation of the shift-share literature (Borusyak et al., 2022) and construct destination-specific leave-one-out (LOO) predicted shocks. To estimate these LOO shocks, we proceed as follows: for each destination country i, we re-estimate our modified gravity model while excluding all bilateral trade flows involving country i from the sample.

$$Y_{ij,t}^{-i} = \exp\left[\alpha^{-i} + \theta_{ij}^{-i} + \theta_{ij}^{-i} * Post_{1990} + \theta_{j,t}^{-i} + \epsilon_{ij,t}^{-i}\right]. \tag{10}$$

For each destination country i, we store the origin-year fixed effects estimated when that country is excluded from the sample, denoted as $\theta_{j,t}^{-i}$. These leave-one-out (LOO) origin-year shocks are not mechanically influenced by bilateral trade or migration flows between countries j and i, but instead capture variation driven by trade or migration between j and the rest of the world. We then compute the predicted bilateral stocks using these LOO origin-year shocks, combined with the bilateral fixed effects predicted from the fully specified model, as follows:

$$\widehat{Y}_{ij,t}^{LOO} = exp\Big[\widehat{\theta_{ij}} + \widehat{\theta_{ij}} * Post_{1990} + \widehat{\theta_{j,t}^{-i}}\Big] \tag{11}$$

Adopting this approach for each country i enables us to estimate destination-specific origin-year shocks that exclude the influence of country i itself. This ensures that the constructed origin-year shocks are not mechanically driven by bilateral trade or migration flows involving the destination country.

Table D.1: Reduced-form IV PPML and 2SLS results – Leave-one-out

	Volume ($\Pi^{V}_{i,e,t}$)			Mean ($\Pi^{M}_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.75	1.24	0.92			
	(0.57)	(0.88)	(0.74)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.92	-1.61*	-0.87			
	(0.75)	(0.89)	(0.80)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.52	1.52**	-0.96			
	(0.43)	(0.59)	(0.82)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-0.80	-1.45*	0.09			
	(0.52)	(0.77)	(1.06)			
$\text{Imp}_{i,t}$ (LS)				4.69*	3.25	1.30
				(2.70)	(2.17)	(1.44)
$\text{Imp}_{i,t}$ (HS)				-0.27	-0.59	0.44
				(0.57)	(0.42)	(0.39)
$\text{Mig}_{i,t}$ (LS)				0.88	0.37	-0.59
				(3.64)	(2.87)	(1.60)
$\text{Mig}_{i,t}$ (HS)				2.89	5.83	3.64
				(11.94)	(8.04)	(4.54)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.40	0.33	0.50			
R^2				0.05	0.07	-0.01
K-Paap F-stat				23.74	22.70	12.70

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe`, while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Application to imports. – The results of this demanding robustness check are presented in Table D.1. Compared to the results in Table 4 of the manuscript, the direction of the estimates remains stable across specifications, although the magnitude of the coefficients is somewhat reduced. This outcome was expected, given that the leave-one-out (LOO) approach reduces the variation available for constructing the instrument. Nevertheless, these findings reinforce the robustness of our identification strategy, which relies on origin-year-specific shocks as a source of exogenous variation.

Application to immigration. – The results presented earlier in Table D.1 show the estimates obtained after constructing skill-specific migration flows using the same leave-one-out (LOO) approach applied in the trade analysis. This method helps eliminate potential mechanical bias arising from destination country i (Borusyak et al., 2022). While the confidence intervals are wider as expected, the findings remain consistent with the main results reported in the manuscript, which provides further validation of our identification strategy in the context of international migration.

D.4 Reduce-Form IV Regression: First-Stage Results

Table D.2 shows the results of the related first stage. Observed import and immigration flows by skill group are regressed on their predicted levels obtained after combining dyadic predictions from Eq. (7), as well as on the control variables and fixed effects used in the second-stage Eq. (5). The predicted levels are nicely correlated with the actual ones, and the coefficients of the instruments are highly significant close to unity. The adjusted R-squared is usually large despite the fact that our zero-stage dyadic regressions abstract from destination-time characteristics.

Table D.2: Actual and Predicted Flows of Imports and Immigrants

	(1) $\text{Imp}^{LS}_{i,e,t}$	(2) $\text{Imp}^{HS}_{i,e,t}$	(3) $\text{Mig}^{LS}_{i,e,t}$	(4) $\text{Mig}^{HS}_{i,e,t}$
$\log \widehat{\text{Imp}}_{i,t}$ (LS)	1.027***			
	(0.099)			
$\log \widehat{\text{Imp}}_{i,t}$ (HS)		0.982***		
		(0.090)		
$\log \widehat{\text{Mig}}_{i,t}$ (LS)			1.135***	
			(0.075)	
$\log \widehat{\text{Mig}}_{i,t}$ (HS)				1.224***
				(0.107)
Observations	577	577	577	577
Countries	52	52	52	52
Adj. R^2	0.91	0.93	0.85	0.86
Year & Country FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; all regressions have been estimated with OLS using the Stata command `reghdfe`.

E Supplementary Empirical Results

E.1 Analyzing Globalization Shocks Separately

We conduct an empirical examination, as outlined in Table E.1 (OLS/PPML) and Table E.2 (Reduced Form/IV), to elucidate the significance of concurrently integrating both migration and trade skill-specific shocks in our empirical analysis. The table delineates distinct estimated effects by introducing one skill-specific shock at a time, spanning from column (1) to (12). Furthermore, we extend our analysis by including either trade or migration-specific shocks in columns (13) to (18), allowing for a comparative assessment with our baseline specification presented in the final three columns of E.1 and E.2. In Panel A, we present the outcomes pertaining to the volume margin. Conversely, Panel B concentrates on the estimates for the mean margin.

The presented results offer valuable insights for our empirical analysis. Across various model specifications and panels, there is noteworthy consistency in the sign of the estimated coefficients. This suggests that the direction of the effects remains robust and is not influenced by potential multicollinearity bias arising from different globalization shocks. Furthermore, the results pertaining to the volume margin underscore the importance of adopting a unified approach to fully comprehend the consequences of globalization shocks on both left and right-wing populist dimensions.

While estimating the effects of trade shocks in isolation reveals estimates not statistically different from zero on the the volume margin of populism, estimating migration and trade shocks simultaneously reveals statistically significant effects of imports, albeit weak, only on the right-hand dimension, while the migration-specific results remain stable regardless of whether trade shocks are included or excluded. Moreover, these results are confirmed both in OLS/PPML and IV/Reduced Form. This suggests that a global framework should be considered to avoid potential misinterpretations that could result from analysing these shocks in isolation. Finally, the unified analysis slightly changes the magnitude of the effect of low-skill imports on the mean margin, without changing the sign or precision of the estimates.

Table E.1: OLS and PPML Results – Globalization Shocks Analyzed Separately

	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
log $\text{Imp}_{i,t}$ (LS)	0.40	0.24	0.43										0.75**	0.90*	0.61				0.81**	1.14**	1.05**
	(0.27)	(0.39)	(0.38)										(0.32)	(0.51)	(0.53)				(0.33)	(0.56)	(0.50)
log $\text{Imp}_{i,t}$ (HS)				0.16	-0.14	0.23							-0.58	-1.03*	-0.29				-0.68	-1.23**	-0.72
				(0.34)	(0.39)	(0.48)							(0.44)	(0.55)	(0.65)				(0.46)	(0.59)	(0.63)
log $\text{Mig}_{i,t}$ (LS)							-0.08	0.21	-0.79***							0.06	1.13**	-1.60***	0.15	1.39**	-1.79***
							(0.15)	(0.23)	(0.28)							(0.35)	(0.52)	(0.55)	(0.37)	(0.55)	(0.54)
log $\text{Mig}_{i,t}$ (HS)										-0.09	0.09	-0.52*				-0.14	-0.92**	0.89	-0.25	-1.21**	0.99
										(0.14)	(0.21)	(0.27)				(0.31)	(0.46)	(0.67)	(0.33)	(0.52)	(0.63)
Observations	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577
Pseudo-R^2	0.40	0.31	0.49	0.39	0.30	0.48	0.39	0.31	0.51	0.39	0.30	0.50	0.40	0.31	0.49	0.39	0.32	0.52	0.40	0.33	0.53
Panel B - Mean Margin																					
$\text{Imp}_{i,t}$ (LS)	3.33**	3.25**	0.29										3.68**	4.00***	-0.15				3.65**	4.00**	-0.17
	(1.42)	(1.27)	(0.58)										(1.68)	(1.49)	(0.63)				(1.70)	(1.55)	(0.64)
$\text{Imp}_{i,t}$ (HS)				0.29	0.16	0.30							-0.25	-0.45	0.32				-0.25	-0.48	0.32
				(0.38)	(0.20)	(0.21)							(0.44)	(0.28)	(0.23)				(0.45)	(0.29)	(0.23)
$\text{Mig}_{i,t}$ (LS)							0.52	1.48	-0.42							-0.83	1.16	-1.51	-0.47	1.58	-1.47
							(1.21)	(1.29)	(0.73)							(2.02)	(2.17)	(1.29)	(1.96)	(2.01)	(1.31)
$\text{Mig}_{i,t}$ (HS)										3.05	4.02	0.29				5.22	1.19	4.56	3.72	-0.34	4.26
										(3.05)	(2.68)	(2.12)				(4.68)	(4.40)	(3.32)	(4.95)	(4.12)	(3.31)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	580	464	469	580	464	469	588	472	473	588	472	473	580	464	469	588	472	473	580	464	469
R^2	0.50	0.39	0.48	0.49	0.37	0.48	0.49	0.37	0.48	0.49	0.37	0.47	0.50	0.40	0.48	0.49	0.37	0.48	0.50	0.40	0.48

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.2: Reduced-Form IV PPML Results – Globalization Shocks Analyzed Separately

	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Panel A - Volume Margin																					
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.18	0.05	0.03										0.79	0.79	1.12				0.81	1.49*	0.82
	(0.39)	(0.62)	(0.56)										(0.59)	(0.96)	(0.74)				(0.55)	(0.84)	(0.81)
log $\widehat{\text{Imp}}_{i,t}$ (HS)				-0.08	-0.27	-0.38							-0.86	-1.10	-1.32				-0.98	-1.99**	-0.60
				(0.50)	(0.68)	(0.66)							(0.81)	(1.06)	(0.94)				(0.68)	(0.87)	(0.83)
log $\widehat{\text{Mig}}_{i,t}$ (LS)							-0.30	0.27	-1.31**							0.46	1.68***	-1.67**	0.61	1.97***	-1.63**
							(0.34)	(0.46)	(0.52)							(0.45)	(0.59)	(0.79)	(0.46)	(0.62)	(0.78)
log $\widehat{\text{Mig}}_{i,t}$ (HS)										-0.58	-0.27	-1.04*				-1.05**	-2.00**	0.51	-1.16**	-2.32***	0.47
										(0.40)	(0.55)	(0.63)				(0.52)	(0.85)	(1.03)	(0.55)	(0.89)	(1.08)
Observations	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577
Pseudo-R^2	0.39	0.30	0.48	0.39	0.30	0.48	0.39	0.31	0.51	0.40	0.30	0.50	0.39	0.31	0.49	0.40	0.32	0.51	0.40	0.34	0.51
Panel B - 2SLS																					
$\text{Imp}_{i,t}$ (LS)	4.27**	1.93	2.01										4.69*	3.37*	1.20				4.70*	3.21	1.28
	(2.04)	(1.53)	(1.26)										(2.50)	(1.95)	(1.36)				(2.61)	(2.12)	(1.39)
$\text{Imp}_{i,t}$ (HS)				0.40	-0.12	0.57							-0.22	-0.58	0.43				-0.23	-0.57	0.43
				(0.41)	(0.27)	(0.35)							(0.55)	(0.40)	(0.37)				(0.56)	(0.41)	(0.38)
$\text{Mig}_{i,t}$ (LS)							0.36	1.38	-0.54							-0.48	0.11	-1.52	0.33	0.58	-0.96
							(2.07)	(2.00)	(1.06)							(3.39)	(2.96)	(1.48)	(3.34)	(2.71)	(1.52)
$\text{Mig}_{i,t}$ (HS)										2.79	6.07	0.85				3.93	5.86	4.49	4.50	5.43	4.26
										(7.34)	(5.30)	(3.32)				(11.54)	(7.92)	(4.02)	(10.88)	(7.36)	(4.32)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	580	464	469	580	464	469	588	472	473	588	472	473	580	464	469	588	472	473	580	464	469
R^2	0.05	0.06	-0.01	0.03	0.03	0.01	0.03	0.03	0.01	0.03	0.03	0.01	0.05	0.07	-0.00	0.03	0.03	0.01	0.05	0.07	-0.00
K-Paap F-stat	69.51	39.26	48.06	220.48	215.87	208.93	68.19	59.90	62.02	51.86	41.89	41.56	40.17	18.39	26.51	27.75	19.97	18.61	29.89	26.02	12.92

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.2 Modified Gravity Model Results

Table E.3 presents our main results using the predicted skill-specific globalization shocks from a modified version of the gravity model presented in equation (7), which looks as follows:

$$Y_{ij,t} = \exp\left[\alpha + \theta_{ij} + \theta_{ij} \times Post_{1990} + \theta_{j,t} + \theta_{i,t} + \epsilon_{ij,t}\right], \tag{12}$$

where $Y_{ij,t}$ is the dyadic skill-specific flow of either imported goods ($\text{Imp}^S_{i,t}$) or immigrants ($\text{Mig}^S_{i,t}$) from origin country j to destination country i at year t. Compared to our benchmark gravity model, we include in the estimation part also the destination-year fixed effects $\theta_{i,t}$, but then we exclude them in the prediction of our skill-specific gravity flows. Such approach should improve the precision of the estimates associated to the origin-year fixed effects, since it purges potential bias in the estimation of the latter. Nevertheless, the inclusion of destination-by-year fixed effects would absorb a substantial amount of variation, leading to predicted flows that may lack sufficient predictive power as instrumental variables.

The results presented in Table E.3 align with our benchmark results outlined in Table 4, reaffirming the robustness of our findings and the stable direction of the estimated effects. It is noteworthy, however, that there is a decline in the F-statistic related to the strength of the instruments, evident from columns (4) to (6). Consequently, the enhancement in the precision of the estimated origin-by-year fixed effects is accompanied by the trade-off of constructing weaker instrumental variables.

Table E.3: Reduced-Form IV PPML and 2SLS Results – Volume and Mean Margins
Modified Gravity Model

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}^{Mod}_{i,t}$ (LS)	0.78	1.96***	0.40			
	(0.54)	(0.74)	(0.69)			
log $\widehat{\text{Imp}}^{Mod}_{i,t}$ (HS)	-0.95	-2.59***	-0.13			
	(0.59)	(0.78)	(0.71)			
log $\widehat{\text{Mig}}^{Mod}_{i,t}$ (LS)	0.75**	2.17***	-1.60**			
	(0.38)	(0.56)	(0.75)			
log $\widehat{\text{Mig}}^{Mod}_{i,t}$ (HS)	-1.22**	-2.32***	0.75			
	(0.49)	(0.73)	(0.97)			
$\text{Imp}_{i,t}$ (LS)				5.45*	3.04	1.94
				(3.05)	(2.63)	(1.39)
$\text{Imp}_{i,t}$ (HS)				-0.39	-0.65	0.37
				(0.60)	(0.49)	(0.38)
$\text{Mig}_{i,t}$ (LS)				3.01	4.16	-1.74
				(6.16)	(4.46)	(2.09)
$\text{Mig}_{i,t}$ (HS)				2.28	-1.61	5.35
				(16.53)	(12.43)	(5.28)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.41	0.35	0.51			
R^2				0.03	0.06	-0.01
K-Paap F-stat				5.91	5.13	9.38

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.3 Volume of Populism: Extensive and Intensive Margins

In this section, we focus on the volume of populism, as measured by the share of votes for populist parties, and on its intensive and extensive margins. In Table E.4 reports the PPML results.

