The Economic Cost of Nationalism

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Abstract

We identify the negative influence of nationalist sentiment on economic growth. Our cross-country evidence confirms the growth-depressing effect of nationalism, projecting that economic growth has been constrained by roughly 12 percent over thirty years. This conclusion is robust across various tests. Paradoxically, nationalism helps reduce environmental damage, lowering overall emissions and intensity, especially in the building, industry, and transportation sectors. We observe that the effect of nationalism in cutting carbon emissions weakens slightly as GDP per capita rises. However, in poorer countries, this environmental impact remains steady regardless of changes in income, suggesting nationalism's role in reducing emissions stays stable despite economic growth.

Keywords: Nationalism; Economic Growth; Political Economy; Environmental Impact

1. Introduction

Economic growth [1] remains a persistent and foundational concern in macroeconomic discourse, shaped by endogenous and exogenous forces. Diverging from conventional emphases on structured drivers like innovation, we reorient our query through a political economy (or, precisely, nationalism) perspective, the lens to offer fresh insights into the dynamics underpinning growth dynamics globally.

The rationale for modelling the nationalism-growth nexus stems from the increasing prominence of nationalistic sentiment, often captured through the tone and frequency of nationalist rhetoric. It is somehow spectacular that nationalism has increasingly surged again after decades of retreat (Mylonas and Tudor, 2021). A salient example is the US, where President Trump rose to power on slogans such as "Make America Great Again" and "America First," embodying a resurgence of inward-looking national priorities. Likewise, under Prime Minister Narendra Modi, nationalist rhetoric has gained prominence, often centered around restoring India's cultural and historical identity. Slogans like "Sabka Saath, Sabka Vikas" (Together with all, development for all) and initiatives emphasizing indigenous production reflect a nationalist shift toward self-reliance (i.e., the "Make in India" campaign). Although distinct in ideological tone, Chinese

[1] For expository convenience, we occasionally conflate terminology by referring to this relationship as the effect of nationalism on economic growth, even though it more precisely pertains to changes in income levels per individual driven by shifts in political regimes. Moreover, in the interest of conciseness, we frequently use the term "GDP" as a shorthand reference to GDP per capita throughout the analysis.

nationalism has also intensified under President Xi Jinping, framed around the "great rejuvenation of the Chinese nation." This nationalistic agenda is reflected in assertive foreign policy moves, domestic propaganda, and slogans like "self-reliance and self-strengthening" in the face of perceived external threats.

Recently, nationalism was no longer a subterranean force but a visible, organizing principle of global politics. Rather than fading under the pressures of a hyper-connected world, nationalist sentiment has intensified, particularly during exogenous crises. The COVID-19 pandemic, while a transnational health emergency, underscored the primacy of national sovereignty in public health governance. States did not act as members of a global collective but instead responded through unilateral policies. For instance, in many countries worldwide, abrupt border closures and internal lockdowns reflected a highly centralized approach to risk containment.

The symbolism accompanying these decisions was equally telling: national leaders invoked patriotic rhetoric, employed national emblems, and emphasized domestic solidarity. Political actors across ideological spectrums, from leftist populists in Latin America to far-right parties in Western Europe, have found renewed legitimacy in nationalistic appeals. As geopolitical uncertainty deepens and institutions like the World Trade Organization appear increasingly constrained, nationalism has reasserted itself not as an ideological relic but as a politically expedient (and electorally resonant) framework. In effect, crises that transcend borders have paradoxically reaffirmed the borders themselves.

The intellectual foundation linking nationalism to economic growth dates back to List (1827), who argued that economic nationalism, manifested through protectionism and state-led industrialization, was essential for fostering national prosperity. Greenfeld (2001) provided a comprehensive sociological account in The Spirit of Capitalism, asserting that nationalism instills ambition, competitiveness, and a collective drive for advancement. Gellner (2015) conceptualized nationalism as a structural response to the demands of industrialization, emphasizing its role in creating a standardized labor force through education and cultural unification.

We dispute prevailing propositions by empirically opening the suppressive effect of nationalism on economic growth. The negative link between nationalism and growth persists robustly yet through indirect pathways. For example, Colantone and Stanig (2018) highlighted how intensified import competition has fueled support for nationalist and protectionist parties across Western Europe. These political movements often embody a blend of anti-elite populism and anti-globalization sentiment, as described by Miller-Idriss (2017). Meanwhile, the resurgence of economic nationalism poses a serious risk to cross-border service integration and undermines the liberalization gains achieved under the General Agreement on Trade in Services (Rammal et al., 2022). Notably, prevailing discussions surrounding nationalism predominantly center on immigration dynamics, as evidenced by the analytical focus in Russo (2021) and Moriconi et al. (2022).

Utilizing a panel of cross-national data from 1979 to 2013, we investigate the macroeconomic implications of the global nationalistic wave that unfolded over the past three decades. Our findings underscore a robust and economically meaningful negative association between nationalism and economic growth. Specifically, the transition from a non-nationalistic to a nationalistic regime is associated with approximately a 12 percent decrease in GDP per capita over a 30-year horizon relative to non-nationalistic countries.

Our empirical drawings, to some extent, are analogous to those of Born et al. (2019), who evaluated the macroeconomic impact of nationalism by treating the June 2016 Brexit referendum as a quasi-natural experiment. Their findings indicate that by the end of 2018, the UK had suffered notable GDP losses as a result of the Brexit outcome. These economic costs appear more pronounced when accounting for agents' forward-looking expectations.

Identifying the causal relationship remains empirically complex. The absence of a standardized metric for capturing nationalism presents a critical measurement challenge. For instance, Mithani (2024) employs a text-based approach, quantifying nationalism through the frequency of nationalistic terms. Yet disparities in methodological design could induce artificial variations in nationalism indices that are disconnected from actual institutional shifts. Further, nationalistic and non-nationalistic regimes may differ systematically along latent institutional dimensions, independently influencing economic outcomes. Consequently, conventional cross-sectional growth regressions may suffer from omitted variable bias and fail to isolate the effect of nationalism per se. Also, Acemoglu et al. (2018) argued that neglecting the dynamic feedback between economic performance and adopting nationalism can result in biased parameter estimates. Last but not least, endogeneity concerns persist even under specifications that control for country-specific effects and lagged economic growth. Shifts toward democratic governance may be endogenous to anticipated economic trajectories, thus complicating the attribution of growth effects solely to nationalism.

Nonetheless, we have three contributions to the literature. The preceding discussion pertains to the intensity with which nationalistic terms appear in news narratives. Unlike Gaies et al. (2022), whose analysis is confined to the mere quantification of word frequencies, our approach moves beyond lexical counting by exploring the intertemporal dynamics and cross-national interplay embedded within nationalist discourses. Our inquiry draws theoretical impetus from Mylonas and Tudor (2021), who emphasized that the contemporary revival of nationalism intricately shapes and reflects the evolving geopolitical interdependencies among nation-states. The scholarly domain lacks empirical methodologies that quantify nationalist rhetoric using a relational, network-based framework. Addressing this void, we not only fill this methodological lacuna but also build upon and significantly broaden the analytical reach of Gaies et al. (2022) by unveiling the structural trade-offs inherent in nationalist policy orientations across governments.

We construct nationalism through the Global Database of Events, Language, and Tone (GDELT) (Mithani, 2024). Our analytical design fundamentally diverges from that precedent by operationalizing nationalism through the lens of social network theory—an approach gaining considerable traction in contemporary socioeconomic studies (Bailey et al., 2018; Wang et al., 2024). This network-theoretic perspective enables us to classify countries as either integrated within or detached from a nation-oriented global network's emergent structure in a given year. In doing so, we isolate peripheral or non-aligned "nodes" (countries) from those embedded in cohesive nationalist clusters. This framework helps rigorously contrast the counterfactual trajectories of economic growth between countries exhibiting nationalistic configurations and those that do not.

Although no empirical design identifies perfectly causal effects, our approach rests on a theoretically grounded identification strategy tailored to estimate the influence of nationalism on GDP dynamics. We begin with a linear dynamic panel model incorporating country-fixed effects to account for temporal dependencies in growth evolution. The key identifying hypothesis is that conditional on lagged GDP and unobserved time-invariant country characteristics, nations experiencing shifts in nationalistic orientation are not undergoing divergent pre-treatment trends in projected growth. In essence, this structure allows the lag terms to proxy for downturns or precursors to nationalistic turns, thereby mitigating endogeneity concerns. Again, our model yields economically meaningful results: over a 30-year horizon, countries with sustained nationalistic alignment exhibit, on average, a 12% higher GDP per capita than their counterfactuals.

We also deepen our estimates through a semiparametric treatment effects model, where nationalism is conceptualized as a discrete intervention affecting the distribution of potential economic outcomes across all future periods. This framework hinges on explicitly modeling the selection mechanism into nationalism based on observables (i.e., lagged GDP per capita) drawing on methodologies developed by Jordà (2005), Angrist and Kuersteiner (2011), and Kline (2011). Importantly, the semiparametric model relaxes assumptions about the functional form of GDP dynamics, offering a more flexible lens to trace the long-run impact of nationalism without imposing restrictive parametric constraints.

Lastly, climate politics has become increasingly interwoven with the rhetoric and dynamics of nationalism, giving rise to the multifaceted concept of "climate nationalism." This notion has attracted substantial academic interest, conveying varying interpretations across political and societal actors. Ahead of the United Nations Climate Conference in Scotland in December 2021, British Prime Minister Boris Johnson invoked this perspective to justify his stance on climate action, stating: "When the Roman Empire fell, it was largely as a result of uncontrolled immigration—the empire could no longer control its borders; people came in from the east and all over the place[2]."

[2] See https://www.theguardian.com/environment/2021/nov/21/climate-denial-far-right-immigration.

The notion of climate nationalism, framing climate change as a direct challenge to national sovereignty and strategic interests, has garnered traction across the ideological spectrum, engaging both conservative and progressive constituencies. Empirical observations of political polarization in advanced industrial democracies reveal that scholarly interpretations of climate nationalism tend to bifurcate into two antithetical paradigms. On one end, right-leaning populist and reactionary groups often instrumentalize climate discourse to advance exclusionary, authoritarian environmental agendas, frequently termed as forms of "eco-fascism" (Moore and Roberts, 2022). Progressive actors, however, conceptualize climate nationalism through civic responsibility, advocating for inclusive, equitable responses to ecological threats that align with broader democratic values (Conversi and Friis Hau, 2021). The intellectual debate surrounding climate nationalism thus frequently hinges on a moral dichotomy, juxtaposing "constructive civic nationalism" that fosters collective environmental stewardship against "ethnic or exclusionary nationalism" that weaponizes climate policy for nativist ends (Braun, 2021).