Table E.4: Baseline PPML Results – Volume of Populist Votes and its Margins

	Volume ($\Pi^V_{i,e,t}$)			Ext. margin ($\Pi^E_{i,e,t}$)			Int. margin ($\Pi^I_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW	(7) All	(8) RW	(9) LW
log $\text{Imp}_{i,t}$ (LS)	0.81**	1.14**	1.05**	0.31	0.17	0.67*	1.19***	1.70***	0.86
	(0.33)	(0.56)	(0.50)	(0.29)	(0.50)	(0.36)	(0.33)	(0.50)	(0.62)
log $\text{Imp}_{i,t}$ (HS)	-0.68	-1.23**	-0.72	-0.13	-0.01	-0.65	-1.05**	-1.88***	-0.36
	(0.46)	(0.59)	(0.63)	(0.38)	(0.58)	(0.54)	(0.45)	(0.55)	(0.80)
log $\text{Mig}_{i,t}$ (LS)	0.15	1.39**	-1.79***	-0.16	0.94**	-1.18***	0.18	1.22**	-1.52***
	(0.37)	(0.55)	(0.54)	(0.30)	(0.44)	(0.38)	(0.34)	(0.53)	(0.50)
log $\text{Mig}_{i,t}$ (HS)	-0.25	-1.21**	0.99	-0.09	-0.95**	0.65*	-0.15	-1.13**	0.90
	(0.33)	(0.52)	(0.63)	(0.27)	(0.43)	(0.37)	(0.35)	(0.50)	(0.57)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	577	577	577	577	577	577	577	577	577
Pseudo-R^2	0.40	0.33	0.53	0.30	0.23	0.30	0.34	0.32	0.46

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; all regressions have been estimated with PPML using the Stata command `ppmlhdfe`.

Imports of low-skill labor intensive goods are positively and significantly associated with right- and left-wing populism. The link with right-wing populism materializes through the intensive margin (share of votes for existing populist parties), while the effect on left-wing populism is less significant and linked to the extensive margin (number of populist parties). By contrast, imports of high-skill labor intensive goods are associated with lower volumes of populism in general, and with lower levels of right-wing populism in particular. The elasticity of the intensive margin of populism to imports of low-skill labor intensive goods is usually greater than unity.

With regard to immigration, its association with the overall volume of populism is insignificant. Our results support, however, a substitution between left-wing and right-wing populism. low-skill immigration is associated with highest volumes of right-wing populism and with smallest volumes for left-wing populism. This substitution operates along both extensive and intensive margins. By contrast, high-skill immigration tends to generate opposite substitution from right-wing to left-wing populism, although the effects are slightly smaller and less significant.

Table E.5 presents the reduced-form IV estimates for the volume margin of populism and of its two components. Focusing first on the volume of populism, the IV estimates are pretty much in line with the results of our baseline PPML regressions. They confirm that the skill structure of globalization shocks plays a key role. Imports of low-skill labor intensive goods foster votes for right-wing populist parties, and the effect mostly materializes through the intensive margin. By contrast, imports of high-skill labor intensive goods decrease the votes for right-wing populist parties. With regard to immigration, the IV results also confirm those of the baseline regressions.

Table E.5: IV – Volume of Populist Votes and its Margins

	Volume ($\Pi^V_{i,e,t}$)			Ext. margin ($\Pi^E_{i,e,t}$)			Int. margin ($\Pi^I_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW	(7) All	(8) RW	(9) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.81	1.49*	0.82	0.60	0.58	0.95	1.45***	2.28***	1.63**
	(0.55)	(0.84)	(0.81)	(0.42)	(0.69)	(0.74)	(0.48)	(0.81)	(0.81)
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.98	-1.99**	-0.60	-0.77*	-0.91	-0.96	-1.33**	-2.72***	-0.72
	(0.68)	(0.87)	(0.83)	(0.46)	(0.77)	(0.69)	(0.56)	(0.93)	(0.94)
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.61	1.97***	-1.63**	0.07	1.44***	-1.35**	0.25	1.39*	-1.32*
	(0.46)	(0.62)	(0.78)	(0.34)	(0.52)	(0.57)	(0.50)	(0.79)	(0.71)
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.16**	-2.32***	0.47	-0.96**	-2.49***	0.27	0.00	-1.25	0.66
	(0.55)	(0.89)	(1.08)	(0.41)	(0.80)	(0.65)	(0.67)	(1.07)	(1.02)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	577	577	577	577	577	577	577	577	577
Pseudo-R^2	0.40	0.34	0.51	0.31	0.25	0.30	0.33	0.31	0.44

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; all regressions have been estimated with PPML using the Stata command `ppmlhdfe`.

Low-skill immigration leads to a substitution of left-wing populism for right-wing populism. This effect mostly materializes along the extensive margin (while it also affects both margins in baseline PPML regressions). High-skill immigration reduces the votes for (and number of) populist parties.

E.4 Additional Results: Volume Margin of Populism

In Table E.6, we examine the effects of globalisation shocks on the volume margin using a time-invariant classification based on our score, considering as populist those parties that have been classified as populist in at least one election. Columns (1) to (3) present the results for the PPML, while columns (4) to (6) show the results of the reduced-form IV estimates. While confirming the direction of our baseline results, we find two major differences. First, globalisation shocks have a significant effect exclusively in the case of parties classified as right-wing, while we do not find almost any effect on left-wing populist parties. Specifically, low-skill imports and migration increase the volume margin for right-wing populist parties, while shocks related to high-skill imports and immigration reduce support for the same parties. Second, also the magnitude of the estimated coefficients, both with standard PPML and with our Reduce-form approach, are reduced. Therefore, these results suggest that relying on a time-invariant classification of populism would underestimate the skill-specific implication of globalization on populism, specifically in its left-wing expression.

Table E.6: Volume Margin of Populist with Time-Invariant classification (PPML and Reduced-Form IV)

	PPML			Reduced-Form		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\text{Imp}_{i,t}$ (LS)	0.06	0.67***	0.08			
	(0.10)	(0.26)	(0.17)			
log $\text{Imp}_{i,t}$ (HS)	0.02	-0.68**	0.31			
	(0.13)	(0.29)	(0.26)			
log $\text{Mig}_{i,t}$ (LS)	0.05	0.55*	0.01			
	(0.09)	(0.30)	(0.29)			
log $\text{Mig}_{i,t}$ (HS)	-0.04	-0.50*	-0.13			
	(0.08)	(0.28)	(0.28)			
log $\widehat{\text{Imp}}_{i,t}$ (LS)				0.04	0.78*	-0.32
				(0.16)	(0.45)	(0.31)
log $\widehat{\text{Imp}}_{i,t}$ (HS)				-0.04	-0.79	0.55
				(0.19)	(0.54)	(0.35)
log $\widehat{\text{Mig}}_{i,t}$ (LS)				0.05	0.99***	-0.19
				(0.12)	(0.33)	(0.33)
log $\widehat{\text{Mig}}_{i,t}$ (HS)				-0.08	-1.10***	-0.07
				(0.15)	(0.39)	(0.39)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	577	577	577
Pseudo-R^2	0.75	0.41	0.50	0.75	0.41	0.50

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in columns (1) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The mean margin is computed over the sample of parties that is never classified as populist in columns (1) to (3) and from (7) to (9), while is computed over the sample of parties that is classified at least once as populist in column (4) to (6) and (10) to (12). The mean margin is an unweighted average of parties populism score from column (1) to (6) and a normalized weighted average in columns (7) to (12).

E.5 Additional Results: Mean Margin of Populism

In this section we expand further our analysis on the mean margin. First, we investigate whether our baseline results are driven by the construction of our dependent variable, which takes into account parties' share of votes. Then, we explore whether our results are driven by mainstream non populist parties, which can express populism stances, or by populist parties. Finally, we decompose whether our results are driven by changes of parties' populism stance (i.e., their populism score) or by their electoral success (i.e., share of votes).

Table E.7: Mean Margin of Populism With Alternative Measures of $\Pi^M_{i,e,t}$ (OLS and 2SLS)

	Parties			Parliament			Parliament (adj.)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW	(7) All	(8) RW	(9) LW
Panel A - OLS									
$\text{Imp}_{i,t}$ (LS)	3.88*	7.36**	2.35	3.87**	7.08**	0.80	3.65**	4.00**	-0.17
	(2.00)	(3.01)	(2.41)	(1.76)	(2.87)	(1.77)	(1.70)	(1.55)	(0.64)
$\text{Imp}_{i,t}$ (HS)	-0.28	-0.42	0.21	-0.27	-0.60	0.25	-0.25	-0.48	0.32
	(0.43)	(0.59)	(0.61)	(0.49)	(0.63)	(0.59)	(0.45)	(0.29)	(0.23)
$\text{Mig}_{i,t}$ (LS)	-2.23	1.97	-6.87*	-0.56	3.52	-6.51*	-0.47	1.58	-1.47
	(1.83)	(3.71)	(3.75)	(2.07)	(3.73)	(3.45)	(1.96)	(2.01)	(1.31)
$\text{Mig}_{i,t}$ (HS)	1.76	-3.64	11.46	3.99	-5.18	13.18	3.72	-0.34	4.26
	(6.26)	(9.98)	(11.26)	(5.23)	(9.63)	(9.72)	(4.95)	(4.12)	(3.31)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	580	464	469	580	464	469	580	464	469
R^2	0.55	0.47	0.52	0.50	0.46	0.53	0.50	0.40	0.48
Panel B - 2SLS									
$\text{Imp}_{i,t}$ (LS)	5.69**	7.85*	7.86**	5.00*	3.41	6.50*	4.70*	3.21	1.28
	(2.64)	(4.38)	(3.20)	(2.79)	(4.96)	(3.56)	(2.61)	(2.12)	(1.39)
$\text{Imp}_{i,t}$ (HS)	-0.57	-1.15	0.07	-0.26	-0.71	0.36	-0.23	-0.57	0.43
	(0.56)	(0.88)	(0.81)	(0.60)	(0.83)	(0.89)	(0.56)	(0.41)	(0.38)
$\text{Mig}_{i,t}$ (LS)	-1.37	0.63	-8.01*	0.30	1.05	-6.84	0.33	0.58	-0.96
	(2.96)	(5.21)	(4.44)	(3.61)	(4.91)	(4.45)	(3.34)	(2.71)	(1.52)
$\text{Mig}_{i,t}$ (HS)	2.33	-1.95	18.83	5.06	-0.29	20.20*	4.50	5.43	4.26
	(11.29)	(16.68)	(13.35)	(11.88)	(16.63)	(11.89)	(10.88)	(7.36)	(4.32)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	580	464	469	580	464	469	580	464	469
R^2	0.06	0.06	0.03	0.05	0.05	0.01	0.05	0.07	-0.00
K-Paap F-stat	29.89	26.02	12.92	29.89	26.02	12.92	29.89	26.02	12.92

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; all regressions have been estimated with OLS and 2SLS using the Stata command `reghdfe` and `ivreghdfe`, in Panel A and B, respectively. The mean margin is an unweighted average of parties populism score from columns (1) to (3), a weighted average from columns (4) to (6), and a normalized weighted average in columns (7) to (9).

Table E.7 focuses on the association between globalization shocks and three alternative way of computing the mean margin of populism. The first three columns shows the association between imports/immigration and the unweighted average level of populism of parties included in our sample. In Cols. (4-6), we focus on the weighted average level of populism, using parties' vote shares as weights. However, since our data set includes parties that won at least one seat in the parliament, it excludes small parties and most independent candidates running for election. Hence the cumulative vote share is less than 100% for many election-year pairs. In the last three columns, we normalize the vote shares of parties represented in the parliament so that their sum is equal to 100%.

Whatever the definition of the dependent variable, we find that imports of low-skill labor intensive goods are positively and significantly associated with the mean margin of total and right-wing populism. The elasticity is large, ranging from 4 to 7.4. These results point out that import shocks positively influence the mean level of populism (i.e., the average extent of populism in a society), both in raw terms and when we account for parties political relevance. By contrast, imports of high-skill labor intensive goods and immigration rates are not significantly correlated with populism. In Panel B of Table E.7, we produce IV results using the same instruments as in the previous section, and rely on a standard 2SLS approach. Panel B is in line with the OLS results.

In Table E.8, we dissect the effects of globalization shocks separately on the vote-weighted mean margin of populism among non populist parties (cols. (1) to (3), and (7) to (9)) and populist parties (cols. (4) to (6) and (10) to (12)). We first rely on a time-invariant classification of parties, therefore splitting parties that have never been classified as populist with our classification and parties that have been classified as populist in at least one election (cols (1) to (6)). We then allow for a time-variant classification of parties (cols (7) to (12)).[10] Notably, globalization shocks do not yield a significant impact on the mean margin of parties that have never expressed a relevant populism stance in their political history. This suggests that these shocks do not uniformly influence all parties in the political landscape. In contrast, the results in columns (3) to (6) and (10) to (12) indicate that parties identified as populist are more likely to be responsive to low-skill imports, particularly among left-wing parties. Additionally, we do see that populist left-wing parties are also more responsive to the skill-specific effects of immigration. The similarity in the estimated coefficients between column (6) and (12) implies that this effect is not driven by the timing of the classification.

Lastly, Table E.9 further decomposes the mean margin between non-populist and populist parties, separating the contribution of the average populism score from that of electoral success (i.e., vote share). The 2SLS and reduced-form IV results in Panel B show that, on average, skill-specific globalization shocks have no significant effect on non-populist parties—neither on their populism score nor on their vote share. These findings suggest that mainstream parties with no history of populist behavior are less likely to adjust along these margins in response to globalization. In contrast, populist parties do appear to respond to globalization shocks. Specifically, left-wing populist parties tend to increase their populist stance when exposed to low-skill imports, although this does not translate into higher electoral success. On the other hand, right-wing populist parties

[10] To have a comparable sample of elections across the two classifications, we replace as zeros those elections that have a missing value of the mean margin of populist over the right or left wing political spectrum with a time-variant classification, but we do have a not missing values with a time-invariant one.

Table E.8: Mean Margin of Populist and Non-Populist Parties (OLS and 2SLS)

	Time Inv.						Time Var.					
	Non populist			Populist			Non populist			Populist		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW
Panel A - OLS												
$\text{Imp}_{i,t}$ (LS)	0.02	1.62	-2.27*	8.09**	5.55	9.63**	0.63	1.38	-1.97*	6.19*	6.16	7.56**
	(0.71)	(1.97)	(1.24)	(3.19)	(6.19)	(3.87)	(0.82)	(1.80)	(1.12)	(3.55)	(5.37)	(3.18)
$\text{Imp}_{i,t}$ (HS)	0.18	0.21	0.28	0.53	-0.33	1.12	0.15	0.51	0.28	-0.61	-0.28	-0.16
	(0.35)	(0.34)	(0.54)	(0.99)	(2.04)	(1.71)	(0.30)	(0.35)	(0.48)	(0.99)	(2.16)	(1.45)
$\text{Mig}_{i,t}$ (LS)	-1.54	0.40	-2.34	-4.72	-2.91	-14.13***	-1.42	2.28	-4.24	-6.98	-9.54	-11.58**
	(1.36)	(2.60)	(2.19)	(3.99)	(6.84)	(5.00)	(1.29)	(2.02)	(2.74)	(4.98)	(6.44)	(5.06)
$\text{Mig}_{i,t}$ (HS)	0.20	-3.41	2.29	12.05	6.76	43.03***	2.74	-5.14	8.22	14.72	14.32	32.66**
	(4.37)	(8.12)	(9.58)	(9.97)	(16.58)	(11.60)	(4.23)	(7.08)	(11.03)	(15.09)	(17.31)	(14.83)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	530	335	363	465	290	289	530	335	363	465	290	289
R^2	0.52	0.52	0.51	0.41	0.38	0.49	0.50	0.51	0.50	0.36	0.36	0.45
Panel B - 2SLS												
$\text{Imp}_{i,t}$ (LS)	-0.13	3.19	-4.25*	11.77***	4.23	18.38***	-0.23	-0.50	-2.75	7.94*	11.87	12.21***
	(1.22)	(3.68)	(2.38)	(3.83)	(9.78)	(5.04)	(1.50)	(4.45)	(2.02)	(4.68)	(10.10)	(3.85)
$\text{Imp}_{i,t}$ (HS)	0.05	-0.08	0.57	-0.30	-3.25	0.52	0.09	0.67	0.54	-1.46	-3.76	-1.13
	(0.33)	(0.46)	(0.64)	(1.26)	(3.17)	(1.69)	(0.29)	(0.53)	(0.62)	(1.40)	(3.10)	(1.75)
$\text{Mig}_{i,t}$ (LS)	-0.71	1.57	-2.04	-4.49	-5.58	-17.13**	-0.86	2.68	-2.99	-7.66	-9.76	-15.63**
	(1.64)	(2.71)	(2.55)	(5.72)	(8.86)	(7.60)	(1.79)	(2.84)	(3.21)	(5.62)	(9.68)	(6.23)
$\text{Mig}_{i,t}$ (HS)	-2.97	-23.03	-1.22	6.80	5.93	62.98***	0.75	-22.18	2.84	12.42	14.37	45.33**
	(5.00)	(14.27)	(10.72)	(18.25)	(22.56)	(18.32)	(6.78)	(14.81)	(13.30)	(21.11)	(23.85)	(21.77)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	530	335	363	465	290	289	530	335	363	465	290	289
R^2	0.02	-0.06	0.07	0.09	0.04	0.06	0.02	-0.05	0.11	0.07	0.06	0.05
K-Paap F-stat	15.17	2.74	14.34	19.28	6.97	16.69	15.17	2.74	14.34	19.28	6.97	16.69

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in columns (1) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The mean margin is computed over the sample of parties that is never classified as populist in columns (1) to (3) and from (7) to (9), while is computed over the sample of parties that is classified at least once as populist in column (4) to (6) and (10) to (12). The mean margin is an unweighted average of the score of parties classified as populist using the time-invariant definition in columns (1) to (6) and a time-varying definition in columns (7) to (12).