To date, empirical evidence regarding the environmental consequences of nationalism remains largely unexplored. We therefore address this gap by systematically assessing the carbon footprint implications of nationalist sentiment. Broadly, we confirm that nationalism dampens CO_2 emissions, a relationship that becomes more salient when measured through emission intensity. Yet the influence of nationalism on emissions at the sectoral level does not achieve statistical significance. Nonetheless, a noteworthy pattern emerges: sectors, including construction, manufacturing, and transport, exhibit the most pronounced, albeit statistically insignificant, potential reductions under heightened nationalism. These sector-specific tendencies tentatively echo the arguments of Rodríguez-Pose and Bartalucci (2024), who contended that such carbon-intensive industries are likely to become focal points in national low-carbon agendas. Within this context, nationalist policies may be pivotal in facilitating climate-aligned structural transformations amid growing global pressures for decarbonization.

Further, the dampening effect of nationalism on emissions is particularly pronounced in high-emitting, pollution-intensive countries. This finding is established through interaction terms between nationalism and period-specific CO_2 emission indicators, such as those for 1979, etc. Besides, the emission-reducing effect of nationalism weakens slightly with rising GDP in the full sample; however, this moderating relationship is statistically muted within the subset of low-income countries. This pattern suggests that the environmental impact of nationalism remains relatively stable in low-income contexts and is less sensitive to marginal fluctuations in GDP.

The structure of the analysis is arranged as follows. Section 2 describes the strategy of the main variables. Section 3 provides detailed descriptions of dynamic linear model specification. Section 4 presents the robustness tests. Section 5 offers evidence of the environmental impacts of nationalism and economic growth.

2. Data and stylized facts

2.1 Nationalism: regularization and operationalization

Our sample includes 193 global countries from 1979 to 2013, though not all variables employed in the current analysis are available over a long period. Given the limited quantification exercise about nationalism in the extant literature, we propose a method grounded in social network theory by exercising the data from the Global Database of Events, Language, and Tone (GDELT) project[3]. GDELT represents one of the most ambitious and comprehensive efforts to systematically monitor and record global human societal events, capturing political, social, and economic interactions across virtually every country worldwide. GDELT employs sophisticated natural language processing and machine learning algorithms to scan an immense corpus of international news media, web sources, and broadcast reports in over 100 languages on a near-real-time basis.

The core innovation of the GDELT project lies in its scale and granularity. It converts unstructured textual data from global news outlets into a structured, coded event database that records "*who did what to whom, where, and when*." This event data is categorized according to an internationally recognized ontology (i.e., the CAMEO event coding scheme) encompassing various actions, including diplomatic exchanges, conflict events, protests, trade agreements, and other socio-political occurrences. Importantly, the GDELT project bridges the gap between qualitative and quantitative social science research, offering a dynamic data source for analyzing causal relationships, similar to our exercise regarding the nationalism-growth puzzle.

We construct the nationalism index at the country-year level by leveraging the GDELT MASTERREDUCEDV2 dataset (1979-2013). This dataset systematically encodes over 77 million global news events using a structured format: Date-Source Actor-Target Actor-CAMEO[4] Event Code, where the Source Actor (hereafter "rhetor") initiates an event directed toward the Target Actor. As Gaies et al. (2022) suggested, our empirical focus is on verbal conflict narratives reflective of nationalistic rhetoric, operationalized through the GDELT-provided variable QuadClass = 3, which identifies news events classified as verbal conflict, excluding cooperative interactions and material conflicts that involve direct physical confrontations. To ensure geographical precision, we first map the latitude and longitude of the source events to countries using spatial join techniques in R[5] (i.e., the 'sf' package) and a standard global administrative shapefile. This process yields a usable sample of approximately 78 million observations, of which 89% are successfully mapped to countries; unmatched

[3] See https://www.gdeltproject.org/.

[4] CAMEO means Conflict and Mediation Event Observations.

[5] The geographic coordinates employed in this analysis, specifically, latitude and longitude, are derived from the Natural Earth repository. For spatial referencing and boundary alignment, we utilize the "Admin 0 – Countries" layer as the foundational geospatial framework upon which our dataset is projected and mapped.

events generally arise from missing or erroneous geocodes or unspecified actors.

Based on the CAMEO target coding scheme, we refined the sample by excluding verbal conflicts directed at non-national targets, including religious groups, international organizations, insurgents, and non-governmental actors. This exclusion ensures that the retained events represent political rhetoric targeted at foreign countries, their governments, political parties, or citizens, consistent with the conceptualization of nationalistic political speech. Specifically, we remove targets coded for religions (i.e., Islam, Christianity, Buddhism), intergovernmental organizations (i.e., African Development Bank, Council of Security and Cooperation in Europe), and non-state violent actors (i.e., insurgents, separatists).

Similarly, we restricted source actors to political entities and government officials (i.e., ruling parties, opposition parties, and government bureaucrats) who serve as primary disseminators of nationalistic rhetoric. This captures the politically salient discourse from formal state and party institutions, recognizing that government officials often function as unofficial mouthpieces of elected politicians. To isolate divisive rhetorical acts, we select seven CAMEO event codes (i.e., 113, 1246, 127, 1313, 1382, 139, and 141) indicative of escalatory claims, such as mobilizing third parties against foreign targets, rejecting dispute resolutions, threatening to sever diplomatic ties, or calling for demonstrations against foreign entities[6].

We finally aggregated the filtered event-level data to create a country-year panel, summing the frequency of nationalistic verbal conflict events per country per year. This aggregation results in a panel of 6,340 observations spanning 193 countries from 1979 through 2013, of which those countries failed to match, and duplication records were all removed. The dataset thus constructed offers a high-resolution, longitudinal measure of nationalistic political rhetoric derived from real-time global news, enabling rigorous empirical investigation into its economic and political consequences.

[6] The selected CAMEO event codes, i.e., 113, 1246, 127, 1313, 1382, 139, and 141, are designed to capture a broad spectrum of politically salient and confrontational state rhetoric. These codes reflect actions such as halting negotiations, rejecting dispute mechanisms, threatening sanctions, and calling for mass mobilization, which are indicative of heightened nationalist discourse. Importantly, this subset not only encompasses general expressions of political nationalism, such as sovereignty assertion and diplomatic hostility, but also systematically captures dimensions of economic nationalism. For instance, codes involving accusations of economic aggression (1246), threats of economic disengagement (1313, 1382), and policy demands (127) often pertain directly to protectionist trade measures, foreign investment restrictions, or strategic economic retaliation. As such, these events reflect nationalist efforts to defend domestic economic interests from perceived foreign encroachment, aligning with the core tenets of economic nationalism documented in political economy literature. The inclusion of these specific codes therefore enables a rigorous empirical approach to identifying both broad nationalist signaling and targeted economic nationalist behavior, especially in the context of foreign policy disputes and geopolitical economic tensions.

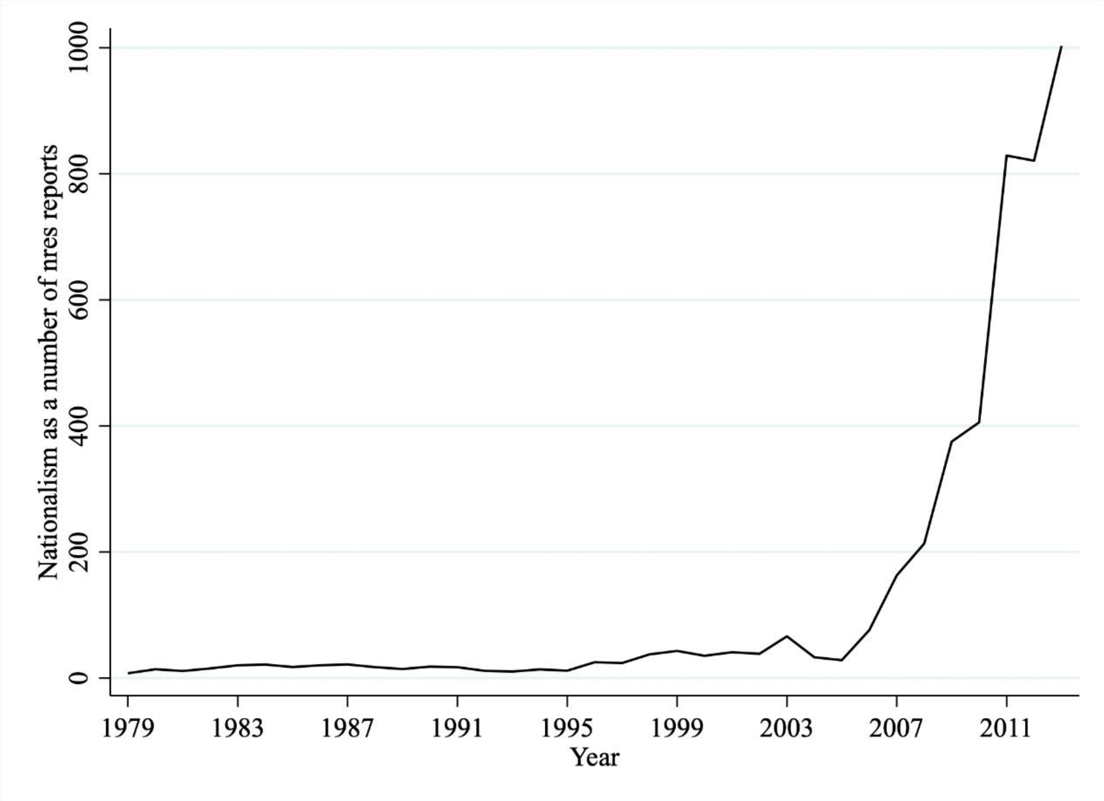

Fig. 1. The frequency of nationalism as a number of news reports between 1979 and 2013.

For validity, Fig. 2 presents temporal patterns in nationalistic political rhetoric across 193 countries between 1979 and 2013, revealing a striking acceleration in such rhetoric in the post-Cold War period. In absolute terms, the number of news-reported nationalistic events per country remained low and stable throughout the 1980s and early 1990s – hovering around two per country per year. Beginning in the late 1990s, however, a marked upward trajectory emerged, coinciding with the global diffusion of digital media and the Internet, as widely discussed by Bieber (2018) and Gaies et al. (2022). This escalation continues through the early 2000s, culminating in an exponential rise in the aftermath of the global financial crisis, reaching over 32 nationalistic events per country annually by 2013. Nonetheless, nationalism constitutes a shrinking proportion of total news content. Thus, the intensity and prevalence of divisive political rhetoric have sharply increased in raw terms, underscoring a growing tendency among political actors to deploy rhetoric that emphasizes national identity, threat narratives, and geopolitical antagonism.

Next, we adopt the network method to construct the nationalism index. The rationale again is that it might be interesting to characterize the bi-(multi)-literal networks of nationalist government, given the stylized facts visualized in Fig. 1.

Assume a network composed of n distinct nodes, each indexed by $i \in [1, \ldots, n]$. A network corresponds to a graph characterized by its adjacency matrix $g \in \mathbb{R}^{n\times n}$, where the entry $g_{ij} \neq 0$ signifies the presence of a direct link between nodes i and j, whereas $g_{ij} = 0$ denotes the absence of such a connection. Our analytical framework accommodates both directed and undirected graph structures and is sufficiently general to encompass weighted and signed networks. The principal results remain valid irrespective of the sign or magnitude assigned to the edges, allowing for highly general link specifications. Nonetheless, to define particular centrality indices, many of which assume binary and non-negative edge values, we focus on a subclass of graphs represented by unweighted, non-negative adjacency matrices.

We define *G(n)* as the set of all permissible network configurations over n nodes. Within the context of an undirected graph $\boldsymbol{g}$, the degree of node i, denoted $d_i(\boldsymbol{g})$, is the cardinality of the set [j: $g_{ij} \neq 0$], capturing the number of edges incident to node i. In directed networks, analogous notions exist: the outdegree of node i counts the number of outgoing edges, while the set defines the indegree [j: $g_{ij} \neq 0$].

A walk from node i to node j is a sequence of (potentially repeated) nodes $i = i_0, \ldots, i_M = j$, satisfying $g_{im,im+1} \neq 0$ for every $m = 0, \ldots, M-1$. A path is a special case of a walk in which all nodes are distinct. Two nodes i and j are said to be connected if at least one such path is linked. A geodesic (or shortest path) proxies the path between two nodes with minimal edges in unweighted networks. The geodesic distance between nodes i and j, denoted $\rho_g(i, j)$, is defined as the edge length of this shortest path, provided such a path exists; otherwise, it is considered infinite. The number of distinct geodesics connecting i and j is also denoted $v_g(i, j)$ by slight abuse of notation. Furthermore, $v_g(k\!: i, j)$ represents the count of geodesics between i and j that traverse node k[7].

Following Wasserman and Faust (1994) and Jackson (2020), four centrality metrics, including degree, closeness, betweenness, and eigenvector, are adopted, as Fan et al. (2023) suggested. We conceptualize a centrality metric as a real-value function c: *G(n)* $\rightarrow \mathbb{R}^{n\times n}$, wherein each component $c_i(g)$ quantifies the prominence or positional importance of node i within a given network structure $g \in G(n)$[8]. Degree centrality[9] quantifies the extent of direct linkages associated

[7] In the context of graphs that are both unweighted and unsigned, the interpretation of the ℓ-th power of an adjacency matrix $\boldsymbol{g}$ is particularly intuitive: each entry g_{ij}^{ℓ} quantifies the total number of directed walks of length ℓ initiating from node $i$and terminating at node j. To formalize local connectivity, let $n_i^{(\ell)}(\boldsymbol{g})$ represent the count of nodes situated at an exact geodesic distance ℓ from node i within the network $\boldsymbol{g}$, defined explicitly as $n_i^{(\ell)}(\boldsymbol{g}) = \left|\{j\!: d_g(i,j) = \ell\}\right|$. In scenarios involving unweighted, undirected, and unsigned graphs, a tree is characterized by the existence of a singular path between any arbitrary pair of nodes i and j, ensuring acyclic and connected structure. An orientation of such a tree can be induced by designating a specific node i^0 as the root and subsequently establishing a directed dominance relation $\succ^d$ as follows: for all nodes i directly adjacent to $i0$ (i.e., g_{i0i} =1), we assert $i^0 \succ^d i$. For any remaining nodes i and j, neither of which is the root, the relation $i \succ^d j$ holds if g_{ij} =1 and the shortest path from i to i^0 is strictly shorter than that from j to i^0. Under this construction, node i serves as the immediate predecessor of j, while j is the direct successor of i. The transitive closure of $\succ^d$ generates a partial ordering $\succ$, where $i \succ$ indicates that i is an ancestral predecessor of j in the oriented hierarchical structure of the tree. Lastly, let $\lambda^{max}(\boldsymbol{g})$ denote the spectral radius, that is, the largest eigenvalue in absolute terms on the right-hand side of the spectrum, associated with a nonnegative adjacency matrix $\boldsymbol{g}$.

[8] These centrality constructs are inherently cardinal in nature, consistent with the conventional definitions and empirical applications prevalent in the existing body of research. While their cardinal form assigns explicit numerical significance to nodes, these measures inherently induce a corresponding ordinal hierarchy, which is frequently employed to derive comparative rankings among network participants.

[9] In directed networks, connectivity is characterized by two distinct metrics: indegree and outdegree. These

with a specific node i, formally represented as $d_i(\boldsymbol{g})$. While this index offers an intuitive and straightforward lens to assess a node's immediate reach or relative prominence, often interpreted as its structural 'popularity, 'it provides a somewhat limited portrayal of a node's strategic relevance within the broader network topology.

Closeness centrality quantifies the average proximity of a given node to all other nodes within a network, relying on the shortest path lengths that connect it to every counterpart. Its computation hinges on the set of minimal path lengths, denoted as $\rho_g(i, j)$, representing the shortest distance between a reference node i and every other node j within the system. Closeness is generated through $\sum_j \rho_g(i, j)$ (Bavelas, 1950; Sabidussi, 1966).

Betweenness centrality quantifies a node's critical role in facilitating interactions across the network by assessing how often it lies on the shortest paths, i.e., geodesics, between pairs of distinct nodes, j and k, excluding the node itself. This metric captures the extent to which a given node acts as an intermediary or bridge, influencing the flow of information or resources within the network structure. As Freeman (1977) suggested, the betweenness metric is,

$$c_i^{bet}(\boldsymbol{g}) = \frac{2}{(n-1)(n-1)} \sum_{(j,k),j\neq i,k\neq i} \frac{v_{\boldsymbol{g}}(i{:}j,k)}{v_{\boldsymbol{g}}(j,k)} \tag{1}$$

Note that betweenness assigns uniform importance to all shortest paths, irrespective of the spatial separation between nodes j and k or alternative routes connecting them.

Eigenvector centrality (Bonacich, 1972) offers a nuanced perspective on the concept of influence within a network by embedding the recursive nature of prestige. Rather than evaluating a node's importance solely through direct connections, it assigns centrality based on the notion that a node gains influence from its immediate links and the centrality of those to whom it is connected. The centrality score of a given node i is defined as being proportional to the aggregate centrality values of its adjacent nodes, expressed as $\lambda c_i = \sum_j g_{ij} c_j$, where the constant of proportionality is strictly positive. When expressed in vector notation, this recursive relationship takes the form $\lambda \boldsymbol{c} = \boldsymbol{gc}$, where λ represents a non-negative proportionality factor.

To capture the extent of nationalist behavior at the country level, we adopt a dichotomous metric based on a country's degree of engagement in international negotiations. Our approach is grounded in the theory that political nationalism often manifests through diplomatic isolation and reduced participation in multilateral governance (Gartzke and Rohner, 2011; Mansfield and Pevehouse,

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measures capture asymmetrical relational dynamics, wherein a node's indegree reflects the extent to which it is a recipient of incoming connections, signifying its capacity to absorb or accumulate information. Instead, its outdegree quantifies the volume of outward links, indicating its potential to disseminate or exert influence across the network.

2006). We begin by constructing a yearly global negotiation network using data on international negotiations from the GDELT database. Each year, nodes in the network represent countries, and edges represent active participation in international negotiations – self-declared, bilateral, or multilateral. This includes treaty signings, trade negotiations, or formal international agreements. A country is classified as a *nationalist* in year *t* if it exhibits zero negotiation activity, i.e., an isolated node with no links in the negotiation network. We define a binary variable: $Nationalism_{it} = 1$ if country *i* has no negotiation links in year *t*, and zero otherwise. This variable is designed to proxy for nationalist posture in foreign policy, characterized by disengagement from the global community. In line with the conventional quasi-natural experimental setup, we use this indicator as the treatment variable, capturing the onset of nationalist orientation over time across countries. This approach ensures time-varying, country-specific variation and aligns conceptually with recent studies applying network isolation to capture autarkic behavior (Hafner-Burton et al., 2009; Haim, 2016), offering an actionable way to identify nationalism in a globalized context.

While this binary measure clearly manifests nationalist tendencies, we recognize that nationalism can be a gradational phenomenon. We also characterize each country's position in the network through four complementary centrality metrics: degree, betweenness, closeness, and eigenvector. To synthesize these dimensions into a parsimonious nationalism manner, we apply Principal Component Analysis[10] (PCA) to the standardized centrality scores (Fan et al., 2023). Within this standardized scale, higher values indicate a progressively intensifying trajectory of nationalist sentiment observed over time in country *i*.

As illustrated in Fig. 2, the global architecture of nationalistic rhetoric underwent a profound transformation between 1979 and 2013, characterized by a marked intensification in scale and connectivity. Over this period, the rhetorical network expanded significantly, as evidenced by a steady proliferation in the number of sovereign participants (nodes) and the bi-(multi)lateral rhetorical ties linking them (edges). In 1979, the discourse landscape comprised 72 nations interconnected through 87 rhetorical pairings. By 2013, the network had grown dramatically to include 249 states and 1,597 rhetorical dyads, reflecting more than a threefold rise in participating entities and nearly a tenfold escalation in rhetorical interconnections. These dynamic shifts in network structure closely mirror the quantitative patterns previously delineated in Fig. 1.