Table E.9: Mean Margin Decomposition (OLS/2SLS) – Time invariant definition

	Score						Votes					
	Non Populist			Populist			Non Populist			Populist		
	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A - OLS & PPML												
$\text{Imp}_{i,t}$ (LS)	0.02	1.62	-2.27*	8.09**	5.55	9.63**						
	(0.71)	(1.97)	(1.24)	(3.19)	(6.19)	(3.87)						
$\text{Imp}_{i,t}$ (HS)	0.18	0.21	0.28	0.53	-0.33	1.12						
	(0.35)	(0.34)	(0.54)	(0.99)	(2.04)	(1.71)						
$\text{Mig}_{i,t}$ (LS)	-1.54	0.40	-2.34	-4.72	-2.91	-14.13***						
	(1.36)	(2.60)	(2.19)	(3.99)	(6.84)	(5.00)						
$\text{Mig}_{i,t}$ (HS)	0.20	-3.41	2.29	12.05	6.76	43.03***						
	(4.37)	(8.12)	(9.58)	(9.97)	(16.58)	(11.60)						
log $\text{Imp}_{i,t}$ (LS)							0.06	-0.44***	0.35*	-0.02	0.26	-0.12
							(0.06)	(0.15)	(0.19)	(0.09)	(0.17)	(0.09)
log $\text{Imp}_{i,t}$ (HS)							-0.09	0.52***	-0.15	0.01	-0.45**	0.17
							(0.06)	(0.20)	(0.18)	(0.12)	(0.20)	(0.21)
log $\text{Mig}_{i,t}$ (LS)							-0.06	-0.12	-0.06	-0.01	0.11	0.10
							(0.06)	(0.14)	(0.13)	(0.09)	(0.20)	(0.18)
log $\text{Mig}_{i,t}$ (HS)							0.05	0.10	-0.01	-0.00	-0.11	-0.03
							(0.05)	(0.13)	(0.11)	(0.08)	(0.17)	(0.19)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	530	335	363	465	290	289	527	332	362	465	290	289
Pseudo-R^2							0.64	0.43	0.46	0.72	0.45	0.60
R^2	0.52	0.52	0.51	0.41	0.38	0.49						
Panel B - 2SLS & PPML												
$\text{Imp}_{i,t}$ (LS)	-0.13	3.19	-4.25*	11.77***	4.23	18.38***						
	(1.22)	(3.68)	(2.38)	(3.83)	(9.78)	(5.04)						
$\text{Imp}_{i,t}$ (HS)	0.05	-0.08	0.57	-0.30	-3.25	0.52						
	(0.33)	(0.46)	(0.64)	(1.26)	(3.17)	(1.69)						
$\text{Mig}_{i,t}$ (LS)	-0.71	1.57	-2.04	-4.49	-5.58	-17.13**						
	(1.64)	(2.71)	(2.55)	(5.72)	(8.86)	(7.60)						
$\text{Mig}_{i,t}$ (HS)	-2.97	-23.03	-1.22	6.80	5.93	62.98***						
	(5.00)	(14.27)	(10.72)	(18.25)	(22.56)	(18.32)						
log $\widehat{\text{Imp}}_{i,t}$ (LS)							0.08	-0.19	0.37	0.07	0.76**	-0.34
							(0.08)	(0.23)	(0.32)	(0.14)	(0.32)	(0.21)
log $\widehat{\text{Imp}}_{i,t}$ (HS)							-0.08	0.39	-0.27	-0.09	-1.02***	0.16
							(0.10)	(0.26)	(0.29)	(0.18)	(0.32)	(0.30)
log $\widehat{\text{Mig}}_{i,t}$ (LS)							-0.10	-0.00	-0.33	0.10	0.40	0.15
							(0.09)	(0.23)	(0.21)	(0.12)	(0.24)	(0.24)
log $\widehat{\text{Mig}}_{i,t}$ (HS)							0.12	-0.11	0.28	-0.19	-0.33	-0.08
							(0.08)	(0.22)	(0.23)	(0.14)	(0.23)	(0.28)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	530	335	363	465	290	289	527	332	362	465	290	289
Pseudo-R^2							0.64	0.42	0.45	0.72	0.46	0.60
R^2	0.02	-0.06	0.07	0.09	0.04	0.06						
K-Paap F-stat	15.17	2.74	14.34	19.28	6.97	16.69						

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses. The mean margin is computed over the sample of parties classified as populist or non populist according to a time invariant definition.

appear to benefit electorally from such exposure, with increases in their vote share. Results using a time-varying classification in Table E.10 confirm these findings.

Overall, these results suggest that while skill-specific globalization shocks may occasionally elicit reactions from mainstream traditional parties, this is not necessarily the norm. In contrast, we provide evidence of a stronger and more systematic response among parties that adopt populist positions—both in terms of their populism scores and their electoral success.

Table E.10: Mean Margin Decomposition (OLS/2SLS) – Time variant definition

	Score						Votes					
	Non Populist			Populist			Non Populist			Populist		
	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A - OLS & PPML												
$\text{Imp}_{i,t}$ (LS)	1.25	3.04*	-1.90	6.19*	6.16	7.56**						
	(0.77)	(1.75)	(1.23)	(3.55)	(5.37)	(3.18)						
$\text{Imp}_{i,t}$ (HS)	0.09	0.21	0.63	-0.61	-0.28	-0.16						
	(0.29)	(0.36)	(0.58)	(0.99)	(2.16)	(1.45)						
$\text{Mig}_{i,t}$ (LS)	-2.14	1.17	-4.17	-6.98	-9.54	-11.58**						
	(1.36)	(2.00)	(2.77)	(4.98)	(6.44)	(5.06)						
$\text{Mig}_{i,t}$ (HS)	5.07	-1.82	5.87	14.72	14.32	32.66**						
	(4.43)	(5.53)	(9.41)	(15.09)	(17.31)	(14.83)						
log $\text{Imp}_{i,t}$ (LS)							-0.00	-0.04	0.22	0.79**	0.38	0.78*
							(0.03)	(0.13)	(0.16)	(0.36)	(0.51)	(0.42)
log $\text{Imp}_{i,t}$ (HS)							0.01	0.11	-0.01	-0.78	-0.76	-1.40**
							(0.05)	(0.17)	(0.15)	(0.50)	(0.56)	(0.65)
log $\text{Mig}_{i,t}$ (LS)							-0.01	-0.05	0.15	0.11	0.37	-1.79***
							(0.05)	(0.12)	(0.15)	(0.36)	(0.46)	(0.55)
log $\text{Mig}_{i,t}$ (HS)							0.02	0.05	-0.13	-0.31	-0.49	0.92
							(0.04)	(0.11)	(0.13)	(0.32)	(0.49)	(0.60)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	578	426	438	465	290	289	575	423	437	465	290	289
Pseudo-R^2							0.13	0.28	0.34	0.37	0.38	0.55
R^2	0.48	0.43	0.47	0.36	0.36	0.45						
Panel B - 2SLS & PPML												
$\text{Imp}_{i,t}$ (LS)	1.41	0.25	-0.93	7.94*	11.87	12.21***						
	(1.64)	(5.19)	(1.99)	(4.68)	(10.10)	(3.85)						
$\text{Imp}_{i,t}$ (HS)	-0.01	0.22	0.77	-1.46	-3.76	-1.13						
	(0.35)	(0.58)	(0.78)	(1.40)	(3.10)	(1.75)						
$\text{Mig}_{i,t}$ (LS)	-2.45	-1.29	-4.55	-7.66	-9.76	-15.63**						
	(1.80)	(2.66)	(3.36)	(5.62)	(9.68)	(6.23)						
$\text{Mig}_{i,t}$ (HS)	6.85	-4.58	6.61	12.42	14.37	45.33**						
	(6.25)	(10.85)	(12.01)	(21.11)	(23.85)	(21.77)						
log $\widehat{\text{Imp}}_{i,t}$ (LS)							-0.03	0.03	0.19	0.99*	1.46*	0.28
							(0.07)	(0.20)	(0.27)	(0.55)	(0.85)	(0.73)
log $\widehat{\text{Imp}}_{i,t}$ (HS)							0.03	0.12	-0.01	-1.08	-1.95**	-0.82
							(0.08)	(0.24)	(0.26)	(0.68)	(0.91)	(0.82)
log $\widehat{\text{Mig}}_{i,t}$ (LS)							-0.07	0.11	-0.12	0.77*	1.03*	-1.38**
							(0.09)	(0.16)	(0.21)	(0.43)	(0.61)	(0.69)
log $\widehat{\text{Mig}}_{i,t}$ (HS)							0.12	-0.11	0.20	-1.55***	-1.26	0.32
							(0.09)	(0.19)	(0.21)	(0.47)	(0.84)	(1.00)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	578	426	438	465	290	289	575	423	437	465	290	289
Pseudo-R^2							0.14	0.28	0.33	0.38	0.39	0.54
R^2	0.02	-0.01	0.07	0.07	0.06	0.05						
K-Paap F-stat	28.91	7.95	13.39	19.28	6.97	16.69						

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses. The mean margin is computed over the sample of parties classified as populist or non populist according to a time variant definition.

E.6 Treating Endogenous Variables Separately

Tables E.11 and E.13 provide the results on the volume and mean margin once the skill-specific import and migration flows are treated as endogenous variables separately and not simultaneously. Although such assumption is rather counter intuitive, since there are no specific evidence that justify an exclusive exogeneity of some skill-specific globalization shocks compared to the others, a consistency in the estimated results would minimize concerns driven by the highly demanding econometric specification while instrumenting four endogenous variables simultaneously. The variable instrumented is: low-skill import (cols. 1-3), high-skill import (cols. 4-6), low-skill immigration (cols. 7-9) and high-skill immigration (cols. 10-12). The last three columns report the estimates once the four variables are treated as endogenous simultaneously for a comparison purpose.

Table E.11: Reduced-Form IV PPML Results – Volume (One Endogenous Variable)

	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW
Predicted Var.	$\text{Imp}_{i,t}$ (LS)			$\text{Imp}_{i,t}$ (HS)			$\text{Mig}_{i,t}$ (LS)			$\text{Mig}_{i,t}$ (HS)			All		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
log $\text{Imp}_{i,t}$ (LS)				0.60*	0.59	0.95*	0.76**	0.95*	0.75	0.74**	0.86*	0.94*			
				(0.34)	(0.39)	(0.50)	(0.33)	(0.51)	(0.54)	(0.30)	(0.49)	(0.48)			
log $\text{Imp}_{i,t}$ (HS)	0.08	-0.26	0.19				-0.63	-1.08*	-0.40	-0.59	-0.85	-0.62			
	(0.41)	(0.51)	(0.61)				(0.45)	(0.59)	(0.56)	(0.42)	(0.53)	(0.56)			
log $\text{Mig}_{i,t}$ (LS)	0.06	1.21**	-1.60***	0.15	1.23**	-1.68***				0.07	0.48*	-0.86***			
	(0.36)	(0.56)	(0.56)	(0.35)	(0.52)	(0.54)				(0.13)	(0.29)	(0.26)			
log $\text{Mig}_{i,t}$ (HS)	-0.14	-0.98*	0.89	-0.24	-1.03**	0.90	-0.06	-0.05	-0.27						
	(0.32)	(0.52)	(0.69)	(0.32)	(0.47)	(0.64)	(0.13)	(0.24)	(0.29)						
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.11	0.38	0.04										0.81	1.49*	0.82
	(0.47)	(0.80)	(0.71)										(0.55)	(0.84)	(0.81)
log $\widehat{\text{Imp}}_{i,t}$ (HS)				-0.64	-0.77	-0.91							-0.98	-1.99**	-0.60
				(0.65)	(0.71)	(0.80)							(0.68)	(0.87)	(0.83)
log $\widehat{\text{Mig}}_{i,t}$ (LS)							-0.21	0.35	-1.09**				0.61	1.97***	-1.63**
							(0.34)	(0.45)	(0.55)				(0.46)	(0.62)	(0.78)
log $\widehat{\text{Mig}}_{i,t}$ (HS)										-0.65*	-0.96	-0.00	-1.16**	-2.32***	0.47
										(0.38)	(0.59)	(0.61)	(0.55)	(0.89)	(1.08)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	577	577	577	577	577	577	577	577	577	577	577	577	577	577	577
Pseudo-R^2	0.39	0.32	0.52	0.40	0.33	0.53	0.40	0.32	0.52	0.41	0.33	0.52	0.40	0.34	0.51

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7).

The direction of the correlations between skill-specific globalization shocks and the volume margin is confirmed across specifications. However, the significance of the correlation of a skill-specific flow is affected if only one skill-specific component is treated as endogenous. For instance, the positive correlation of low-skill migration on right-wing populism is not statistically significant once only low-skill immigration (cols. 7-9) or only high skill immigration is treated as endogenous (cols. 10-12). Hence, treating the entire flows (either migration or import) as endogenous appears as an important empirical choice, given the degree of correlation among trade and migration flows presented in Table E.14. Table E.12 confirms this intuition: once either imports or migration flows are treated as endogenous, the estimates are consistent with our benchmark results.

Concerning the mean margin, Table E.13 shows that the estimates are rather stable disregarding the selection of endogenous variables. The F-stat reported in columns (1) to (12) suggest that each instrument is strong enough for its corresponding endogenous variable. Moreover, columns (13) to (15) report, as an alternative proxy of the strength of the instrumental variables, the Shea Partial R^2 (Shea, 1997) associated to each instrument once the other instrumental variables are partial out. The values of the partial R^2 fluctuates around 0.5, providing evidence of our instrumental variables relevance.

Table E.12: Reduced-Form IV PPML Results – Volume (Two Endogenous Variables)

	All	RW	LW	All	RW	LW
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Var.	$\text{Imp}_{i,t}$ (LS)(HS)			$\text{Mig}_{i,t}$ (LS)(HS)		
	(1)	(2)	(3)	(4)	(5)	(6)
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.81	1.25	1.26			
	(0.58)	(0.92)	(0.77)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.94	-1.51*	-1.39			
	(0.79)	(0.92)	(0.87)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)				0.55	1.96***	-1.80**
				(0.46)	(0.59)	(0.80)
log $\widehat{\text{Mig}}_{i,t}$ (HS)				-1.12**	-2.33***	0.64
				(0.51)	(0.81)	(1.04)
log $\text{Imp}_{i,t}$ (LS)				0.79***	1.21**	0.71
				(0.29)	(0.51)	(0.51)
log $\text{Imp}_{i,t}$ (HS)				-0.67	-1.37**	-0.31
				(0.42)	(0.54)	(0.62)
log $\text{Mig}_{i,t}$ (LS)	0.14	1.31**	-1.55***			
	(0.34)	(0.57)	(0.55)			
log $\text{Mig}_{i,t}$ (HS)	-0.22	-1.09**	0.81			
	(0.31)	(0.52)	(0.71)			
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	577	577	577
Pseudo-R^2	0.39	0.33	0.53	0.41	0.34	0.52

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7).