[10] To ensure the robustness of the PCA, we conducted Bartlett's test of sphericity, which yielded a statistically significant result ($\chi^2 = 2061.361$, df = 6, *p*-value < 1%). This outcome substantiates the presence of sufficient intercorrelations among the four extracted centrality indicators, validating the methodological suitability of applying PCA in this context.

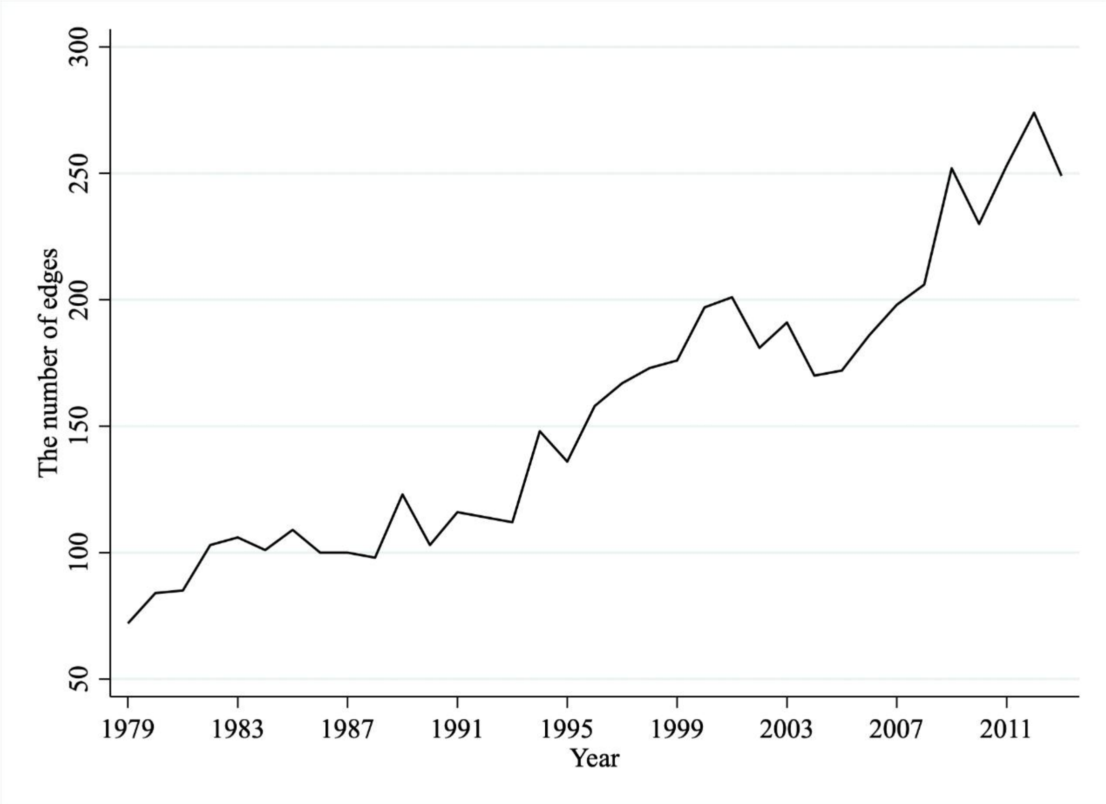


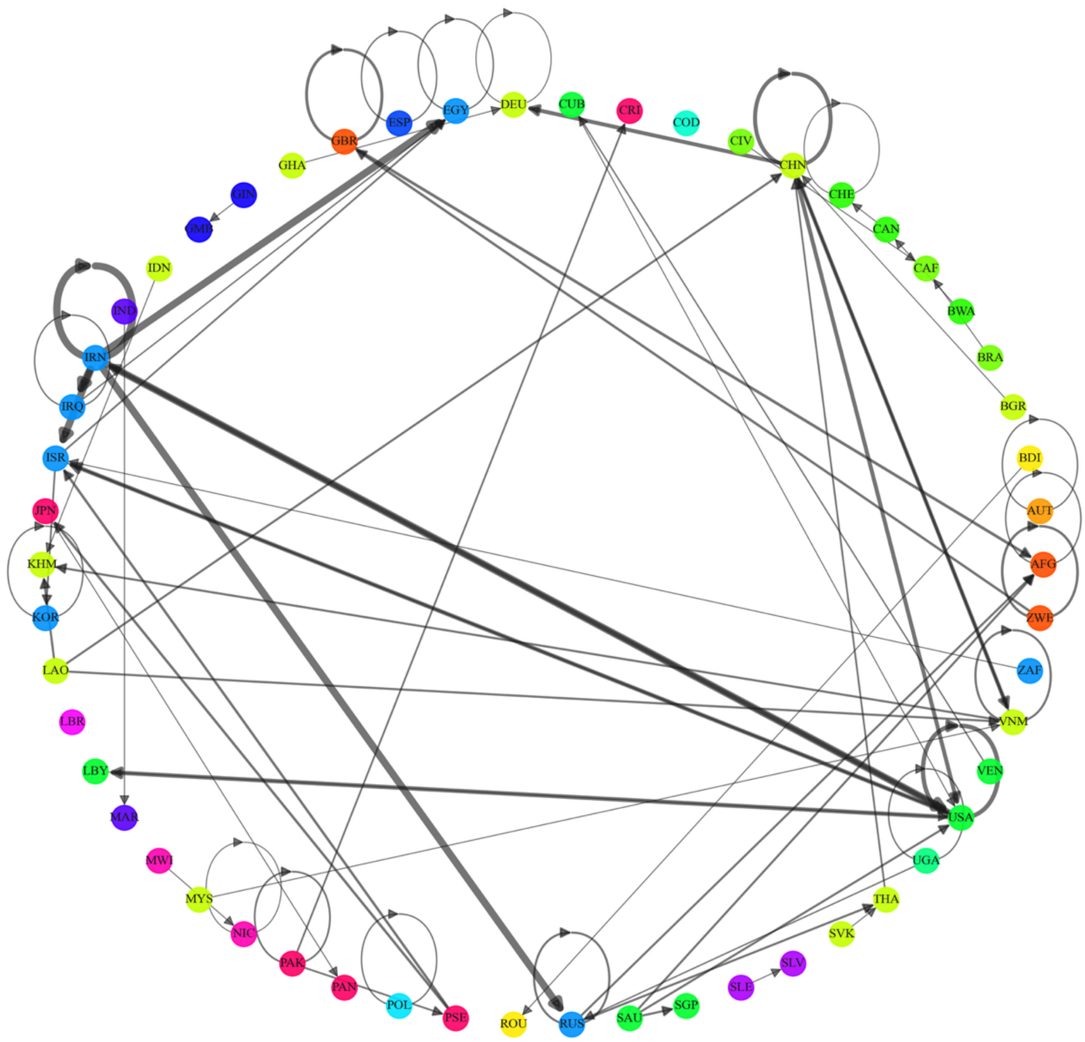
Fig. 2. The number of edges between 1979 and 2013.
Notes: This figure captures the number of unique undirected dyads per year; multiple interactions between the same country pair are aggregated into a single weighted edge.

Fig. 3 offers a detailed depiction of the transnational architecture of nationalist rhetoric across different periods. The 1979 visualization reveals a fragmented and loosely connected network featuring a relatively small group of countries linked by weak ties, indicative of the nascent stages of nationalist discourse's global diffusion. In this early phase, economically advanced Western nations, such as Germany, the UK, and the US, dominate the rhetoric landscape, consistent with expectations that established powers tend to lead nationalist narratives during formative periods. China's nationalist discourse in 1979 shows heightened engagement with the US and Vietnam, while Iran demonstrates significant rhetorical interactions with the US and Russia, suggesting geopolitically motivated nationalist communication.

Instead, the 2013 network presents a considerably more consolidated and densely interconnected structure, with the US emerging as the preeminent voice in nationalist rhetoric worldwide. This observation corroborates the theoretical framework posited by Mylonas and Tudor (2021), which emphasizes the central role of hegemonic powers in shaping and amplifying nationalist narratives on the global stage by major actors such as the US. Moreover, China appears primarily as a receptor of nationalist discourse, frequently directed from India and the US, reflecting evolving geopolitical dynamics and shifting rhetorical strategies.

A notable and consistent feature in both networks is the presence of self-looping edges within specific countries, indicating internally focused nationalist rhetoric. This inward projection aligns with theories of nationalism that underscore the importance of domestic identity consolidation and protectionist narratives as key components of nationalist discourse.