Table E.13: IV Results – Mean Margin

	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW	All	RW	LW
Predicted Var.	$\text{Imp}_{i,t}$ (LS)			$\text{Imp}_{i,t}$ (HS)			$\text{Mig}_{i,t}$ (LS)			$\text{Mig}_{i,t}$ (HS)			All		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
$\text{Imp}_{i,t}$ (LS)	5.21*	2.27	2.12	3.35*	4.48***	-0.66	3.70**	4.04**	-0.16	3.60**	3.85**	-0.17	4.70*	3.21	1.28
	(2.77)	(2.33)	(1.58)	(1.68)	(1.60)	(0.71)	(1.71)	(1.56)	(0.64)	(1.72)	(1.57)	(0.64)	(2.61)	(2.12)	(1.39)
$\text{Imp}_{i,t}$ (HS)	-0.48	-0.21	0.01	-0.04	-0.76*	0.67*	-0.27	-0.49*	0.32	-0.25	-0.43	0.32	-0.23	-0.57	0.43
	(0.59)	(0.38)	(0.30)	(0.49)	(0.42)	(0.39)	(0.45)	(0.29)	(0.23)	(0.46)	(0.30)	(0.23)	(0.56)	(0.41)	(0.38)
$\text{Mig}_{i,t}$ (LS)	-0.38	1.42	-1.43	-0.51	1.70	-1.48	1.33	2.68	-1.07	-1.73	-0.64	-1.62	0.33	0.58	-0.96
	(1.94)	(2.01)	(1.30)	(1.95)	(2.02)	(1.33)	(4.44)	(3.50)	(2.22)	(3.64)	(2.55)	(1.64)	(3.34)	(2.71)	(1.52)
$\text{Mig}_{i,t}$ (HS)	3.37	0.29	4.08	3.76	-0.66	4.23	-1.12	-3.14	3.14	8.73	8.29	4.90	4.50	5.43	4.26
	(4.94)	(4.20)	(3.54)	(4.99)	(4.05)	(3.30)	(11.18)	(8.36)	(5.93)	(14.12)	(7.87)	(5.75)	(10.88)	(7.36)	(4.32)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	580	464	469	580	464	469	580	464	469	580	464	469	580	464	469
R^2	0.05	0.07	-0.01	0.05	0.08	0.01	0.05	0.08	0.02	0.05	0.07	0.02	0.05	0.07	-0.00
K-Paap F-stat	44.52	20.70	32.31	169.53	147.57	196.20	69.22	37.91	59.15	39.77	38.81	115.30	29.89	26.02	12.92
Shea Partial $R^2_{Imp_{LS}}$													0.48	0.39	0.45
Shea Partial $R^2_{Imp_{HS}}$													0.75	0.71	0.76
Shea Partial $R^2_{Mig_{LS}}$													0.63	0.59	0.67
Shea Partial $R^2_{Mig_{HS}}$													0.53	0.52	0.64

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.14: Correlations Between Globalization Flows

	Actual Flows (logs)			
	log $\text{Imp}_{i,t}$ (LS)	log $\text{Imp}_{i,t}$ (HS)	log $\text{Mig}_{i,t}$ (LS)	log $\text{Mig}_{i,t}$ (HS)
log $\text{Imp}_{i,t}$ (LS)	1			
log $\text{Imp}_{i,t}$ (HS)	0.854***	1		
log $\text{Mig}_{i,t}$ (LS)	0.257***	0.310***	1	
log $\text{Mig}_{i,t}$ (HS)	0.148***	0.213***	0.927***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Predicted Flows (logs)			
	log $\widehat{\text{Imp}}_{i,t}$ (LS)	log $\widehat{\text{Imp}}_{i,t}$ (HS)	log $\widehat{\text{Mig}}_{i,t}$ (LS)	log $\widehat{\text{Mig}}_{i,t}$ (HS)
log $\widehat{\text{Imp}}_{i,t}$ (LS)	1			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	0.832***	1		
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.233***	0.329***	1	
log $\widehat{\text{Mig}}_{i,t}$ (HS)	0.120**	0.225***	0.932***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Actual Flows			
	$\text{Imp}_{i,t}$ (LS)	$\text{Imp}_{i,t}$ (HS)	$\text{Mig}_{i,t}$ (LS)	$\text{Mig}_{i,t}$ (HS)
$\text{Imp}_{i,t}$ (LS)	1			
$\text{Imp}_{i,t}$ (HS)	0.720***	1		
$\text{Mig}_{i,t}$ (LS)	0.256***	0.296***	1	
$\text{Mig}_{i,t}$ (HS)	0.0557	0.122**	0.708***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Predicted Flows			
	$\widehat{\text{Imp}}_{i,t}$ (LS)	$\widehat{\text{Imp}}_{i,t}$ (HS)	$\widehat{\text{Mig}}_{i,t}$ (LS)	$\widehat{\text{Mig}}_{i,t}$ (HS)
$\widehat{\text{Imp}}_{i,t}$ (LS)	1			
$\widehat{\text{Imp}}_{i,t}$ (HS)	0.744***	1		
$\widehat{\text{Mig}}_{i,t}$ (LS)	0.215***	0.293***	1	
$\widehat{\text{Mig}}_{i,t}$ (HS)	0.00337	0.0913*	0.674***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

E.7 Additional Results: Role of Electoral System

Tables E.15 and E.16 explore the potential implications driven by the country-specific institutional setting defining the electoral rules. Relying on the Electoral System Design database developed by the International Institute for Democracy and Electoral Assistance (IDEA) (Reynolds et al., 2008), we collect information on countries' electoral system from 1990 to recent years, and we construct a dummy variable that takes a value of one if the electoral system is characterized by a proportional representation (PR).

Proportional representation implies a direct translation of the votes for a party into a corresponding proportion of seats in the parliament. It might be argued that new and small populist parties benefit from such type of electoral system. Due to the lack of information on the pre-1990 period, we impute the electoral system of each country over such period based on their electoral system in the first available election year. Table E.15 shows that controlling for having a proportional system do not influence the skill-specific effect of migration and imports on the volume and mean margins of populism.

Additionally, Table E.16 includes interaction terms with low-skill specific globalization shocks. Interestingly, the results show that imports have a strong and positive effect on the left-wing volume margin in countries with a proportional representation, while there is no specific effect on right-wing margins. This result suggests that left-wing populist parties, in presence of skill-specific import shocks, are particularly able to exploit the institutional setting to enhance their electoral gains.

Table E.15: Reduced-Form IV PPML and 2SLS Results – Controlling for PR

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
PR	-1.08*	-1.30	0.43	-0.15	-0.09	0.05
	(0.65)	(1.00)	(0.75)	(0.09)	(0.09)	(0.09)
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.89	1.74**	0.71			
	(0.55)	(0.85)	(0.83)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.93	-2.10**	-0.54			
	(0.67)	(0.86)	(0.86)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.53	2.10***	-1.72**			
	(0.46)	(0.58)	(0.78)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.23**	-2.68***	0.57			
	(0.52)	(0.77)	(1.08)			
$\text{Imp}_{i,t}$ (LS)				4.93*	3.39	1.37
				(2.65)	(2.04)	(1.40)
$\text{Imp}_{i,t}$ (HS)				-0.21	-0.53	0.43
				(0.57)	(0.40)	(0.39)
$\text{Mig}_{i,t}$ (LS)				0.23	0.57	-0.93
				(3.34)	(2.71)	(1.53)
$\text{Mig}_{i,t}$ (HS)				4.15	4.78	4.21
				(10.79)	(7.26)	(4.39)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	574	574	574	577	462	467
Pseudo-R^2	0.41	0.36	0.52			
R^2				0.05	0.08	-0.00
K-Paap F-stat				27.82	23.75	14.37

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.16: Reduced-Form IV PPML and 2SLS Results – Interactions with PR

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.76	2.20**	0.11			
	(0.63)	(0.88)	(1.05)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.82	-2.10**	-1.07			
	(0.64)	(0.93)	(0.83)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.07	1.81***	-2.32***			
	(0.48)	(0.69)	(0.83)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.34**	-2.77***	1.37			
	(0.53)	(0.74)	(1.00)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) × PR	0.21	-0.62	2.40**			
	(0.51)	(0.64)	(0.95)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) × PR	0.76*	0.39	0.38			
	(0.46)	(0.63)	(0.69)			
$\text{Imp}_{i,t}$ (LS)				7.13*	5.52*	-0.79
				(3.78)	(3.21)	(2.10)
$\text{Imp}_{i,t}$ (HS)				-0.14	-0.50	0.42
				(0.56)	(0.40)	(0.39)
$\text{Mig}_{i,t}$ (LS)				4.76	3.19	-1.16
				(3.85)	(3.01)	(2.78)
$\text{Mig}_{i,t}$ (HS)				2.60	4.08	4.36
				(11.04)	(7.35)	(3.85)
$\text{Imp}_{i,t}$ (LS) × PR				-2.26	-2.11	2.10
				(2.73)	(2.53)	(1.71)
$\text{Mig}_{i,t}$ (LS) × PR				-4.66*	-2.96	0.22
				(2.67)	(2.52)	(2.73)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	574	574	574	577	462	467
Pseudo-R^2	0.42	0.37	0.54			
R^2				0.05	0.08	0.01
K-Paap F-stat				16.56	13.22	10.71

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.8 Additional Results: Detailed Robustness Checks

In the subsections below, we conduct a robustness analysis and produce results with alternative lag structure for computing globalization shocks, alternative party classifications, alternative measures of migration shocks (including interactions between migration inflows and stocks) and import shocks, alternative classification of low-skill intensive shocks, interactions with period and region dummies, alternative structure of year-specific fixed effects (6-years), and including economic-specific controls, such as employment rate and GDP per capita.

E.8.1 Alternative Lag Structures

Table E.17: IV Results with Globalization Shocks at Time t

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{it}$ (LS)	0.56	0.81	1.05			
	(0.54)	(0.83)	(0.86)			
log $\widehat{\text{Imp}}_{it}$ (HS)	-0.84	-0.83	-1.31			
	(0.82)	(1.01)	(0.97)			
log $\widehat{\text{Mig}}_{it}$ (LS)	0.42	1.68***	-1.56**			
	(0.45)	(0.53)	(0.74)			
log $\widehat{\text{Mig}}_{it}$ (HS)	-1.10**	-2.01**	0.34			
	(0.54)	(0.81)	(0.97)			
Imp_{it} (LS)				7.86	5.65	1.13
				(5.07)	(4.07)	(2.47)
Imp_{it} (HS)				-0.35	-0.64	0.79
				(1.06)	(0.67)	(0.71)
Mig_{it} (LS)				0.12	0.07	-2.04
				(6.56)	(5.43)	(3.20)
Mig_{it} (HS)				5.90	9.75	5.83
				(23.09)	(14.88)	(8.65)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	593	593	593	593	474	478
Pseudo-R^2	0.41	0.33	0.51			
R^2				0.04	0.07	0.01
K-Paap F-stat				24.49	12.46	18.33

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.18: IV Results with Globalization Shocks at Time $t-1$

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
$\log \widehat{\text{Imp}}_{i,t-1}$ (LS)	0.98**	1.68**	0.85			
	(0.48)	(0.79)	(0.75)			
$\log \widehat{\text{Imp}}_{i,t-1}$ (HS)	-1.39***	-2.24***	-1.08			
	(0.52)	(0.70)	(0.75)			
$\log \widehat{\text{Mig}}_{i,t-1}$ (LS)	0.73	2.25***	-1.72**			
	(0.45)	(0.70)	(0.79)			
$\log \widehat{\text{Mig}}_{i,t-1}$ (HS)	-1.39**	-2.67***	0.46			
	(0.54)	(0.99)	(0.94)			
$\text{Imp}_{i,t-1}$ (LS)				6.97	6.52	1.71
				(4.62)	(4.47)	(2.27)
$\text{Imp}_{i,t-1}$ (HS)				-0.23	-1.06	0.81
				(1.09)	(0.83)	(0.69)
$\text{Mig}_{i,t-1}$ (LS)				-0.63	0.63	-2.19
				(6.53)	(5.27)	(3.04)
$\text{Mig}_{i,t-1}$ (HS)				10.47	10.62	8.08
				(20.77)	(15.09)	(8.29)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	580	580	580	580	464	469
Pseudo-R^2	0.41	0.35	0.52			
R^2				0.04	0.05	0.00
K-Paap F-stat				17.24	10.79	12.16

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.19: IV Results with Globalization Shocks at Time $t-2$

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t-2}$ (LS)	0.74	1.36	0.75			
	(0.51)	(0.92)	(0.83)			
log $\widehat{\text{Imp}}_{i,t-2}$ (HS)	-1.08**	-1.66*	-1.40*			
	(0.54)	(0.93)	(0.84)			
log $\widehat{\text{Mig}}_{i,t-2}$ (LS)	0.85**	2.42***	-1.56*			
	(0.41)	(0.72)	(0.81)			
log $\widehat{\text{Mig}}_{i,t-2}$ (HS)	-1.52***	-2.82***	0.33			
	(0.47)	(1.04)	(0.96)			
$\text{Imp}_{i,t-2}$ (LS)				8.06	7.68	1.79
				(5.41)	(4.85)	(2.52)
$\text{Imp}_{i,t-2}$ (HS)				-0.70	-1.21	0.80
				(1.25)	(0.90)	(0.78)
$\text{Mig}_{i,t-2}$ (LS)				-0.74	1.37	-2.54
				(6.56)	(5.43)	(3.06)
$\text{Mig}_{i,t-2}$ (HS)				10.99	8.34	7.71
				(19.51)	(16.51)	(8.06)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	572	572	572	572	459	463
Pseudo-R^2	0.41	0.36	0.52			
R^2				0.02	0.01	-0.00
K-Paap F-stat				28.50	10.02	23.78

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.20: IV Results with Globalization Shocks Between $t-2$ and t

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
$\log \widehat{\text{Imp}}_{i,t-2\to t}$ (LS)	0.61	1.15	0.68			
	(0.57)	(0.97)	(0.89)			
$\log \widehat{\text{Imp}}_{i,t-2\to t}$ (HS)	-0.88	-1.71*	-0.78			
	(0.67)	(0.92)	(0.83)			
$\log \widehat{\text{Mig}}_{i,t-2\to t}$ (LS)	0.73	2.30***	-1.57**			
	(0.45)	(0.68)	(0.78)			
$\log \widehat{\text{Mig}}_{i,t-2\to t}$ (HS)	-1.44***	-2.88***	0.23			
	(0.51)	(0.99)	(1.02)			
$\text{Imp}_{i,t-2\to t}$ (LS)				2.88	2.31	0.80
				(1.81)	(1.45)	(0.93)
$\text{Imp}_{i,t-2\to t}$ (HS)				-0.18	-0.39	0.26
				(0.38)	(0.29)	(0.26)
$\text{Mig}_{i,t-2\to t}$ (LS)				0.04	0.56	-0.73
				(2.22)	(1.82)	(1.02)
$\text{Mig}_{i,t-2\to t}$ (HS)				2.84	2.66	2.79
				(7.28)	(5.47)	(2.85)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	572	572	572	572	459	463
Pseudo-R^2	0.41	0.35	0.52			
R^2				0.04	0.06	-0.01
K-Paap F-stat				25.02	13.56	22.36

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.21: IV Results with Globalization Shocks Between Two Elections

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t-e\to t}$ (LS)	0.78	0.86	2.16**			
	(0.59)	(0.99)	(1.03)			
log $\widehat{\text{Imp}}_{i,t-e\to t}$ (HS)	-0.58	-1.00	-1.70*			
	(0.63)	(0.96)	(0.87)			
log $\widehat{\text{Mig}}_{i,t-e\to t}$ (LS)	0.40	1.73***	-1.76**			
	(0.48)	(0.63)	(0.83)			
log $\widehat{\text{Mig}}_{i,t-e\to t}$ (HS)	-0.90*	-2.06***	0.86			
	(0.50)	(0.76)	(1.12)			
$\text{Imp}_{i,t-e\to t}$ (LS)				1.05	1.29*	0.06
				(0.74)	(0.71)	(0.39)
$\text{Imp}_{i,t-e\to t}$ (HS)				-0.16	-0.28	0.08
				(0.20)	(0.20)	(0.10)
$\text{Mig}_{i,t-e\to t}$ (LS)				-1.18	-0.54	-0.76
				(1.44)	(1.01)	(0.66)
$\text{Mig}_{i,t-e\to t}$ (HS)				-1.44	-0.16	-0.12
				(3.45)	(2.12)	(1.73)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	582	582	582	582	463	473
Pseudo-R^2	0.41	0.34	0.53			
R^2				0.03	0.04	0.00
K-Paap F-stat				7.97	4.55	7.03

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.8.2 Alternative Party Classifications and Populism Score Measures

Table E.22: IV Results with Lax and Strict Definitions of Populist Parties

	Lax Definition (>0.9 SD)			Strict Definition (>1.1 SD)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.80	1.07	0.92	0.58	0.22	1.24
	(0.55)	(0.90)	(0.86)	(0.61)	(0.93)	(0.94)
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.77	-1.32	-0.69	-0.66	-0.38	-1.44
	(0.68)	(0.94)	(0.86)	(0.75)	(0.94)	(0.90)
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.51	1.63**	-1.81**	0.70	1.94***	-1.39
	(0.46)	(0.65)	(0.72)	(0.44)	(0.73)	(0.86)
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-0.94	-1.81**	0.60	-1.37**	-2.37**	-0.07
	(0.58)	(0.89)	(1.03)	(0.56)	(1.00)	(1.16)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	577	577	577
Pseudo-R^2	0.39	0.33	0.47	0.38	0.32	0.54

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in columns (1) to (6) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7).

Table E.23: IV Results Using the 3C Populism Score

	Volume ($\Pi^{V}_{i,e,t}$)			Mean ($\Pi^{M}_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
$\log \widehat{\text{Imp}}_{i,t}$ (LS)	0.15	0.64	1.02			
	(0.58)	(0.68)	(1.04)			
$\log \widehat{\text{Imp}}_{i,t}$ (HS)	-0.14	-0.63	-0.07			
	(0.74)	(0.86)	(1.29)			
$\log \widehat{\text{Mig}}_{i,t}$ (LS)	1.07***	2.17***	-1.01*			
	(0.39)	(0.59)	(0.53)			
$\log \widehat{\text{Mig}}_{i,t}$ (HS)	-1.71***	-2.46***	-0.79			
	(0.47)	(0.84)	(0.71)			
$\text{Imp}_{i,t}$ (LS)				8.12*	5.94**	2.67
				(4.44)	(2.82)	(2.32)
$\text{Imp}_{i,t}$ (HS)				-0.01	-0.73	0.87*
				(0.79)	(0.72)	(0.49)
$\text{Mig}_{i,t}$ (LS)				3.78	5.76	-2.05
				(4.30)	(3.50)	(3.09)
$\text{Mig}_{i,t}$ (HS)				-4.29	-4.88	8.63
				(14.61)	(9.35)	(8.92)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.46	0.35	0.63			
R^2				0.01	0.06	-0.01
K-Paap F-stat				29.89	26.02	12.92

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.24: IV Results Using the 15C Populism Score

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.50	1.03	1.17			
	(0.54)	(0.69)	(1.10)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.26	-1.20	0.03			
	(0.61)	(0.83)	(0.92)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.73**	1.90***	-0.45			
	(0.29)	(0.45)	(0.39)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-0.73*	-1.79***	0.08			
	(0.39)	(0.54)	(0.51)			
$\text{Imp}_{i,t}$ (LS)				7.75	3.98	4.13
				(6.82)	(2.93)	(3.17)
$\text{Imp}_{i,t}$ (HS)				-0.07	-0.49	0.56
				(1.02)	(0.64)	(0.44)
$\text{Mig}_{i,t}$ (LS)				7.61	4.03	1.13
				(5.59)	(3.38)	(3.39)
$\text{Mig}_{i,t}$ (HS)				21.31	11.10	10.68
				(22.13)	(11.49)	(9.58)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.51	0.43	0.57			
R^2				0.01	0.02	-0.02
K-Paap F-stat				29.89	26.02	12.92

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.25: IV Results Replacing the CTP with the Net Autarky

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.65	1.16	1.91**			
	(0.63)	(0.77)	(0.95)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.05	-1.23	-2.59***			
	(0.78)	(0.85)	(0.82)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.34	1.47**	-2.13***			
	(0.56)	(0.66)	(0.73)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-0.65	-1.61**	1.06			
	(0.67)	(0.79)	(1.01)			
$\text{Imp}_{i,t}$ (LS)				4.08	3.50	0.72
				(3.20)	(2.35)	(1.45)
$\text{Imp}_{i,t}$ (HS)				-0.22	-0.54	0.42
				(0.69)	(0.49)	(0.36)
$\text{Mig}_{i,t}$ (LS)				-0.36	1.61	-1.30
				(4.06)	(2.97)	(1.59)
$\text{Mig}_{i,t}$ (HS)				5.27	2.61	3.83
				(12.90)	(7.93)	(5.32)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.37	0.30	0.66			
R^2				0.04	0.07	0.01
K-Paap F-stat				29.89	26.02	12.92

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.8.3 Exclusion of Parties with changing ideology

In our baseline results, we categorize parties along the right-left political spectrum using the right-left index (rile) provided by the MPD (Budge and Laver, 2016). Specifically, we designate parties falling within the first tercile as LW, those in the third tercile as RW, and parties in the second tercile as centrist. As this right-left index is derived from parties' manifestos, it can exhibit variations over time. Consequently, a party's classification on the right-left spectrum may change over time.

To assess the robustness of our results to shifts in parties' ideological positioning, this section presents findings after (i) excluding parties classified as LW in half of the elections and RW in the other half (Table E.26); (ii) excluding parties classified as LW in at least 40% of the elections and RW in another 40% (Table E.27); (iii) excluding parties classified as LW in at least 30% of the elections and RW in another 30% (Table E.28). Overall, the results concerning the volume margin remain highly robust even after excluding these parties. The correlations between skill-specific globalization shocks and the volume margin are less significant in relation to the mean margin, but the direction of the effects persists.

Table E.26: IV Results After Excluding Unstable Parties (Classified as LW or RW in 50% of the Elections)

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.81	1.51*	0.71			
	(0.55)	(0.85)	(0.89)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.98	-1.99**	-0.92			
	(0.68)	(0.86)	(0.87)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.61	1.96***	-1.66**			
	(0.46)	(0.62)	(0.79)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.16**	-2.28**	0.46			
	(0.55)	(0.89)	(1.05)			
$\text{Imp}_{i,t}$ (LS)				4.70*	3.54	5.85*
				(2.61)	(4.93)	(3.18)
$\text{Imp}_{i,t}$ (HS)				-0.23	-0.72	0.39
				(0.56)	(0.83)	(0.86)
$\text{Mig}_{i,t}$ (LS)				0.33	0.91	-6.57
				(3.34)	(4.95)	(4.25)
$\text{Mig}_{i,t}$ (HS)				4.50	0.21	16.73
				(10.88)	(16.80)	(12.11)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	463	466
Pseudo-R^2	0.40	0.34	0.54			
R^2				0.05	0.05	0.02
K-Paap F-stat				29.89	23.66	13.29

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The analysis excludes parties that have been categorized as LW in 50% of the elections in which they participated, and as RW in the remaining half.

Table E.27: IV Results After Excluding Unstable Parties (Classified as LW or RW in 40% of the Elections)

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.81	1.55*	0.56			
	(0.55)	(0.87)	(0.93)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.98	-2.02**	-0.73			
	(0.68)	(0.87)	(0.97)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.61	1.77***	-1.66**			
	(0.46)	(0.61)	(0.82)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.16**	-2.06**	0.38			
	(0.55)	(0.90)	(1.04)			
$\text{Imp}_{i,t}$ (LS)				4.70*	4.03	5.76*
				(2.61)	(4.81)	(3.09)
$\text{Imp}_{i,t}$ (HS)				-0.23	-0.72	0.36
				(0.56)	(0.83)	(0.86)
$\text{Mig}_{i,t}$ (LS)				0.33	0.07	-7.60
				(3.34)	(4.54)	(4.78)
$\text{Mig}_{i,t}$ (HS)				4.50	2.51	16.84
				(10.88)	(16.02)	(12.32)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	463	465
Pseudo-R^2	0.40	0.32	0.54			
R^2				0.05	0.05	0.03
K-Paap F-stat				29.89	23.66	13.29

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The analysis excludes parties that have been categorized both as LW in at least 40% of the elections in which they participated and as RW in at least another 40% .

Table E.28: IV Results After Excluding Unstable Parties (Classified as LW or RW in 30% of the Elections)

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.81	1.92**	0.62			
	(0.55)	(0.92)	(1.10)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.98	-2.10**	-0.94			
	(0.68)	(0.89)	(1.00)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.61	1.80***	-1.49*			
	(0.46)	(0.62)	(0.85)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.16**	-1.95**	0.10			
	(0.55)	(0.94)	(1.12)			
$\text{Imp}_{i,t}$ (LS)				4.70*	3.80	4.49
				(2.61)	(4.91)	(3.24)
$\text{Imp}_{i,t}$ (HS)				-0.23	-0.56	0.52
				(0.56)	(0.90)	(0.85)
$\text{Mig}_{i,t}$ (LS)				0.33	0.97	-6.17
				(3.34)	(4.62)	(4.62)
$\text{Mig}_{i,t}$ (HS)				4.50	7.18	7.50
				(10.88)	(14.42)	(14.21)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	455	459
Pseudo-R^2	0.40	0.34	0.52			
R^2				0.05	0.08	0.05
K-Paap F-stat				29.89	18.07	12.86

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The analysis excludes parties that have been categorized both as LW in at least 30% of the elections in which they participated and as RW in at least another 30% .

E.8.4 Alternative Measures of Migration Shocks

Table E.29: IV Results with Skill-Selection Imputed Using Data for the Year 2000

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.84	1.43	0.88			
	(0.59)	(0.90)	(0.84)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.99	-1.85**	-0.71			
	(0.71)	(0.92)	(0.80)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.60	1.71**	-1.19			
	(0.54)	(0.69)	(0.76)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.06*	-1.82*	-0.07			
	(0.58)	(0.99)	(1.01)			
$\text{Imp}_{i,t}$ (LS)				4.49*	3.15	1.22
				(2.61)	(2.12)	(1.40)
$\text{Imp}_{i,t}$ (HS)				-0.27	-0.59	0.43
				(0.55)	(0.41)	(0.37)
$\text{Mig}_{i,t}$ (LS)				4.69	2.03	-0.19
				(3.80)	(3.03)	(1.79)
$\text{Mig}_{i,t}$ (HS)				-13.36	-0.16	1.12
				(14.69)	(8.44)	(4.54)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.40	0.32	0.51			
R^2				0.03	0.08	-0.00
K-Paap F-stat				12.51	14.60	22.64

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.30: IV Results Using Interactions with 1960 Immigrants' Share in Total Population

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.87	1.47*	0.73			
	(0.54)	(0.84)	(0.76)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.05	-1.98**	-0.90			
	(0.66)	(0.85)	(0.86)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.28	1.71***	-1.81**			
	(0.48)	(0.63)	(0.79)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.13**	-2.25***	0.04			
	(0.52)	(0.87)	(1.05)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) $\times$ dSH^B_{1960}	0.75	0.40	1.18			
	(0.51)	(1.11)	(0.77)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) $\times$ dSH^T_{1960}	1.47**	1.62	3.74**			
	(0.72)	(1.09)	(1.50)			
$\text{Imp}_{i,t}$ (LS)				4.44	4.25*	0.84
				(2.68)	(2.33)	(1.52)
$\text{Imp}_{i,t}$ (HS)				-0.14	-0.70	0.47
				(0.57)	(0.43)	(0.38)
$\text{Mig}_{i,t}$ (LS)				-1.64	0.99	-1.41
				(4.37)	(3.35)	(2.04)
$\text{Mig}_{i,t}$ (HS)				5.07	8.12	3.00
				(10.95)	(7.66)	(4.46)
$\text{Mig}_{i,t}$ (LS) $\times$ dSH^B_{1960}				4.53	3.93	-1.02
				(4.82)	(4.78)	(1.97)
$\text{Mig}_{i,t}$ (LS) $\times$ dSH^T_{1960}				1.81	-3.20	1.51
				(4.52)	(3.62)	(2.60)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.41	0.34	0.53			
R^2				0.05	0.09	0.01
K-Paap F-stat				25.97	6.27	13.56

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. d$Share^B_{1960}$ and d$Share^T_{1960}$ are dummies equal to one if the country belong the bottom or top quartile in terms o immigration share in the 1960, respectively.

E.8.5 Alternative Measures of Import Shocks

Table E.31: IV Results with Labor-Intensive Imports

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.99	1.64	-1.02			
	(0.77)	(1.10)	(1.32)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.86	-1.90**	-2.38			
	(0.72)	(0.96)	(1.60)			
log $\widehat{\text{Imp}}_{i,t}$ (LAB)	-0.29	-0.22	3.71*			
	(0.72)	(0.92)	(2.15)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.60	1.97***	-1.70**			
	(0.45)	(0.62)	(0.86)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.15**	-2.32***	0.38			
	(0.56)	(0.90)	(1.16)			
$\text{Imp}_{i,t}$ (LS)				5.20**	4.63**	1.63
				(2.57)	(2.06)	(1.34)
$\text{Imp}_{i,t}$ (HS)				-0.11	-0.33	0.54
				(0.66)	(0.45)	(0.41)
$\text{Imp}_{i,t}$ (LAB)				-0.92	-2.15*	-0.69
				(1.35)	(1.14)	(0.68)
$\text{Mig}_{i,t}$ (LS)				-0.27	-0.39	-1.49
				(3.77)	(3.08)	(1.47)
$\text{Mig}_{i,t}$ (HS)				5.38	6.60	5.10
				(10.90)	(6.99)	(3.80)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.40	0.34	0.53			
R^2				0.05	0.06	0.01
K-Paap F-stat				16.34	6.21	21.96

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.32: IV Results with Imports of Medium-Skilled Intensive Goods

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.98	0.63	2.23**			
	(0.87)	(1.12)	(0.95)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.80	-2.85*	0.79			
	(0.84)	(1.48)	(0.74)			
log $\widehat{\text{Imp}}_{i,t}$ (MS)	-0.37	1.83	-3.00***			
	(1.36)	(2.09)	(1.07)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.60	2.03***	-1.64**			
	(0.45)	(0.62)	(0.80)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.13**	-2.49***	0.89			
	(0.53)	(0.97)	(0.99)			
$\text{Imp}_{i,t}$ (LS)				6.97**	4.36	2.77*
				(2.95)	(2.96)	(1.43)
$\text{Imp}_{i,t}$ (HS)				0.23	-0.30	0.71*
				(0.70)	(0.48)	(0.41)
$\text{Imp}_{i,t}$ (MS)				-1.75	-0.94	-1.17**
				(1.34)	(1.29)	(0.50)
$\text{Mig}_{i,t}$ (LS)				-0.67	0.30	-1.84
				(3.48)	(2.88)	(1.44)
$\text{Mig}_{i,t}$ (HS)				7.36	6.84	6.48
				(10.77)	(7.50)	(4.45)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.40	0.34	0.52			
R^2				0.06	0.07	0.01
K-Paap F-stat				22.46	22.63	28.46

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.8.6 Origin-specific Measures of Migration and Imports shocks