Nationalistic Rhetoric Network in 1979



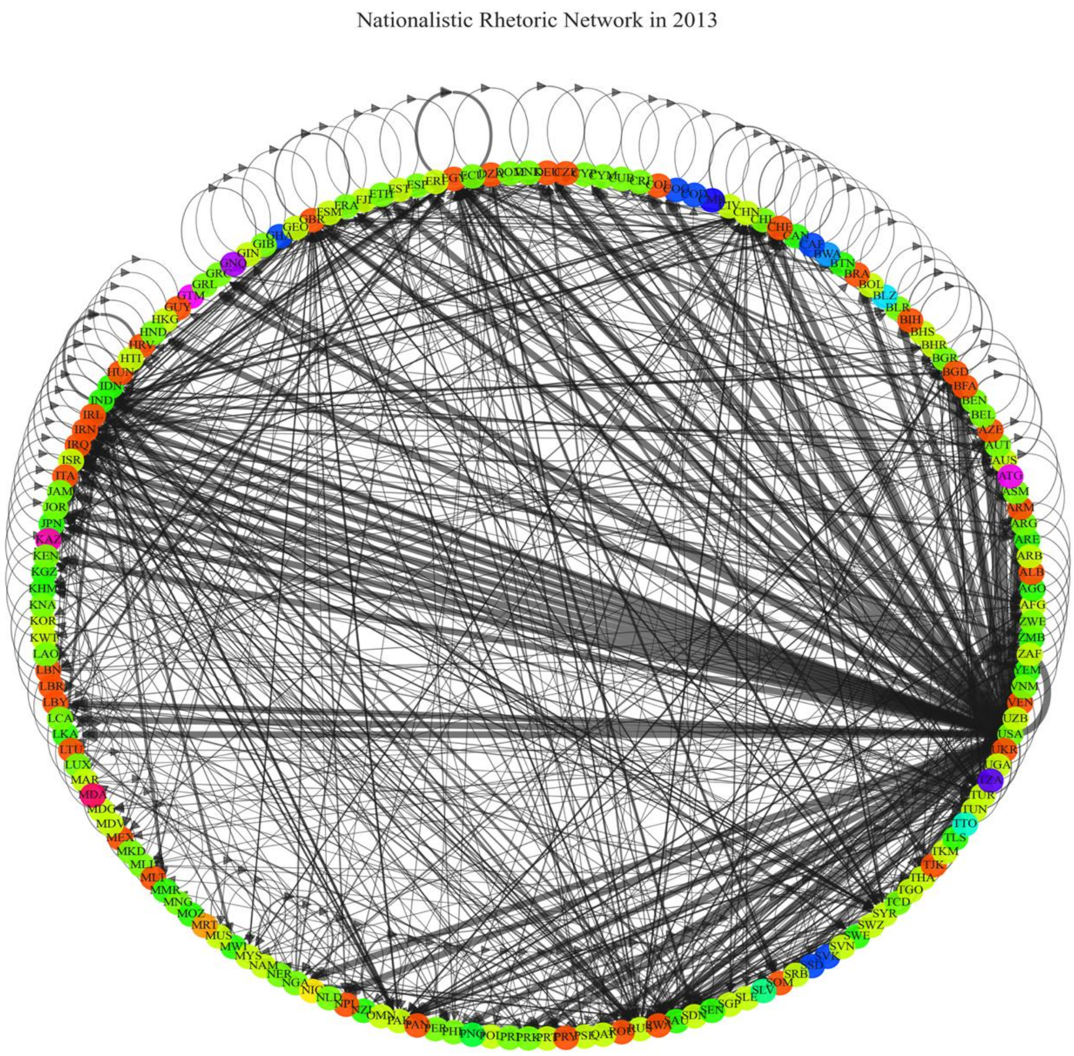


Fig. 3. Nationalism network structures in 1979 and 2013.

Notes: The network graph is constructed by representing countries as nodes placed uniformly around a unit circle to ensure equal visual spacing and avoid clustering bias. Each node's color corresponds to the community it belongs to, which is detected using the Louvain community detection algorithm. Different colors indicate distinct clusters of countries that are more closely connected regarding nationalistic rhetoric interactions, reflecting groups with stronger mutual relationships. The edges between nodes represent the direction and strength of nationalistic rhetoric flows from one country to another, where the thickness of each edge is proportional to the magnitude of the rhetoric, i.e., thicker lines indicate stronger or more frequent rhetorical connections.

2.2 Economic growth

We seek to isolate the influence of nationalism on the logarithmic measure of GDP per capita, capturing the implications of the rhetorical environment for long-term economic growth. In alignment with conventional economic metrics, we utilize per capita gross domestic product, expressed in constant 2000 US dollars, as a representative measure of economic performance. This variable is a proxy for our dependent construct derived from the World Bank Indicator database.

Although nationalism in our analysis is measured as a dichotomous variable, we further investigate the relative fluctuations in economic growth by identifying countries that exhibit non-contemporaneous expressions of nationalistic rhetoric. We thus confine the temporal dynamics to approximately 20 successive rolling windows to ensure temporal consistency and robustness. As illustrated in Fig. 4, economic growth has a discernible upward trajectory before initiating nationalistic discourse. Following the emergence of nationalistic expression, the evolution of economic growth diverges markedly from its pre-treatment trajectory, exhibiting a pronounced decline. This contrast suggests a structural shift linked to the timing of nationalistic sentiment. The dynamic pattern of GDP per capita displayed in Fig. 4 offers preliminary yet compelling evidence pointing to the potentially detrimental consequences of heightened nationalism on growth performance.

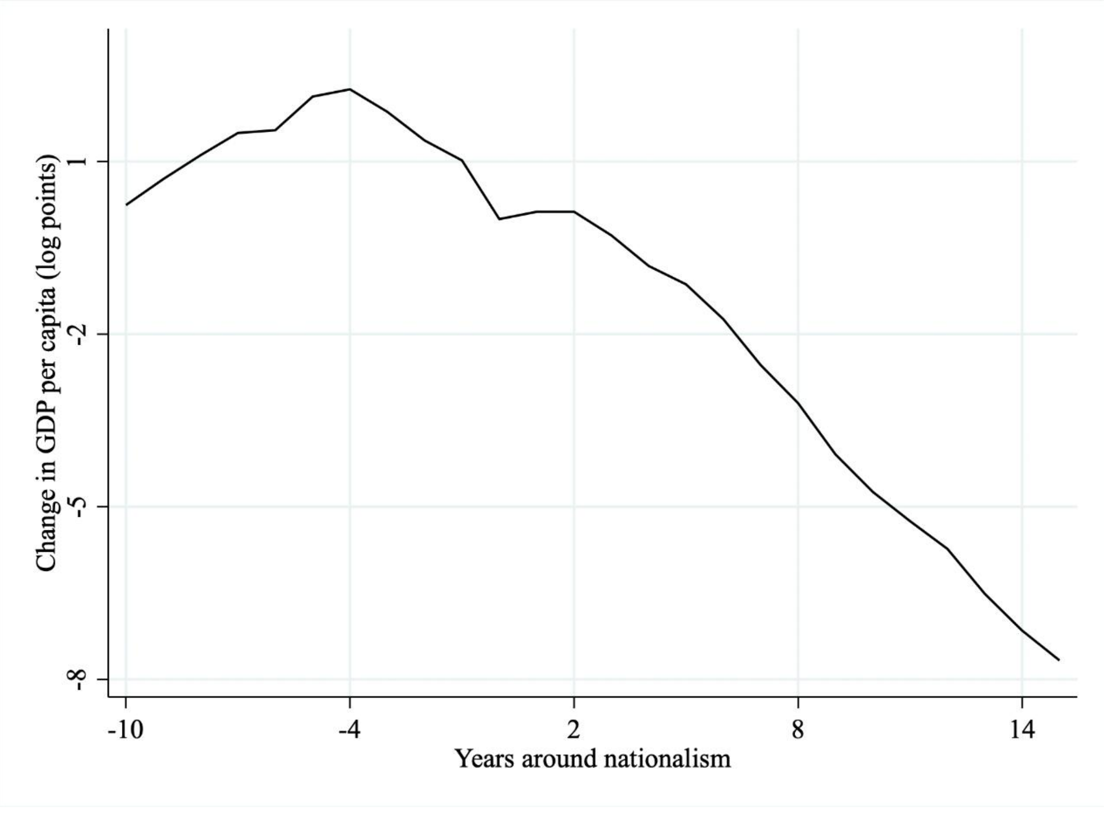


Fig. 3. Relative year performance of nationalism after country sends rhetoric signals.

Notes: The figure illustrates the log-transformed GDP per capita trajectory near a nationalism signal, benchmarked against contemporaneous non-signal countries. For analytical consistency, the log level of GDP per capita is normalized to zero in the year immediately preceding nationalistic behavior. The horizontal axis denotes the temporal distance, measured in years, from the onset of the nationalistic shift.

2.3 Other variables

In addition to the primary indicators, a comprehensive set of supplementary controls, sourced from the World Bank, is incorporated. Indicator database. These include macroeconomic aggregates such as gross investment and total trade (imports plus exports). Cross-border financial dynamics are captured via net foreign assets as a proportion of GDP, based on the internationally harmonized dataset of Lane and Milesi-Ferretti (2007). Furthermore, a binary indicator of domestic sociopolitical instability, characterizing the incidence of riots and uprisings, is derived from the Cross-National Time-Series Data Archive curated by Banks and Wilson (2013). We source emissions data from the World Bank Indicator database and Ritchie and Roser (2020). For regional analyses, the sample is partitioned into seven macro-regions consistent with the World Bank's classification schema: Sub-Saharan Africa, East Asia and Pacific, Eastern Europe and Central Asia, Western Europe plus other advanced economies, Latin America and the Caribbean, the Middle East and North Africa, and South Asia.

Table 1 presents the summary statistics for the full sample and disaggregated figures distinguishing countries based on the temporal occurrence of nationalist rhetoric. As anticipated, countries identified with nationalist tendencies exhibit generally more favorable macroeconomic indicators than their non-nationalistic counterparts. Notably, when nations are flagged for nationalist sentiment, their average economic standing declines by approximately $26 US dollars.

Table 1
Statistical summary of main variables in full and subsamples.

	Full sample			Nationalistic sample			Non-nationalistic sample		
Variable	Obs.	Mean	S.D.	Obs.	Mean	S.D.	Obs.	Mean	S.D.
GDP per capita	6533	1535.904	247.313	2906	1521.361	226.701	3627	1547.557	262.113
Government debt share (% GDP)	5730	57.648	60.236	2376	58.381	57.953	3354	57.128	61.805
Trade (% GDP)	6451	1.220	8.599	2843	0.777	5.119	3608	1.569	10.550
Unrest rate	5625	23.644	42.494	2341	15.891	36.567	3284	29.172	45.462
Total population	7560	26.531	110.029	3780	5.166	17.681	3780	47.897	151.625
Population ages 15-64 (% total population)	9275	0.605	0.070	5475	0.006	0.068	3800	0.613	0.072
Population ages 0-14 (% female population)	9275	0.100	0.026	5475	0.102	0.024	3800	0.097	0.028

3. Dynamic regression estimates

Section 3 offers a benchmark estimate based on a dynamic (linear) panel regression model to validate the nationalism-growth nexus.

3.1 Baseline verification

In the first exercise here, we consider a fully dynamic model structure, expressed as,

$$y_{it} = \beta Nationalism_{it} + \sum_{k=1}^{p} \tau_k y_{it-k} + l_i + \mu_t + \varepsilon_{it} \tag{2}$$

where y_{it} represents the natural logarithm of GDP per capita for country *i* in year t, while $Nationalism_{it}$ is a dichotomous variable, which is ascribed in Section 2.1; l_i corresponds to a comprehensive set of country-specific fixed effects, designed to account for all unchanging national attributes that may influence the outcome variable. μ_t represents a full suite of time-fixed impacts, ensuring that global or standard temporal shocks are netted out from the analysis. ε_{it} encompasses all unobserved, time-varying factors that potentially affect growth but are not explicitly modeled.

To accommodate the inherent persistence in GDP trajectories, the regression framework incorporates p lags of economic growth, capturing the dynamic evolution of economic performance over time. Let t_0 (=1979) denote the baseline year of the panel dataset. The empirical strategy is grounded in the following identifying conditions:

Assumption 1 [Sequential exogeneity]: *The conditional expectation of the disturbance term is assumed to satisfy $E[\varepsilon_{it}/\ y_{it}{-}1, \ldots, y_{ct0}, Nationalism_{it}, \ldots, Nationalism_{it}, l_i, \mu_t] = 0$. for all realizations of past GDP, historical nationalism status, and both fixed effects, holding for every country i and year $t \geq t_0$. This restriction implies that conditional on the model's covariates and fixed components, the innovation in economic growth is orthogonal to prior realizations of the dependent variable and the nationalism indicator, ensuring the validity of causal inference under the specified dynamic panel setup.*

Under Assumption 1, our framework rests on the assumption that countries experiencing shifts in nationalist orientation, whether toward more pronounced or attenuated nationalism, are not simultaneously on divergent economic trajectories relative to countries with comparable recent economic performance (captured through lagged GDP per capita) and similar structural characteristics (captured by country fixed effects). While this exclusion restriction is strong, it is not implausible. Crucially, the use of lagged income controls not only accounts for post-crisis nationalist surges but also absorbs latent macroeconomic drivers that shape both income evolution and the salience of nationalist ideology. The common trend issue cannot fundamentally be resolved, given the stylized fact that shifts in nationalism are frequently accompanied by institutional and policy realignments, ranging from changes in trade openness and regulatory structures to fiscal reorientation and welfare reconfiguration. Rather than undermining identification, these policy responses represent substantive pathways through which nationalism exerts its economic effects. Accordingly, we interpret these endogenous adjustments not as confounders but as integral to the mechanism by which nationalism influences macroeconomic outcomes.

Relying on Assumption 1 alongside the stationarity condition, Eq. (1) is estimated using the conventional fixed-effects (within) estimator[11]. Columns 1 and 2 of Table 2 present estimates obtained under alternative GDP per capita lag specifications. For interpretative clarity, our nationalism has been scaled by 100. Robust standard errors are employed throughout to accommodate heteroskedasticity. To ensure robustness and facilitate cross-model comparability, we document estimates corresponding to lag lengths of 1, 2, 4, and 8 periods, as displayed across columns 1 through 4. A notably high degree of inertia characterizes economic growth trajectory, as evidenced by the estimated coefficient of 0.953 on the one-period lag of the logarithm of GDP per capita. This substantial magnitude implies that past income levels exert a strong and enduring influence on current economic performance, underscoring the path-dependent nature of growth dynamics. Following Assumption 1, each estimated coefficient lies below unity in absolute value. Further, our nationalism coefficient remains persistently negative and statistically significant, indicating a detrimental association with growth. For instance, a nationalism coefficient -0.5 emerges with statistical significance at the 5% threshold.

Building upon our analytical framework, we compute the long-run transition dynamics of nationalism on GDP per capita, specifically assessing the effect on the steady-state value of GDP per capita, denoted $y_{c,\infty}$, when nationalism shifts permanently from zero to unity for all future periods s ≥ 0. To assess the enduring economic consequences of a structural shift toward nationalism, we calculate the cumulative long-run effect on GDP per capita using the expression $\hat{\beta}/1-\sum_{k=1}^{p}\hat{\tau}_p$, where $\hat{\beta}$ denotes the estimated coefficient. Applying this method, column 1 shows that a permanent reorientation toward nationalism leads to a sharp and persistent contraction in economic performance, culminating in a long-term decline of approximately 13 percent in GDP per capita. In contrast, a sustained shift toward democratic governance yields a cumulative gain of about 8 percent of GDP per capita over 20 years[12].

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[11] As a foundational step for subsequent analysis, we implement a transformation that captures intra-country variations over time: $y_{it}-\frac{1}{T_i}\sum_s y_{is}=\beta\left(NI_{it}-\frac{1}{T_i}\sum_s NR_{is}\right)+\sum_{k=1}^{p}\tau_k\left(y_{it-k}-\frac{1}{T_i}\sum_s y_{is-p}\right)+\mu_t+\left(\varepsilon_{it}-\frac{1}{T_i}\sum_s\varepsilon_{is}\right)$, specifically, a "within" fashion, where T_i denotes the frequency with which a country enters the estimation sample. Under the assumptions that NR_{it} and y_{it-2} satisfy sequential exogeneity, and that GDP per capita follows stationarity, the within estimator is known to exhibit an asymptotic bias diminishing at a rate proportional to *1/T*. Given the extended temporal span of our dataset, this estimator serves as an appropriate and theoretically consistent baseline for our empirical framework.

[12] We estimate the enduring effects of a sustained shift to nationalistic environment, contrasting it against a hypothetical scenario where the nation remains perpetually non-nationalistic. For robustness, **Appendix A**

Column 2 augments the specification by introducing two lags of GDP per capita, thereby enriching the dynamic structure of the model. The estimates reveal a nuanced temporal response: the first lag exerts a positive influence, while the second exhibits an adverse effect. Despite these contrasting signs, the aggregate persistence in GDP dynamics remains comparable to that reported in column 1. In this setting, the estimated long-run contractionary effect of nationalism is approximately 8 percent (i.e., a similar coefficient in column 1). Column 3, our preferred setup extends the lag structure further by incorporating four lagged terms of GDP per capita. The dynamic profile closely mirrors that observed in column 2. Notably, the nationalism coefficient is estimated at -0.5, translating into a cumulative long-term reduction in GDP per capita of 6 percent. Column 4 further expands the temporal scope by including an additional four lags – bringing the total to eight – though their coefficients are omitted from the table. Instead, a joint significance test is reported, the *p*-value of which indicates that these additional lags do not collectively influence present economic performance. The degree of GDP persistence and the inferred long-run effect of nationalism in this extended model remain closely aligned with the estimates documented in column 3.

The fixed-effects estimates presented in columns 1 through 4 are subject to a bias that arises at a rate inversely proportional to the temporal dimension of the panel (1/T), i.e., Nickell bias. This distortion emerges due to violations of the strict exogeneity condition inherent in dynamic panel frameworks (Alvarez and Arellano, 2003; Nickell, 1981). Given that our dataset exhibits a relatively long period, this asymptotic bias is expected to be negligible in our empirical context. Consequently, employing the within-group estimator for these initial specifications is a theoretically sound and empirically justified benchmark.

The remainder of Table 2 presents a suite of generalized method of moments (GMM) estimators designed to mitigate the Nickell bias and yield consistent parameter estimates even when the temporal dimension remains finite. These estimators capitalize on the sequential exogeneity assumption, which gives rise to a set of valid moment conditions for efficient identification in dynamic settings, such as $\mathbb{E}[(\varepsilon_{it} - \varepsilon_{it-1})(y_{is}, Nationalism_{is+1})'] = 0$, for all $s \leq t\text{-}2$. We estimate Eq. (2) using the GMM approach, as shown in columns 5-8. The estimates in column 7 closely align with those in column 3, confirming the computational reliability of the within estimator. The lower panel reports *p*-values from serial correlation tests. Still, no evidence of serial correlation emerging with four or more lags supports the validity of our preferred specification in column 7.

While Table 2 remains reliable if Assumption 1 holds plus stationary condition. Given the validity of Assumption 1 mentioned previously, we applied the Levin et al. (2002) test. Table 2 presents the adjusted *t*-statistics from this test beneath each within-group estimate. In every case, the null hypothesis of a unit root in GDP is decisively rejected.

presents a supplementary estimation that incorporates the potential for the country to undergo nationalism at a later stage.

Table 2

Impact of nationalism on economic growth [log-transformed GDP per capita].

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Estimates [Within]				Estimates [Arellano and Bond]			
Dep. Var.	Log GDP per capita	Log GDP per capita	Log GDP per capita	Log GDP per capita	Log GDP per capita	Log GDP per capita	Log GDP per capita	Log GDP per capita
Nationalism	-0.6164**	-0.5240**	-0.5202**	-0.8765***	-1.0496***	-0.8898**	-0.8059**	-1.0712***
	[0.2507]	[0.2448]	[0.2523]	[0.2653]	[0.3847]	[0.3607]	[0.3716]	[0.3545]
Effect of nationalism after 20 years	-13.0199**	-9.9399**	-8.4081**	-11.1241***	-8.8243***	-9.0873***	-7.6071**	-9.5584***
	[5.3774]	[4.3461]	[3.6620]	[2.9314]	[3.0415]	[3.3450]	[3.2127]	[2.8975]
Long-term effect of nationalism	-8.0840**	-7.5951**	-7.4179**	-11.0961***	-8.1232***	-8.4730***	-7.4364**	-9.7055***
	[3.1955]	[3.3427]	[3.3151]	[2.9200]	[2.8088]	[3.1383]	[3.1414]	[2.8843]
Economic growth persistence	0.9527***	0.9473***	0.9381***	0.9212***	0.8811***	0.9021***	0.8941***	0.8879***
	[0.0103]	[0.0104]	[0.0111]	[0.0130]	[0.0150]	[0.0171]	[0.0164]	[0.0153]
L1. Log (GDP per capita)	0.9527***	1.1857***	1.1252***	1.1044***	0.8811***	1.1072***	1.0464***	1.0380***
	[0.0103]	[0.0684]	[0.0692]	[0.0773]	[0.0150]	[0.0771]	[0.0737]	[0.0798]
L2. Log (GDP per capita)		-0.2384***	-0.1016	-0.0963		-0.2051***	-0.0790	-0.0737
		[0.0637]	[0.0854]	[0.0928]		[0.0646]	[0.0816]	[0.0887]
L3. Log (GDP per capita)			-0.0018	0.0064			0.0033	0.0097
			[0.0409]	[0.0430]			[0.0415]	[0.0440]
L4. Log (GDP per capita)			-0.0837***	-0.0662**			-0.0768***	-0.0597**
			[0.0274]	[0.0265]			[0.0256]	[0.0257]
p-value, L5-8. Log (GDP per capita)				0.4943				0.5942
N	6340	6147	5761	4991	6147	5954	5568	4799
Cross-Sectional Obs.	193	193	193	192	193	193	193	192

	0.206	0.361	0.523	0.201
p-value, AR(2)				
p-value, Levin, Lin, and Chu test	0.000	0.000	0.000	0.000

Notes: *, **, *** signify the significance level of 10%, 5%, and 1%, respectively. Standard errors, reported in parentheses, are corrected for potential heteroskedasticity and autocorrelation within countries. This table shows the effects of nationalism on GDP per capita (log-transformed). Columns 1 to 4 use a fixed effects method, which compares changes within each country over time. Columns 5 to 8 use the GMM method (Arellano and Bond, 1991). The *p*-value of AR (2) checks serial autocorrelation. Columns 4 and 8 include eight lagged GDP per capita values to capture past effects better, but only the test result for the last four lags is shown. The *p*-value of lags 5-8 GDP per capita in columns 4 and 8 is used for the joint significance test.