Table E.33: IV Results with Skill-Origin Specific Flows

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
$\log \widehat{\text{Imp}}_{i,t}$ (LS-LI)	0.83***	1.47***	0.53*			
	(0.15)	(0.28)	(0.32)			
$\log \widehat{\text{Imp}}_{i,t}$ (LS-HI)	-0.01	-0.06	0.36			
	(0.38)	(0.74)	(0.95)			
$\log \widehat{\text{Imp}}_{i,t}$ (HS-LI)	0.05	-0.41	0.38			
	(0.21)	(0.43)	(0.26)			
$\log \widehat{\text{Imp}}_{i,t}$ (HS-HI)	-1.37**	-1.89**	-1.43			
	(0.67)	(0.87)	(1.01)			
$\log \widehat{\text{Mig}}_{i,t}$ (LS-LI)	0.96***	2.12***	-2.07**			
	(0.34)	(0.53)	(0.87)			
$\log \widehat{\text{Mig}}_{i,t}$ (LS-HI)	0.15	-0.40	0.86*			
	(0.42)	(0.60)	(0.47)			
$\log \widehat{\text{Mig}}_{i,t}$ (HS-LI)	-1.32***	-2.27***	1.35			
	(0.38)	(0.53)	(1.04)			
$\log \widehat{\text{Mig}}_{i,t}$ (HS-HI)	-0.32	0.13	-1.69***			
	(0.50)	(0.76)	(0.53)			
$\text{Imp}_{i,t}$ (LS-LI)				10.90	2.62	4.35
				(7.59)	(6.39)	(5.65)
$\text{Imp}_{i,t}$ (LS-HI)				3.91	1.70	1.48
				(2.54)	(2.30)	(1.27)
$\text{Imp}_{i,t}$ (HS-LI)				2.64	-0.59	5.30
				(3.17)	(2.04)	(3.66)
$\text{Imp}_{i,t}$ (HS-HI)				-0.50	-0.35	0.05
				(0.53)	(0.46)	(0.33)
$\text{Mig}_{i,t}$ (LS-LI)				-1.92	3.61	-4.00*
				(6.02)	(5.03)	(2.11)
$\text{Mig}_{i,t}$ (LS-HI)				8.03*	3.22	3.13
				(4.23)	(4.06)	(1.94)
$\text{Mig}_{i,t}$ (HS-LI)				13.29	3.40	11.26**
				(12.16)	(7.14)	(4.66)
$\text{Mig}_{i,t}$ (HS-HI)				-27.84	-19.27	-6.87
				(21.01)	(19.42)	(7.70)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.45	0.42	0.54			
R^2				0.03	0.04	0.01
K-Paap F-stat				6.25	2.83	1.87

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.8.7 Analysis by Sub-sample

Table E.34: IV Results Using Interactions with Post-1990 Dummy

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	1.05*	2.47***	0.68			
	(0.59)	(0.80)	(0.81)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.80	-2.02**	-0.70			
	(0.78)	(0.91)	(0.86)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.59	2.11***	-1.63**			
	(0.42)	(0.56)	(0.82)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.33**	-3.12***	0.51			
	(0.65)	(0.76)	(1.08)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) × $d_{post1990}$	-0.57	-1.56***	0.36			
	(0.35)	(0.46)	(0.33)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) × $d_{post1990}$	0.68*	2.12***	-0.44			
	(0.39)	(0.62)	(0.29)			
$\text{Imp}_{i,t}$ (LS)				5.89**	4.25**	0.50
				(2.74)	(1.61)	(1.62)
$\text{Imp}_{i,t}$ (HS)				0.02	0.11	0.18
				(0.59)	(0.55)	(0.38)
$\text{Mig}_{i,t}$ (LS)				0.00	1.19	-1.52
				(3.11)	(2.89)	(1.75)
$\text{Mig}_{i,t}$ (HS)				-2.52	-0.68	6.91
				(11.23)	(7.62)	(4.70)
$\text{Imp}_{i,t}$ (LS) $\times d_{post1990}$				-3.27	-5.46**	2.27
				(2.07)	(2.10)	(1.44)
$\text{Mig}_{i,t}$ (LS) $\times d_{post1990}$				4.86**	4.31*	-1.25
				(1.94)	(2.50)	(1.40)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.42	0.40	0.52			
R^2				0.04	0.05	-0.00
K-Paap F-stat				12.79	3.93	16.87

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.35: IV Results Using Interactions with Post-2001 Dummy

	Volume ($\Pi^{V}_{i,e,t}$)			Mean ($\Pi^{M}_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	1.14**	1.57*	1.87**			
	(0.57)	(0.86)	(0.86)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.31*	-2.08**	-1.49*			
	(0.74)	(0.92)	(0.86)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.64	1.97***	-1.66**			
	(0.45)	(0.62)	(0.83)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.14**	-2.31**	0.56			
	(0.55)	(0.90)	(1.07)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) $\times$ $d_{post2001}$	0.56*	0.14	1.13***			
	(0.31)	(0.37)	(0.34)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) $\times$ $d_{post2001}$	-0.03	0.01	0.18			
	(0.19)	(0.27)	(0.40)			
$\text{Imp}_{i,t}$ (LS)				4.96	3.69*	0.17
				(3.09)	(2.14)	(1.66)
$\text{Imp}_{i,t}$ (HS)				-0.17	-0.44	0.34
				(0.59)	(0.45)	(0.35)
$\text{Mig}_{i,t}$ (LS)				-0.49	0.09	-2.03
				(3.90)	(3.13)	(1.46)
$\text{Mig}_{i,t}$ (HS)				4.43	5.56	5.89
				(11.22)	(7.50)	(3.80)
$\text{Imp}_{i,t}$ (LS) $\times d_{post2001}$				-1.04	-1.45	1.00
				(2.06)	(1.80)	(0.95)
$\text{Mig}_{i,t}$ (LS) $\times d_{post2001}$				2.66	2.26	1.30
				(2.58)	(1.60)	(1.22)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.41	0.34	0.54			
R^2				0.05	0.07	0.03
K-Paap F-stat				15.47	19.17	11.03

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.36: IV Results Using Interactions with EU28 Dummy

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.48	1.28	0.08			
	(0.52)	(0.84)	(0.97)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.99	-1.97**	-0.90			
	(0.68)	(0.95)	(0.78)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	-0.14	1.39*	-2.30***			
	(0.43)	(0.81)	(0.89)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-0.91	-2.08**	0.85			
	(0.56)	(0.96)	(1.01)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) $\times$ d_{EU28}	1.17**	0.48	2.22***			
	(0.49)	(0.68)	(0.83)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) $\times$ d_{EU28}	1.27***	0.85	0.97			
	(0.46)	(0.96)	(0.81)			
$\text{Imp}_{i,t}$ (LS)				5.89**	5.14***	1.08
				(2.89)	(1.92)	(1.50)
$\text{Imp}_{i,t}$ (HS)				-0.41	-0.48	0.34
				(0.66)	(0.41)	(0.40)
$\text{Mig}_{i,t}$ (LS)				-6.08	-3.18	-2.99**
				(3.83)	(2.35)	(1.37)
$\text{Mig}_{i,t}$ (HS)				14.61	12.72*	7.74
				(11.70)	(6.76)	(4.71)
$\text{Imp}_{i,t}$ (LS) $\times d_{EU28}$				-1.71	-3.25*	0.23
				(3.21)	(1.73)	(1.73)
$\text{Mig}_{i,t}$ (LS) $\times d_{EU28}$				9.06***	5.01	2.84*
				(3.02)	(3.13)	(1.62)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.43	0.34	0.54			
R^2				0.03	0.09	-0.02
K-Paap F-stat				8.02	4.38	9.84

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.37: IV Results Using Interactions for Welfare Expenditure

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.50	1.32	0.29			
	(0.54)	(0.82)	(0.86)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.51	-1.80*	0.08			
	(0.65)	(0.95)	(0.82)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.46	2.16***	-2.20***			
	(0.49)	(0.70)	(0.85)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.28**	-2.55***	0.47			
	(0.57)	(0.97)	(1.07)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) $\times$ d_{Welf}	1.04*	0.85	0.57			
	(0.54)	(0.95)	(0.77)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) $\times$ d_{Welf}	0.80	0.03	1.52*			
	(0.53)	(0.96)	(0.80)			
$\text{Imp}_{i,t}$ (LS)				5.73**	2.76	2.39
				(2.73)	(2.15)	(1.91)
$\text{Imp}_{i,t}$ (HS)				-0.07	-0.63	0.54
				(0.54)	(0.44)	(0.39)
$\text{Mig}_{i,t}$ (LS)				-4.43	0.18	-4.09***
				(4.36)	(3.37)	(1.02)
$\text{Mig}_{i,t}$ (HS)				9.05	6.29	7.64*
				(11.25)	(7.31)	(4.33)
$\text{Imp}_{i,t}$ (LS) $\times d_{Welf}$				-3.37	1.01	-2.40
				(2.27)	(2.24)	(1.84)
$\text{Mig}_{i,t}$ (LS) $\times d_{Welf}$				7.73**	0.77	4.58***
				(3.47)	(3.61)	(1.26)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.41	0.34	0.52			
R^2				0.04	0.06	0.01
K-Paap F-stat				18.18	9.36	3.05

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.38: IV Results Using Interactions with Human Capital

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.29	1.83	0.07			
	(1.44)	(1.94)	(1.61)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.12	-1.79	4.89*			
	(1.27)	(1.86)	(2.79)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	3.35**	6.32***	0.82			
	(1.30)	(2.21)	(2.24)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-3.46***	-7.33***	-3.14			
	(1.32)	(1.80)	(2.07)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) × log HC_{it-2}	0.18	-0.77	0.57			
	(1.47)	(1.85)	(1.88)			
log $\widehat{\text{Imp}}_{i,t}$ (HS) × log HC_{it-2}	-0.75	-0.15	-6.04**			
	(1.42)	(2.01)	(2.97)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) × log HC_{it-2}	-3.27**	-4.93*	-2.87			
	(1.54)	(2.61)	(2.18)			
log $\widehat{\text{Mig}}_{i,t}$ (HS) × log HC_{it-2}	2.77*	5.70**	4.35**			
	(1.61)	(2.29)	(2.11)			
$\text{Imp}_{i,t}$ (LS)				26.32***	25.18***	3.78
				(7.97)	(5.61)	(5.64)
$\text{Imp}_{i,t}$ (HS)				-10.64**	-13.03***	-1.27
				(4.40)	(3.50)	(3.40)
$\text{Mig}_{i,t}$ (LS)				1.66	14.12	-3.47
				(9.91)	(10.41)	(5.53)
$\text{Mig}_{i,t}$ (HS)				-39.65	-17.67	-2.27
				(47.22)	(31.85)	(11.36)
$\text{Imp}_{i,t}$ (LS) × log HC_{it-2}				-22.30***	-21.60***	-2.60
				(7.53)	(5.90)	(5.89)
$\text{Imp}_{i,t}$ (HS) × log HC_{it-2}				9.90**	11.55***	1.55
				(4.03)	(3.12)	(3.20)
$\text{Mig}_{i,t}$ (LS) × log HC_{it-2}				0.80	-12.98	2.85
				(7.89)	(8.50)	(5.66)
$\text{Mig}_{i,t}$ (HS) × log HC_{it-2}				33.84	18.96	4.55
				(33.87)	(22.39)	(9.00)
log HC_{it-2}	-3.57	3.71	-0.91	-0.66	-0.48	0.12
	(6.32)	(9.17)	(9.51)	(0.61)	(0.54)	(0.37)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.41	0.36	0.53			
R^2				0.10	0.15	0.02
K-Paap F-stat				10.20	6.05	15.61

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe`, while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.39: IV Results Excluding Latin American Countries

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.76	1.40	0.43			
	(0.57)	(0.88)	(0.85)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.03	-1.88**	-0.35			
	(0.74)	(0.90)	(0.88)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.68	1.92***	-1.62**			
	(0.45)	(0.62)	(0.80)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.36**	-2.29***	0.23			
	(0.56)	(0.89)	(1.19)			
$\text{Imp}_{i,t}$ (LS)				4.81*	3.20	1.16
				(2.73)	(2.17)	(1.40)
$\text{Imp}_{i,t}$ (HS)				-0.21	-0.56	0.46
				(0.55)	(0.41)	(0.37)
$\text{Mig}_{i,t}$ (LS)				0.34	0.34	-0.66
				(3.37)	(2.70)	(1.42)
$\text{Mig}_{i,t}$ (HS)				4.25	6.05	3.39
				(11.16)	(7.51)	(4.26)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	547	547	547	550	452	444
Pseudo-R^2	0.40	0.33	0.53			
R^2				0.05	0.07	0.00
K-Paap F-stat				27.52	29.74	13.21

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The sample of countries exclude Argentina, Chile and Mexico.

Table E.40: IV Results With Balanced Sample of Countries

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	2.43***	3.74***	1.53**			
	(0.73)	(1.01)	(0.65)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-2.70***	-2.58*	-4.08***			
	(0.96)	(1.37)	(1.19)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.33	2.31***	-2.03**			
	(0.53)	(0.89)	(0.88)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-0.87	-4.15***	2.61**			
	(0.68)	(1.31)	(1.09)			
$\text{Imp}_{i,t}$ (LS)				5.79*	8.34***	-0.07
				(3.23)	(1.56)	(1.37)
$\text{Imp}_{i,t}$ (HS)				0.10	-0.84**	0.56
				(0.69)	(0.31)	(0.36)
$\text{Mig}_{i,t}$ (LS)				-1.97	-4.04*	1.21
				(3.99)	(2.28)	(1.99)
$\text{Mig}_{i,t}$ (HS)				8.14	11.49*	-1.03
				(11.80)	(6.44)	(7.32)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	363	363	363	363	290	324
Pseudo-R^2	0.52	0.49	0.62			
R^2				0.07	0.11	0.02
K-Paap F-stat				10.40	4.75	10.01

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The sample of countries includes countries which have their first election before 1970.

E.8.8 Alternative Year Fixed-Effects structure

Table E.41: IV Results With 6-years Fixed Effects

	Volume ($\Pi^{V}_{i,e,t}$)			Mean ($\Pi^{M}_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.77	1.54*	1.09			
	(0.49)	(0.89)	(0.89)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-0.47	-1.33	-0.53			
	(0.60)	(0.90)	(1.06)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.65	2.02***	-1.12			
	(0.49)	(0.51)	(0.85)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-0.98**	-1.89***	0.08			
	(0.43)	(0.63)	(1.14)			
$\text{Imp}_{i,t}$ (LS)				4.20*	2.87*	1.74
				(2.26)	(1.65)	(1.16)
$\text{Imp}_{i,t}$ (HS)				-0.16	-0.44	0.20
				(0.53)	(0.33)	(0.36)
$\text{Mig}_{i,t}$ (LS)				-0.25	0.23	-1.01
				(3.33)	(2.88)	(1.40)
$\text{Mig}_{i,t}$ (HS)				5.86	7.66	2.87
				(10.47)	(7.38)	(3.46)
Country FE	✓	✓	✓	✓	✓	✓
6-Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.33	0.25	0.42			
R^2				0.05	0.07	-0.01
K-Paap F-stat				14.16	7.52	8.36

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The analysis include country and 6-years fixed effects.

E.8.9 Inclusion of Economy related controls

Table E.42: IV Results After Including Economy-Related Controls

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.82	1.55*	1.26			
	(0.52)	(0.80)	(0.82)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.27*	-2.35***	-1.08			
	(0.66)	(0.81)	(0.76)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.57	1.89***	-1.38*			
	(0.45)	(0.60)	(0.81)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.13**	-2.24**	0.45			
	(0.56)	(0.88)	(1.06)			
$\text{Imp}_{i,t}$ (LS)				4.32*	3.43*	1.22
				(2.39)	(2.03)	(1.36)
$\text{Imp}_{i,t}$ (HS)				-0.22	-0.55	0.44
				(0.56)	(0.42)	(0.38)
$\text{Mig}_{i,t}$ (LS)				0.39	0.68	-0.90
				(3.43)	(2.80)	(1.58)
$\text{Mig}_{i,t}$ (HS)				4.57	5.46	4.16
				(10.76)	(7.47)	(4.45)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.41	0.34	0.52			
R^2				0.05	0.08	-0.00
K-Paap F-stat				14.96	9.73	10.90

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`. The analysis includes the following country-specific control variables: logarithm of human capital index, logarithm of population, logarithm of number of parties per election, logarithm of employment rate, logarithm of real GDP per capita.

E.9 Additional Results: Including Emigration and Exports

We complement our analysis of the effect of trade and migration on the dynamics of populism by including in our set of explanatory variables skill-specific emigration and export flows. Given the bilateral dimension of our skill-specific migration and trade data, the construction of the variables as outflows rather than inflows is simply determined by aggregating the dyadic levels of trade and migration from the origin-country perspective, rather from the destination-country perspective. The objective of this extension is to investigate whether the inclusion of emigration and export influences our skill-specific results driven by immigration and imports. We treat emigration and export shocks as exogenous, as endogenizing eight variables simultaneously would be heroic.