4. Robustness tests

This section leverages sufficient tests to verify the reliability of our baseline estimates.

4.1 Basic robustness methods

A primary concern regarding potential bias in our estimates stems from heterogeneous GDP trajectories across countries experiencing a rise in nationalist sentiment. To mitigate this issue, Table 3 introduces a set of controls that account for baseline economic conditions, i.e., column 1. Specifically, we interact year-fixed effects with categorical indicators denoting each country's position in the global GDP per capita distribution as of 1979. Based on Angus Maddison's historical GDP data, this stratification enables identification by comparing countries at comparable levels of initial economic development. The inclusion of these controls does not substantively alter our findings. The within-estimator coefficient on nationalism remains robust at -0.8 (p-value<5%), yielding a long-run elasticity of approximately -12 percent, i.e., column 2. The GMM estimates in Panel B exhibit similar magnitudes, albeit with marginally attenuated coefficients.

Nationalist regimes often provoke investor uncertainty due to institutional shifts, weakened rule of law, or capital controls. For example, high debt ratios amplify investor concerns. International investors are less willing to hold sovereign debt if nationalism threatens fiscal discipline. This raises sovereign risk premiums, limits capital inflows, and slows GDP per capita growth via reduced investment. Column 3 considers the government debt ratio as a confounder (i.e., four lags). No evidence demonstrates the substantial variations in our main estimates.

Column 4 tabulates whether nationalist surges disproportionately influence our results in the former Soviet bloc. We introduce interaction terms between a dummy variable for Soviet and Soviet-aligned nations and year indicators for 1989, 1990, 1991, and post-1992 periods. These additional controls exert minimal influence on the magnitude of the nationalism-growth relationship, with the long-run effect slightly decreasing to -11 percent.

Despite the favorable trends in economic growth during post-nationalism, as depicted in Fig. 1, estimates could be biased, potentially attributable to sociopolitical instability that often precedes a shift toward nationalist governance. This observation raises concerns about confounding pre-trends. We thus include four lags of civil unrest indicators into our baseline model. The results in column 5 remain largely consistent, suggesting that unrest-related shocks do not account for the observed growth patterns.

An additional concern is that nationalism may be endogenous to external economic disturbances, i.e., shifts in trade dynamics or cross-border capital movements, that independently influence growth. Therefore, column 6 introduces four lags of trade exposure, while column 7 incorporates lagged values of net financial inflows. Although these variables may themselves respond to nationalist policies, rendering them potentially endogenous, the estimated impact of nationalism remains statistically stable and qualitatively similar.

Furthermore, demographic transitions may simultaneously drive both economic performance and the emergence of nationalist ideologies. In column 8, we control for lagged population size and demographic composition, specifically the shares of the population under 16 and over 64 years of age. These adjustments also exert negligible influence on our central estimates, reinforcing the robustness of the nationalism-growth linkage.

Table 3

Effect of nationalism on GDP per capita [log-transformed], conditional on regressors.

	Baseline controls	Baseline controls [with year-FE]	Government debt ratio [With lags]	Soviet crisis dummies	Unrest [With lags]	Trade [With lags]	Financial flows [With lags]	Demographic structure [With lags]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Estimates [Within]							
Nationalism	-0.5202**	-0.8008**	-0.5163**	-0.6290**	-0.6328**	-0.5642**	-0.6414***	-0.5248**
	[0.2523]	[0.3134]	[0.2111]	[0.2821]	[0.2496]	[0.2425]	[0.2243]	[0.2473]
Long-run effect of nationalism	-8.4081**	-12.0081***	-10.4601***	-10.5777**	-10.4977***	-9.4233***	-11.6823***	-8.3701**
	[3.6620]	[4.2073]	[3.8250]	[4.1212]	[3.7514]	[3.5475]	[3.8608]	[3.6225]
Effect of nationalism after 20 years	-7.4179**	-11.1446***	-8.1604***	-9.6618**	-8.9830***	-8.1798**	-9.8109***	-7.3937**
	[3.3151]	[3.9984]	[2.9345]	[3.8497]	[3.2940]	[3.1897]	[3.3189]	[3.2542]
Persistence of GDP process	0.9381***	0.9333***	0.9506***	0.9405***	0.9397***	0.9401***	0.9451***	0.9373***
	[0.0111]	[0.0158]	[0.0090]	[0.0118]	[0.0147]	[0.0113]	[0.0102]	[0.0131]
N	5761	3883	4886	4678	4799	5679	5035	5761
Cross-Sectional Obs.	193	144	190	157	169	193	187	193
	Panel B: Estimates [Arellano and Bond]							
Nationalism	-0.8059**	-0.8136*	-0.6885**	-0.6638*	-0.8623**	-0.9619***	-0.8854**	-0.8373**
	[0.3716]	[0.4261]	[0.3148]	[0.3930]	[0.4390]	[0.3577]	[0.3830]	[0.3415]
Long-run effect of nationalism	-7.6071**	-6.4318**	-7.6756**	-5.9246*	-3.6845**	-9.0054***	-4.3280**	-6.8916***
	[3.2127]	[2.9865]	[3.1437]	[3.3099]	[1.6629]	[3.0686]	[1.8060]	[2.3853]

Effect of nationalism after 20 years	-7.4364**	-6.4334**	-7.0137**	-5.9249*	-3.6775**	-8.7534***	-4.2889**	-6.8131***
	[3.1414]	[2.9850]	[2.8051]	[3.3054]	[1.6598]	[2.9676]	[1.7842]	[2.3724]
Persistence of GDP process	0.8941***	0.8735***	0.9103***	0.8880***	0.7660***	0.8932***	0.7954***	0.8785***
	[0.0164]	[0.0239]	[0.0140]	[0.0160]	[0.0309]	[0.0180]	[0.0262]	[0.0214]
N	4285	3739	3633	4285	3952	3976	3924	4216
Cross-Sectional Obs.	193	144	190	157	169	193	187	193
p-value, AR(2)	0.523	0.316	0.989	0.274	0.314	0.264	0.799	0.611

Notes: *, **, *** signify the significance level of 10%, 5%, and 1%, respectively. Standard errors, reported in parentheses, are corrected for potential heteroskedasticity and autocorrelation within countries. This table shows the effects of nationalism on GDP per capita (log-transformed). Columns 1 to 4 use a fixed effects method, which compares changes within each country over time. Columns 5 to 8 use the GMM method (Arellano and Bond, 1991). The *p*-value of AR (2) checks serial autocorrelation.

So far, we have provided preliminary evidence to showcase the inhibitory impact of nationalism on economic growth. The primary challenge to the credibility of the preceding estimates arises from dynamic political and economic factors that concurrently influence nationalism and growth (i.e., factors not addressed by country-fixed effects), which only account for time-invariant heterogeneity. We now turn to a closer examination of these potential biases.

Now, assume economic growth could exhibit a near-unit root nature. Eq. (2) is transformed as,

$$y_{it} - \rho y_{it-1} = \beta Nationalism_{it} + \sum_{k=1}^{p-1} \phi_k (y_{it-1} - y_{it-1-k}) + l_i + \mu_t + \varepsilon_{it} \quad (3)$$

In Eq. (3), $\rho = \left(\sum_{k=0}^{p} \tau_k\right)$ regulates the level of persistence of growth, and $\phi_k = \left(\sum_{k=0}^{p} \tau_k - \rho\right)$ (with τ_k the coefficients we captured for the equation in levels). We identified high persistence in GDP per capita, with autoregressive coefficients ranging between 0.90 and 0.95. To further probe the implications of this persistence, we re-estimate Eq. (3) under alternative calibrations of ρ, varying it systematically from 0.90 up to the unit root threshold of one. The case of $\rho = 1$ reflects a scenario in which GDP follows a perfect non-stationary process. Our focus remains on highly persistent processes, given concerns that conventional fixed-effects estimators may suffer from Nickell bias (see **Appendix B**), potentially leading to downward-biased estimates of ρ.

Table 4 summarizes the estimation results under these imposed values of ρ, where Panel A presents within-group estimates, and Panel B shows the corresponding two-stage least squares (2SLS) results. Each specification's dependent variable is constructed as the deviation of current GDP from ρ times its lag, while lagged GDP growth rates serve as key regressors. This transformation ensures the stationarity of the model as long as the sum of the coefficients on the lagged growth terms remains below 1.9, thereby mitigating concerns related to near-unit root behavior in GDP. Importantly, as ρ approaches unity, both short-run and long-run effects of nationalism on GDP per capita appear to intensify. This pattern indicates that allowing for greater persistence in GDP amplifies the estimated impact of nationalism institutions on GDP per capita[13].

[13] Prior to estimating the semiparametric treatment effects, we perform supplementary robustness assessments. These include the use of an alternative proxy for nationalism derived from PCA and its constituent indicators, as well as an outlier diagnostics test, to rigorously validate the reliability of our baseline specification, as depicted in **Appendix C**.

Table 4

Effect of nationalism on GDP per capita [log-transformed] based on different persistence of the GDP.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Imposed persistence $\rho = \sum \tau_k$:	*ρ = 0.90*	*ρ = 0.92*	*ρ = 0.94*	*ρ = 0.96*	*ρ = 0.98*	*ρ = 0.99*	*ρ = 1.00*
Nationalism	-0.7658***	-0.6988***	-0.6317***	-0.5646**	-0.4973**	-0.4636**	-0.4299*
	(0.2568)	(0.2467)	(0.2393)	(0.2348)	(0.2332)	(0.2336)	(0.2348)
Long-run effect of nationalism	-7.6579***	-8.7352***	-10.5289***	-14.1139**	-24.8637**	-46.3593**	7.744e+15*
	(2.5682)	(3.0843)	(3.9885)	(5.8689)	(11.6620)	(23.3640)	(4.230e+15)
Effect of nationalism after 20 years	-7.4904***	-8.1660***	-8.9612**	-9.8791**	-10.9070**	-11.4504*	-12.0015*
	(2.5573)	(2.9623)	(3.5205)	(4.2935)	(5.3694)	(6.0588)	(6.8759)
N	5568	5568	5568	5568	5568	5568	5568
Cross-Sectional Obs.	193	193	193	193	193	193	193

Notes: *, **, *** signify the significance level of 10%, 5%, and 1%, respectively. Standard errors, reported in parentheses, are corrected for potential heteroskedasticity and autocorrelation within countries. This table reports the estimated impact of democratic governance on GDP per capita, with each column reflecting a different assumed degree of persistence in the GDP process. The results are derived through fixed-effects estimates based on within-country variation, incorporating four lagged terms of GDP per capita as controls. All regressions include country- and year-fixed effects and four lagged GDP per capita values.