We first explore in Table E.43 the skill-specific effect of outflows on the volume and mean margin with a standard PPML/OLS framework, since endogeneity driven by reverse-causation is likely to be less salient in this context. Note that (Dancygier et al., 2025) find a relationship between populism and emigration, but causation is hard to establish and we control for an important mechanism of transmission of emigration shocks, namely the level of human capital. Our estimates show a positive and statistically significant relationship between the volume of left-wing populism and exports of high-skill intensive goods or low-skill emigration. We do not find significant correlation for the volume of overall or right-wing populism, nor for the mean margin. These results suggests that emigration and exports are correlated with the left-wing dimension of populism, which can potentially be due to the influence of unobserved factors.

Going one step further, Table E.44 includes simultaneously the skill-specific inflows and outflows of trade and migration in a standard PPML/OLS framework. Importantly, the baseline effects of low-skill immigration and imports are confirmed for both volume and mean margins of populism. Moreover, the positive relationship between the volume of left-wing populism and exports (both low and high-skill intensive) or low-skill emigration is also confirmed. Right-wing populism is less responsive to outflows of goods and people. Table E.45 shows that those findings are also confirmed – although being less precisely estimated – once we instrument skill-specific immigration and import shocks.

Table E.43: PPML and OLS Results – Export and Emigration

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
log $\text{Exp}_{i,t}$ (LS)	0.12	0.20	0.32			
	(0.24)	(0.31)	(0.36)			
log $\text{Exp}_{i,t}$ (HS)	0.09	-0.65*	0.81***			
	(0.29)	(0.38)	(0.29)			
log $\text{Emig}_{i,t}$ (LS)	0.27	-0.18	1.10			
	(0.38)	(0.48)	(0.70)			
log $\text{Emig}_{i,t}$ (HS)	0.09	0.56	-0.57			
	(0.38)	(0.50)	(0.68)			
$\text{Exp}_{i,t}$ (LS)				0.00	1.42	0.06
				(0.97)	(1.03)	(0.48)
$\text{Exp}_{i,t}$ (HS)				-0.15	-0.07	0.12
				(0.32)	(0.26)	(0.11)
$\text{Emig}_{i,t}$ (LS)				1.99	-3.00	2.17
				(2.79)	(2.32)	(1.42)
$\text{Emig}_{i,t}$ (HS)				-8.42	8.99	-2.35
				(11.69)	(8.71)	(5.49)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	578	578	578	580	464	469
Pseudo-R^2	0.42	0.33	0.54			
R^2				0.49	0.38	0.49

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.44: PPML and OLS Results – Import, Immigration, Export and Emigration

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log Imp$_{i,t}$ (LS)	1.24***	1.31**	1.78***			
	(0.38)	(0.53)	(0.55)			
log Imp$_{i,t}$ (HS)	-1.04*	-0.74	-1.81***			
	(0.54)	(0.61)	(0.69)			
log Exp$_{i,t}$ (LS)	0.07	0.01	0.54*			
	(0.23)	(0.28)	(0.32)			
log Exp$_{i,t}$ (HS)	0.15	-0.71**	0.72**			
	(0.24)	(0.35)	(0.35)			
log Emig$_{i,t}$ (LS)	0.31	-0.37	0.86			
	(0.40)	(0.51)	(0.54)			
log Emig$_{i,t}$ (HS)	0.14	0.81	-0.29			
	(0.42)	(0.56)	(0.52)			
log Mig$_{i,t}$ (LS)	0.02	1.34**	-1.82***			
	(0.30)	(0.52)	(0.59)			
log Mig$_{i,t}$ (HS)	0.02	-0.89*	1.26**			
	(0.28)	(0.53)	(0.59)			
Imp$_{i,t}$ (LS)				4.46**	3.86**	-0.18
				(2.14)	(1.80)	(0.96)
Imp$_{i,t}$ (HS)				-0.20	-0.48	0.31
				(0.53)	(0.45)	(0.29)
Exp$_{i,t}$ (LS)				-1.60	-0.03	0.18
				(1.27)	(1.12)	(0.64)
Exp$_{i,t}$ (HS)				-0.13	0.04	0.03
				(0.32)	(0.36)	(0.10)
Mig$_{i,t}$ (LS)				-0.28	1.54	-1.48
				(1.75)	(1.90)	(1.18)
Mig$_{i,t}$ (HS)				3.87	-0.35	4.21
				(4.45)	(4.00)	(3.17)
Emig$_{i,t}$ (LS)				2.59	-1.94	2.00
				(2.69)	(2.00)	(1.28)
Emig$_{i,t}$ (HS)				-10.60	4.75	-1.41
				(11.14)	(7.79)	(5.03)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	575	575	575	580	464	469
Pseudo-R^2	0.44	0.37	0.59			
R^2				0.51	0.40	0.49

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.45: Reduced-Form IV PPML and 2SLS Results
Endogenous Import and Immigration / Exogenous Export and Emigration

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	1.69***	1.74**	2.84***			
	(0.56)	(0.80)	(0.96)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-2.01***	-1.93**	-3.32***			
	(0.74)	(0.95)	(1.28)			
log $\text{Exp}_{i,t}$ (LS)	0.12	0.08	0.50			
	(0.23)	(0.28)	(0.34)			
log $\text{Exp}_{i,t}$ (HS)	0.25	-0.57	1.18***			
	(0.25)	(0.39)	(0.41)			
log $\text{Emig}_{i,t}$ (LS)	0.21	-0.28	0.94*			
	(0.32)	(0.46)	(0.50)			
log $\text{Emig}_{i,t}$ (HS)	0.19	0.64	-0.37			
	(0.33)	(0.52)	(0.52)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.41	1.83***	-1.59**			
	(0.38)	(0.66)	(0.73)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-0.69	-1.92*	0.93			
	(0.53)	(1.06)	(0.84)			
$\text{Imp}_{i,t}$ (LS)				6.12*	3.98	1.37
				(3.32)	(2.65)	(2.18)
$\text{Imp}_{i,t}$ (HS)				-0.31	-1.01	0.40
				(0.76)	(0.79)	(0.59)
$\text{Mig}_{i,t}$ (LS)				-0.09	0.86	-1.32
				(2.91)	(2.62)	(1.46)
$\text{Mig}_{i,t}$ (HS)				4.69	5.50	4.36
				(9.46)	(6.98)	(4.19)
$\text{Exp}_{i,t}$ (LS)				-2.21	-0.13	-0.34
				(1.50)	(1.27)	(0.93)
$\text{Exp}_{i,t}$ (HS)				-0.11	0.38	-0.00
				(0.32)	(0.49)	(0.14)
$\text{Emig}_{i,t}$ (LS)				2.82	-1.62	2.15
				(2.72)	(1.97)	(1.34)
$\text{Emig}_{i,t}$ (HS)				-11.54	3.97	-2.21
				(11.05)	(8.11)	(5.22)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	575	575	575	580	464	469
Pseudo-R^2	0.44	0.36	0.58			
R^2				0.06	0.07	0.01
K-Paap F-stat				15.22	20.26	8.01

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.10 Additional Results: Globalization and Turnout

Table E.46 explores the potential implication of globalization shocks on electoral participation. Relying on the Voting Turnout Database of the International Institute for Democracy and Electoral Assistance (IDEA), which documents electoral participation in parliamentary and presidential elections from 1945, we compare the skill-specific effect of immigration and imports estimated in our full sample of countries (Cols. 1-2) and in the sample of countries where voting is not compulsory (Cols. 3-4). Moreover, we use two complementary proxies for electoral participation: the total number of votes divided by the total number of names in the voters' register (Cols. 1 and 3), and the total number of votes divided by the population in age of voting (Cols. 2 and 4). While the first dependent variable relies on the standard definition of voting turnout, the second one accounts (labeled as VAP Turnout) for the fact that voters' registration is not always reliable or that some individuals face unexpected problems when enrolling in electoral register. Nonetheless, the two variables are highly correlated (0.835).

Whatever the definition or the sample, we find that imports are not significantly correlated with turnout. Concerning immigration, the results are sensible to the sample and the definition. Immigration of low-skill workers is positively and significantly correlated with voting turnout in the overall sample, however the correlation is not statistically different from zero in the other specifications. Similarly, inflows of high-skill immigrants is negatively correlated with electoral participation, however it is statistically different from zero only among countries with a not compulsory voting system and on the standard definition of voting turnout. Overall, these results suggest that the implication of globalization shocks on voting turnout are not driving our results.

Alternatively, Table E.47 includes the standard measure of voting turnout as additional control in our benchmark specification. Although being a "bad control" due to the simultaneous determination of the populism variables and voting turnout, the skill-specific globalization estimates are not influenced by the inclusion of electoral participation as a potential confounding factor. Moreover, turnout is not significantly correlated with any margin of populism.

Table E.46: Turnout and Globalization (2SLS)

	All Countries		Not Compulsory Voting	
	(1)	(2)	(3)	(4)
	Turnout	VAP Turnout	Turnout	VAP Turnout
$\text{Imp}_{i,t}$ (LS)	-0.27	-0.25	-0.90**	-0.56
	(0.31)	(0.31)	(0.37)	(0.35)
$\text{Imp}_{i,t}$ (HS)	0.06	0.06	0.01	0.02
	(0.10)	(0.10)	(0.12)	(0.11)
$\text{Mig}_{i,t}$ (LS)	1.09**	0.51	0.63	0.09
	(0.49)	(0.43)	(0.66)	(0.59)
$\text{Mig}_{i,t}$ (HS)	-1.87	-0.85	-2.43	-0.34
	(1.64)	(1.25)	(1.50)	(1.27)
log Pop_{it-2}	0.12**	0.13**	-0.01	-0.01
	(0.05)	(0.06)	(0.07)	(0.06)
log HC_{it-2}	-0.24**	-0.12	-0.47***	-0.33***
	(0.11)	(0.10)	(0.10)	(0.09)
log Parties_{it}	-0.03*	-0.04***	-0.02	-0.04**
	(0.01)	(0.01)	(0.02)	(0.01)
Country FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	561	560	444	444
R^2	0.08	0.07	0.16	0.08
K-Paap F-stat	16.56	16.49	51.67	52.97

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients have been estimated with 2SLS using the Stata command `ivreghdfe`. The dependent variables is: the total number of votes divided by the number of names in voters' register (col. (1) and (3)) and the total number of votes divided by the population in age of voting (col. (2) and (4)). The sample includes: all available countries in columns (1) and (2), while only countries where voting is not compulsory in columns (3) and (4).

Table E.47: Reduced-Form IV PPML and 2SLS Results – Controlling for Turnout

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
log $\widehat{\text{Imp}}_{i,t}$ (LS)	1.08*	1.79**	0.75			
	(0.56)	(0.80)	(0.78)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.44**	-2.08**	-1.17			
	(0.66)	(0.89)	(0.81)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.41	1.63**	-1.90**			
	(0.45)	(0.65)	(0.83)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.02*	-2.12**	0.95			
	(0.58)	(0.95)	(1.03)			
Turnout	0.13	1.86	-0.95	0.19	0.26	0.12
	(1.42)	(2.25)	(1.98)	(0.28)	(0.23)	(0.24)
$\text{Imp}_{i,t}$ (LS)				4.37*	3.66*	1.09
				(2.45)	(2.08)	(1.33)
$\text{Imp}_{i,t}$ (HS)				-0.30	-0.59	0.38
				(0.56)	(0.40)	(0.37)
$\text{Mig}_{i,t}$ (LS)				-0.15	-0.59	-0.97
				(3.31)	(2.65)	(1.55)
$\text{Mig}_{i,t}$ (HS)				5.21	6.05	4.34
				(10.46)	(7.24)	(4.24)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	558	558	558	561	447	458
Pseudo-R^2	0.40	0.35	0.52			
R^2				0.05	0.07	0.00
K-Paap F-stat				13.69	8.46	17.93

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.11 IV Results with Interaction Terms

In Tables E.48 to E.50, we start from a parsimonious version of Eq. (5) and Table 3 – including imports of low-skill labor intensive goods $\left(\mathrm{Imp}_{i,e,t}^{LS}\right)$ and low-skill immigration $\left(\mathrm{Mig}_{i,e,t}^{LS}\right)$ – and supplement it with interactions between globalization shocks and other potential drivers of populism. The new specification is given by Eq. (6).

We create four dummies to capture whether (i) the country experienced a year of negative real income growth in the last two years before the election (a proxy for an *economic crisis*), (ii) the country experienced a variation in the share of manufacturing value added in GDP in the last two years that belongs to the bottom quartile of the distribution (a proxy for *de-industrialization*), (iii) the level of diversity in the origin mix of imports and genetic distance of the migration inflows belongs to the top decile of the distribution (a proxy for the underlying *cultural diversity* involved in imported goods or brought by immigrants), and (iv) the share of internet users belongs to the top decile of the population (a proxy for the *prevalence of social media*).

Table E.48: Reduced-Form IV PPML and 2SLS Results – Volume and Mean Margins Interaction With Economic Crisis ($\mathrm{dG}_{i,t}$)

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
$dG_{i,t}$	0.54	-0.57	-0.98	-0.08	-0.03	-0.10*
	(0.73)	(1.50)	(1.30)	(0.09)	(0.06)	(0.06)
log $\widehat{\mathrm{Imp}}_{i,t}$ (LS)	0.80	1.57*	0.60			
	(0.53)	(0.82)	(0.85)			
log $\widehat{\mathrm{Imp}}_{i,t}$ (HS)	-1.07	-2.00**	-0.73			
	(0.69)	(0.87)	(0.74)			
log $\widehat{\mathrm{Mig}}_{i,t}$ (LS)	0.58	1.85***	-1.46*			
	(0.45)	(0.69)	(0.84)			
log $\widehat{\mathrm{Mig}}_{i,t}$ (HS)	-1.24**	-2.37***	0.45			
	(0.55)	(0.82)	(1.11)			
log $\widehat{\mathrm{Imp}}_{i,t}$ (LS) $\times$ $dG_{i,t}$	0.02	-0.34	0.69**			
	(0.14)	(0.31)	(0.32)			
log $\widehat{\mathrm{Mig}}_{i,t}$ (LS) $\times$ $dG_{i,t}$	0.22	0.26	-0.68**			
	(0.15)	(0.29)	(0.29)			
$\mathrm{Imp}_{i,t}$ (LS)				4.30*	3.60*	0.36
				(2.47)	(1.93)	(1.20)
$\mathrm{Imp}_{i,t}$ (HS)				-0.26	-0.56	0.41
				(0.55)	(0.41)	(0.30)
$\mathrm{Mig}_{i,t}$ (LS)				0.91	0.45	-1.07
				(3.95)	(2.97)	(1.24)
$\mathrm{Mig}_{i,t}$ (HS)				2.62	5.71	3.50
				(11.73)	(7.76)	(4.05)
$\mathrm{Imp}_{i,t}$ (LS) $\times$ $dG_{i,t}$				1.86	-1.08	2.85**
				(1.39)	(1.11)	(1.16)
$\mathrm{Mig}_{i,t}$ (LS) $\times$ $dG_{i,t}$				-1.65	0.76	-1.13
				(1.72)	(1.34)	(0.97)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.41	0.35	0.53			
R^2				0.05	0.08	0.03
K-Paap F-stat				17.13	10.44	8.90

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.49: Reduced-Form IV PPML and 2SLS Results – Volume and Mean Margins Interaction With De-Industrialization ($\text{dD}_{i,t}$)

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
$dD_{i,t}$	0.66	1.93*	-0.53	0.05	-0.02	0.04
	(0.64)	(1.17)	(0.91)	(0.05)	(0.06)	(0.04)
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.72	1.38	0.70			
	(0.57)	(0.85)	(0.88)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.03	-2.23**	-0.64			
	(0.72)	(0.92)	(0.78)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.55	1.79***	-1.56*			
	(0.47)	(0.68)	(0.80)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.10**	-2.14**	0.56			
	(0.56)	(0.89)	(1.13)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) $\times$ $dD_{i,t}$	0.22*	0.56**	0.13			
	(0.13)	(0.22)	(0.23)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) $\times$ $dD_{i,t}$	-0.05	-0.03	-0.23			
	(0.10)	(0.20)	(0.19)			
$\text{Imp}_{i,t}$ (LS)				4.80*	3.03	1.84
				(2.82)	(2.11)	(1.57)
$\text{Imp}_{i,t}$ (HS)				-0.22	-0.62	0.45
				(0.56)	(0.40)	(0.38)
$\text{Mig}_{i,t}$ (LS)				0.52	0.27	-0.77
				(3.12)	(2.54)	(1.39)
$\text{Mig}_{i,t}$ (HS)				4.87	4.62	5.21
				(11.51)	(7.99)	(4.22)
$\text{Imp}_{i,t}$ (LS) $\times$ $dD_{i,t}$				-0.15	0.80	-0.94*
				(0.85)	(0.55)	(0.56)
$\text{Mig}_{i,t}$ (LS) $\times$ $dD_{i,t}$				-0.53	0.54	-0.60
				(1.48)	(1.61)	(0.50)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.41	0.35	0.51			
R^2				0.05	0.08	0.01
K-Paap F-stat				22.17	17.87	10.61

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.50: Reduced-Form IV PPML and 2SLS Results – Volume and Mean Margins Interaction With Internet Coverage ($\text{dI}_{i,t}$)

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
$dI_{i,t}$	4.67**	6.52	4.61	-0.16	-0.23**	-0.12
	(2.35)	(4.11)	(3.39)	(0.19)	(0.11)	(0.08)
log $\widehat{\text{Imp}}_{i,t}$ (LS)	1.02*	1.65*	0.97			
	(0.56)	(0.91)	(0.75)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.26*	-2.20**	-0.73			
	(0.67)	(0.90)	(0.83)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.65	2.15***	-1.67**			
	(0.44)	(0.58)	(0.77)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.13**	-2.40***	0.54			
	(0.55)	(0.92)	(1.03)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) × $dI_{i,t}$	1.23*	3.23***	0.27			
	(0.66)	(1.03)	(1.07)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) × $dI_{i,t}$	0.64	-0.16	1.17			
	(0.62)	(0.77)	(1.27)			
$\text{Imp}_{i,t}$ (LS)				4.11	2.59	0.64
				(2.71)	(2.05)	(1.44)
$\text{Imp}_{i,t}$ (HS)				-0.18	-0.64	0.43
				(0.59)	(0.41)	(0.34)
$\text{Mig}_{i,t}$ (LS)				-0.30	1.44	-2.17
				(4.43)	(3.41)	(1.62)
$\text{Mig}_{i,t}$ (HS)				5.58	3.30	6.83*
				(11.20)	(8.04)	(3.59)
$\text{Imp}_{i,t}$ (LS) × $dI_{i,t}$				0.07	2.30	0.89
				(2.98)	(1.39)	(1.11)
$\text{Mig}_{i,t}$ (LS) × $dI_{i,t}$				2.40	-1.02	1.64
				(3.68)	(1.90)	(1.46)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.42	0.36	0.52			
R^2				0.05	0.08	0.03
K-Paap F-stat				23.00	12.74	9.95

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.51: Reduced-Form IV PPML and 2SLS Results – Volume and Mean Margins Interaction With Trade Diversity (dHHI$_{it}$) and Genetic Distance (dGD$_{it}$)

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
$dHHI_{i,t}$	-1.80	-5.07***	-2.21	0.40***	0.27***	0.15***
	(1.18)	(1.62)	(2.38)	(0.08)	(0.09)	(0.04)
$dGD_{i,t}$	-2.30*	-1.76	-4.40	0.16	0.04	0.06
	(1.23)	(2.83)	(2.82)	(0.14)	(0.10)	(0.13)
log $\widehat{\text{Imp}}_{i,t}$ (LS)	0.94*	1.58**	0.97			
	(0.56)	(0.80)	(0.72)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.15*	-2.17**	-0.97			
	(0.69)	(0.91)	(0.77)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	1.22**	2.35***	-1.06			
	(0.48)	(0.68)	(0.78)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.67**	-2.51**	0.01			
	(0.68)	(0.98)	(1.12)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) $\times$ $dHHI_{i,t}$	-0.48*	-1.51***	-0.43			
	(0.28)	(0.38)	(0.57)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) $\times$ $dGD_{i,t}$	-0.61***	-0.67	-0.91			
	(0.23)	(0.66)	(0.57)			
Imp$_{i,t}$ (LS)				4.25*	3.49	0.79
				(2.53)	(2.11)	(1.50)
Imp$_{i,t}$ (HS)				-0.21	-0.57	0.42
				(0.54)	(0.42)	(0.37)
Mig$_{i,t}$ (LS)				0.48	-0.09	-0.39
				(3.29)	(2.35)	(1.40)
Mig$_{i,t}$ (HS)				5.00	7.35	2.69
				(11.20)	(6.98)	(4.63)
Imp$_{i,t}$ (LS) $\times$ $dHHI_{i,t}$				-5.93***	-3.93**	-2.41**
				(2.02)	(1.85)	(1.04)
Mig$_{i,t}$ (LS) $\times$ $dGD_{i,t}$				-2.10	5.33	-6.67
				(6.22)	(7.92)	(4.77)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.42	0.37	0.52			
R^2				0.08	0.09	0.03
K-Paap F-stat				29.25	8.63	7.76

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

E.12 Exploring Diversity and Genetic Distance Specific results

Figure E.1 and Tables E.52 and E.53 explore the potential interaction effect of diversity in low-skill imports and immigration on populism once accounting for the relative genetic closeness of the shocks to the host country population. We rely on genetic closeness as a proxy of cultural relatedness (Spolaore and Wacziarg, 2016).

First we compute for low-skill specific inflows $f \in \{Mig, Imp\}$ a Greenberg Index as follows:

$$HHIG^f_{c,t} = \sum_{i=1}^{I} s^f_{c,i,t} \times (1 - s^f_{c,i,t}) \times g_{c,i}, \tag{13}$$

where $s^f_{i,t}$ is the low-skill origin specific inflow from country i over the total low-skill inflow to destination country c at year t. Such index augments the standard Herfindal index by including measures of time-invariant bilateral genetic distance ($g_{c,i}$) to capture relatedness across origin and destination countries (Spolaore and Wacziarg, 2009). By doing so, the contribution of each origin-specific flow to diversity is weighted by its relative closeness to the recipient country. To investigate the potential amplifying effect on our low-skill specific variables, we construct dummies equal to one if the low-skill specific inflows belong to the first decile of the distribution in terms of Greenberg index and we interact them with our low-skill inflows.

Second, we compute both for immigration and imports a measure of closeness to the host country population, by computing measures of average genetic distances as follows:

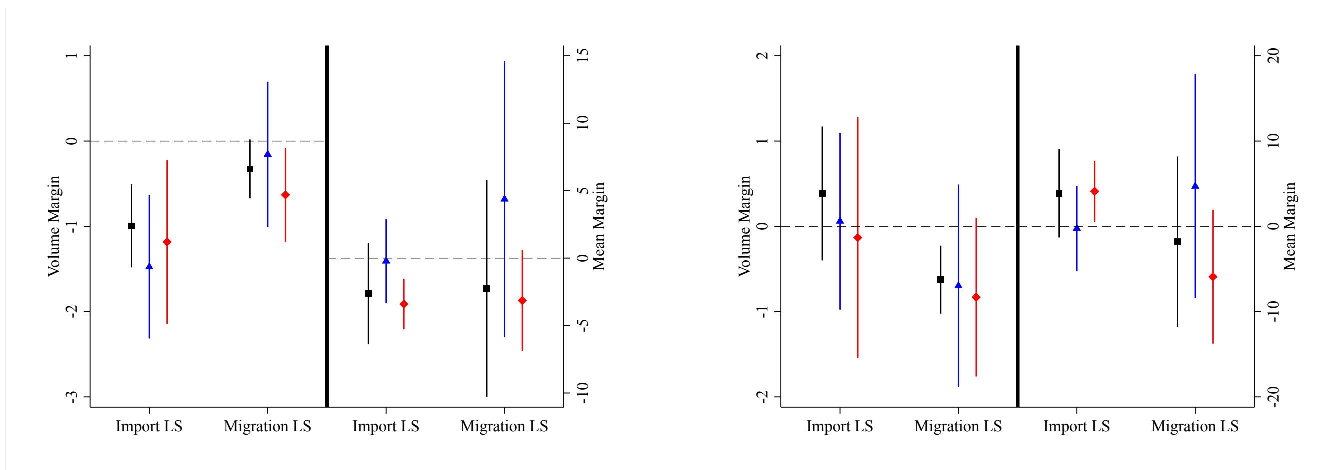
$$GDA^f_{c,t} = \sum_{i=1}^{I} s^f_{c,i,t} g_{c,i}. \tag{14}$$

The globalization-shock specific $GDA^f_{c,t}$ captures the extent of relatedness of the shocks to the recipient country society. To explore the potential amplifying effect of shocks determined by genetically distant countries, we construct dummies equal to one if the low-skill specific inflows belong to the first decile of the distribution in terms of average genetic distance.

Figure E.1(a) and Table E.52 shows the results using the simple Greenberg Indexes for trade and migration. The results show that diversity in imports reduces the positive effect of low-skill intensive imports on both margins of populism. Moreover, we find a negative and statistically significant coefficient associated to the interaction with diversity among immigrants and left wing populism. These results suggest, if any, that higher variety in imports could hamper the trade-specific determinant of the recent rise of populism, while diversity in migration enhances the drop in support for left wing populists.

Figure E.1(b) and Table E.53 provides the results once rely on measures of average (genetic) distance of the flows. Interestingly, the contribution of the relatedness of the flows on populism varies across shocks type. Receiving low skill immigrants from genetically distant countries reduces the support for populism, in particular left wing populism. On the other hand, imports from

Figure E.1: Interactions with Amplifiers for Volume and Mean Margins
Reduced-Form IV PPML and 2SLS Results - Diversity and Genetic Distance Specific Results



(a) Greenberg Index

(b) Average Genetic Distance

Notes: Black (square), blue (triangle) and red (diamond) objects correspond to overall, right wing and left wing dimensions, respectively. Dependent variable is the volume margin on the left panels, while is the mean margin in the right panels. The estimates represent the coefficients of the interaction term between migration (LS) and imports (LS) with a dummy equal to one (top-decile) as proxy for trade diversity and migration diversity. 90% confidence intervals are reported.

culturally distant countries contributes to the rise of the extent of populism among left wing parties, as it is proxied by the mean margin.

Table E.52: Reduced-Form IV PPML and 2SLS Results – Volume and Mean Margins Interaction With a Greenberg Trade Diversity Index (dHHIG^I_{it}), and a Greenberg Migration Diversity Index (dHHIG^M_{it})

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	RW	LW	All	RW	LW
$dHHIG^I_{i,t}$	-4.33***	-5.75**	-5.19**	0.03	-0.04	0.19**
	(1.45)	(2.32)	(2.54)	(0.15)	(0.11)	(0.07)
$dHHIG^M_{i,t}$	-1.49	-0.40	-2.58*	0.11	-0.06	0.10*
	(1.06)	(2.34)	(1.46)	(0.14)	(0.11)	(0.06)
log $\widehat{\text{Imp}}_{i,t}$ (LS)	1.17**	2.30***	1.18*			
	(0.57)	(0.66)	(0.68)			
log $\widehat{\text{Imp}}_{i,t}$ (HS)	-1.20*	-2.50***	-0.89			
	(0.66)	(0.78)	(0.67)			
log $\widehat{\text{Mig}}_{i,t}$ (LS)	0.82*	1.95***	-1.07			
	(0.44)	(0.60)	(0.80)			
log $\widehat{\text{Mig}}_{i,t}$ (HS)	-1.26*	-2.16**	0.05			
	(0.65)	(0.90)	(1.12)			
log $\widehat{\text{Imp}}_{i,t}$ (LS) × $dHHIG^I_{i,t}$	-0.99***	-1.48***	-1.18**			
	(0.30)	(0.51)	(0.58)			
log $\widehat{\text{Mig}}_{i,t}$ (LS) × $dHHIG^M_{i,t}$	-0.33	-0.16	-0.63*			
	(0.21)	(0.52)	(0.34)			
$\text{Imp}_{i,t}$ (LS)				4.36*	3.13	1.09
				(2.59)	(2.18)	(1.38)
$\text{Imp}_{i,t}$ (HS)				-0.23	-0.52	0.30
				(0.56)	(0.42)	(0.33)
$\text{Mig}_{i,t}$ (LS)				-0.24	0.39	-1.98
				(3.47)	(2.66)	(1.24)
$\text{Mig}_{i,t}$ (HS)				4.55	5.57	5.44
				(10.64)	(7.26)	(4.44)
$\text{Imp}_{i,t}$ (LS) × $dHHIG^I_{i,t}$				-2.63	-0.22	-3.40***
				(2.24)	(1.86)	(1.12)
$\text{Mig}_{i,t}$ (LS) × $dHHIG^M_{i,t}$				-2.26	4.37	-3.14
				(4.80)	(6.11)	(2.22)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.42	0.35	0.53			
R^2				0.06	0.08	0.05
K-Paap F-stat				17.77	18.09	10.44

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.

Table E.53: Reduced-Form IV PPML and 2SLS Results – Volume and Mean Margins Interaction With Average Genetic Distance for Trade (dGD^I_{it}) and Migration (dGD^M_{it})

	Volume ($\Pi^V_{i,e,t}$)			Mean ($\Pi^M_{i,e,t}$)		
	(1) All	(2) RW	(3) LW	(4) All	(5) RW	(6) LW
$dGD^I_{i,t}$	1.33	0.81	-1.64	-0.24	-0.02	-0.25*
	(1.59)	(2.13)	(3.71)	(0.20)	(0.17)	(0.14)
$dGD^M_{i,t}$	-2.29*	-1.88	-3.87	0.16	0.06	0.06
	(1.25)	(3.12)	(2.66)	(0.15)	(0.10)	(0.13)
$\log \widehat{\text{Imp}}_{i,t}$ (LS)	0.88	1.52*	1.22*			
	(0.55)	(0.82)	(0.69)			
$\log \widehat{\text{Imp}}_{i,t}$ (HS)	-1.04	-2.19**	-0.78			
	(0.69)	(0.94)	(0.73)			
$\log \widehat{\text{Mig}}_{i,t}$ (LS)	1.07**	2.16***	-1.24			
	(0.47)	(0.58)	(0.87)			
$\log \widehat{\text{Mig}}_{i,t}$ (HS)	-1.51***	-2.40***	0.12			
	(0.59)	(0.88)	(1.09)			
$\log \widehat{\text{Imp}}_{i,t}$ (LS) $\times$ $dGD^I_{i,t}$	0.39	0.06	-0.13			
	(0.48)	(0.63)	(0.86)			
$\log \widehat{\text{Mig}}_{i,t}$ (LS) $\times$ $dGD^M_{i,t}$	-0.62***	-0.70	-0.83			
	(0.24)	(0.72)	(0.57)			
$\text{Imp}_{i,t}$ (LS)				4.79*	3.51	1.37
				(2.70)	(2.18)	(1.50)
$\text{Imp}_{i,t}$ (HS)				-0.30	-0.59	0.36
				(0.55)	(0.42)	(0.36)
$\text{Mig}_{i,t}$ (LS)				-0.39	-0.23	-1.03
				(3.53)	(2.30)	(1.76)
$\text{Mig}_{i,t}$ (HS)				7.04	7.48	4.66
				(11.63)	(6.67)	(5.03)
$\text{Imp}_{i,t}$ (LS) $\times$ $dGD^I_{i,t}$				3.87	-0.25	4.12*
				(3.09)	(2.98)	(2.14)
$\text{Mig}_{i,t}$ (LS) $\times$ $dGD^M_{i,t}$				-1.80	4.70	-5.90
				(5.97)	(7.83)	(4.68)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Observations	577	577	577	580	464	469
Pseudo-R^2	0.42	0.35	0.53			
R^2				0.06	0.08	0.03
K-Paap F-stat				24.34	9.70	7.51

Notes: ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively; clustered standard errors at the country level are reported in parentheses; coefficients presented in column (1) to (3) have been estimated with PPML using the Stata command `ppmlhdfe` and predicted globalization variables from the model estimated in equation (7), while coefficients in column (4) to (6) have been estimated with 2SLS using the Stata command `ivreghdfe`.