4.2 Treatment effect: Semiparametric verifications

Our baseline framework used a dynamic linear model to control for growth changes. This method helped remove the bias caused by the GDP drop, i.e., unexpected changes due to unpredicted shocks. Yet such an innovation relies on the linear assumption, treating the effects of moving into and out of nationalism as equal in size but opposite in direction. However, our setup might limit how the long-term impact of nationalism on economic growth can evolve by extending a linear trend into the future. We thus adopt a semiparametric strategy that models how countries exhibit nationalism behavior without assuming a specific pattern for growth over time. While we still need to model either the likelihood of nationalism or expected GDP growth under authoritarianism. In what follows, we explain this method and present the related results.

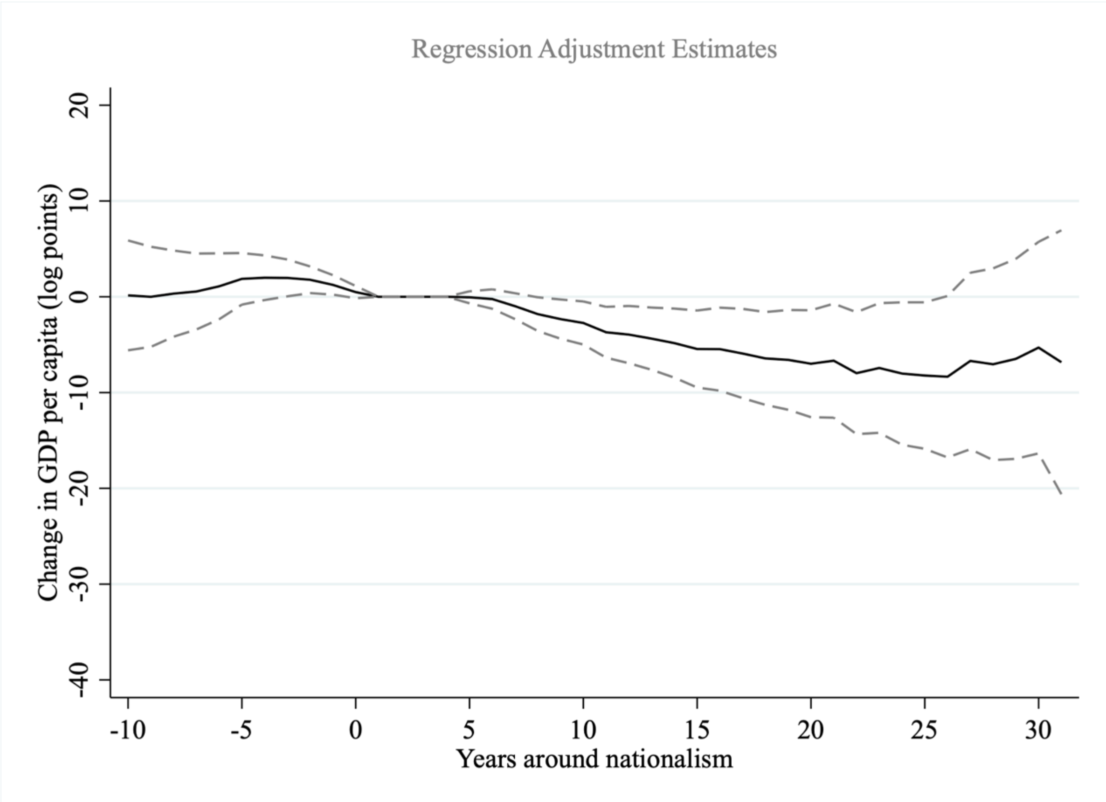
Following Jordà (2005) and Acemoglu et al. (2018), assume y_{it}^{s} represents the hypothetical GDP per capita (log-transformed) of country *i* at time $t + s$, conditional on experiencing political regime *Nationalism* ∈ [0, 1] at time t. Here, *Nationalism* = 1 signifies a shift from non-nationalistic to nationalistic behaviors at time t, characterized by $Nationalism_{it} = 1$ and $Nationalism_{it-1} = 0$; conversely, d = 0 indicates continued non-nationalistic status. Define the counterfactual growth variations over the interval from t – 1 to $t + s$ as $\Delta y_{it}^{s}(Nationalism) = y_{it}^{s}(Nationalism) - y_{it-1}$, capturing the regime-dependent evolution in economic GDP per capita. In line with the potential outcomes framework commonly employed in causal inference, the binary variable d functions as the treatment indicator, and $\Delta y_{it}^{s}(Nationalism)$ for s ≥ 0 reflects the treatment-contingent response trajectory. The causal impact of nationalism at time t on subsequent GDP per capita levels for transitioning countries is then understood as the difference in these counterfactual paths and thus, we have $\beta^{s} = \mathbb{E}[\Delta y_{it}^{s}(1) - \Delta y_{it}^{s}(0) | Nationalism_{it} = 1, Nationalism_{it} = 0]$.

The above transformation does not impose structural assumptions on growth dynamics. Instead, these estimates capture the short-run consequences of a nationalist shift occurring at time t, which may be subject to reversal in future periods, rather than measuring the effect of a sustained nationalist regime. By conditioning on instances where a country adopts nationalism at t but has not done so in $t - 1$ (i.e., $Nationalism_{it} = 1$ and $Nationalism_{it-1} = 0$), the analysis isolates the average treatment effect on the treated. A central empirical challenge lies in the potential non-random selection into nationalism, as countries undergoing nationalist transitions may systematically differ in counterfactual outcomes from non-nationalist ones. This identification issue is addressed assuming that the propensity to adopt nationalism is driven entirely by observable characteristics. That said, past GDP levels and common temporal shocks lead to the second assumption:

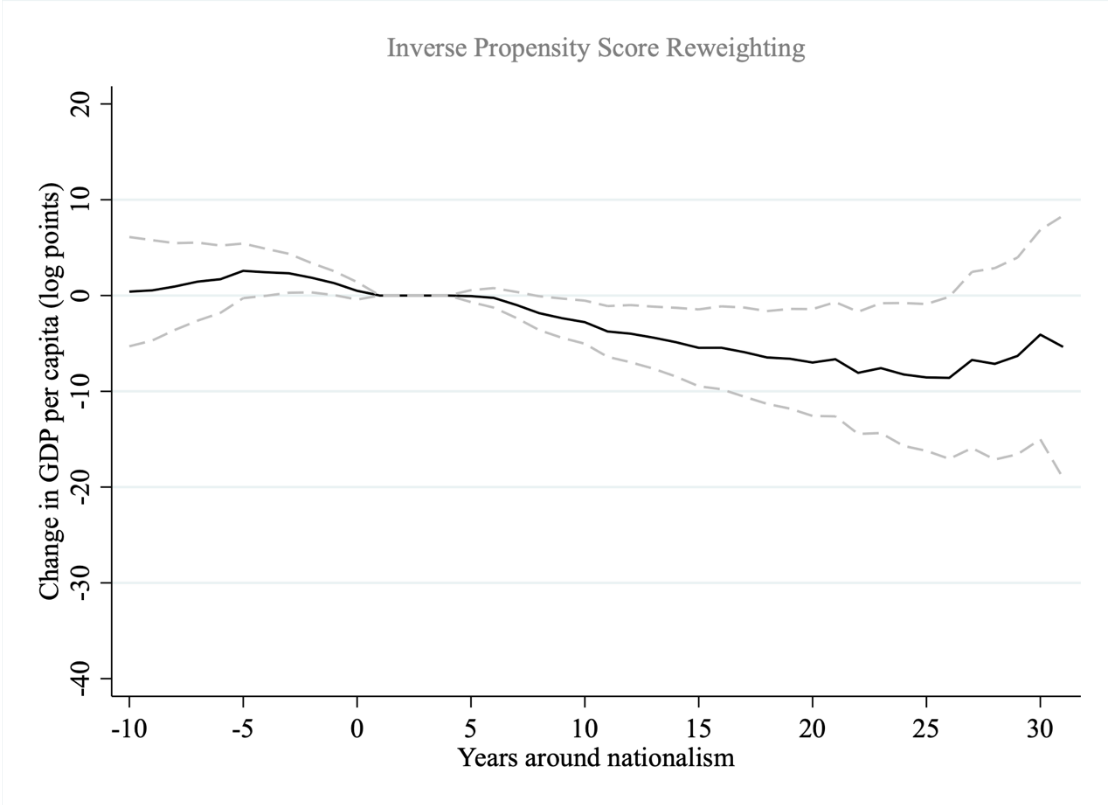
Assumption 2 [Selection on observables]: $\Delta y_{it}^{s}(Nationalism) \perp Nationalism_{it} \| Nationalism_{it-1} = 0, y_{it-1}, \dots, y_{it-4}$ for all *i*, t and y_{it-1}, …, y_{it-4} and s ≥ 0

Under Assumption 2, countries that adopt nationalist policies may appear to do so following periods of economic stress (i.e., a GDP decline), suggesting a non-random trigger. However, Assumption 2 permits this correlation with pre-treatment GDP dips while asserting that, conditional on this economic history, there are no other omitted, time-varying variables that jointly determine both the likelihood of transitioning to nationalism and the future growth path. In simpler terms, Assumption 2 allows for observable economic precursors to nationalism but rules out unobservable causes that could simultaneously affect the decision to adopt nationalist policies and influence future economic outcomes. This is critical in ensuring that any estimated effects of nationalism on growth are not biased by omitted variables, as long as those variables are captured via lags of GDP and common time shocks. Assumption 2 has been supported by Acemoglu et al. (2005), and in our tests, see **Appendix D**.

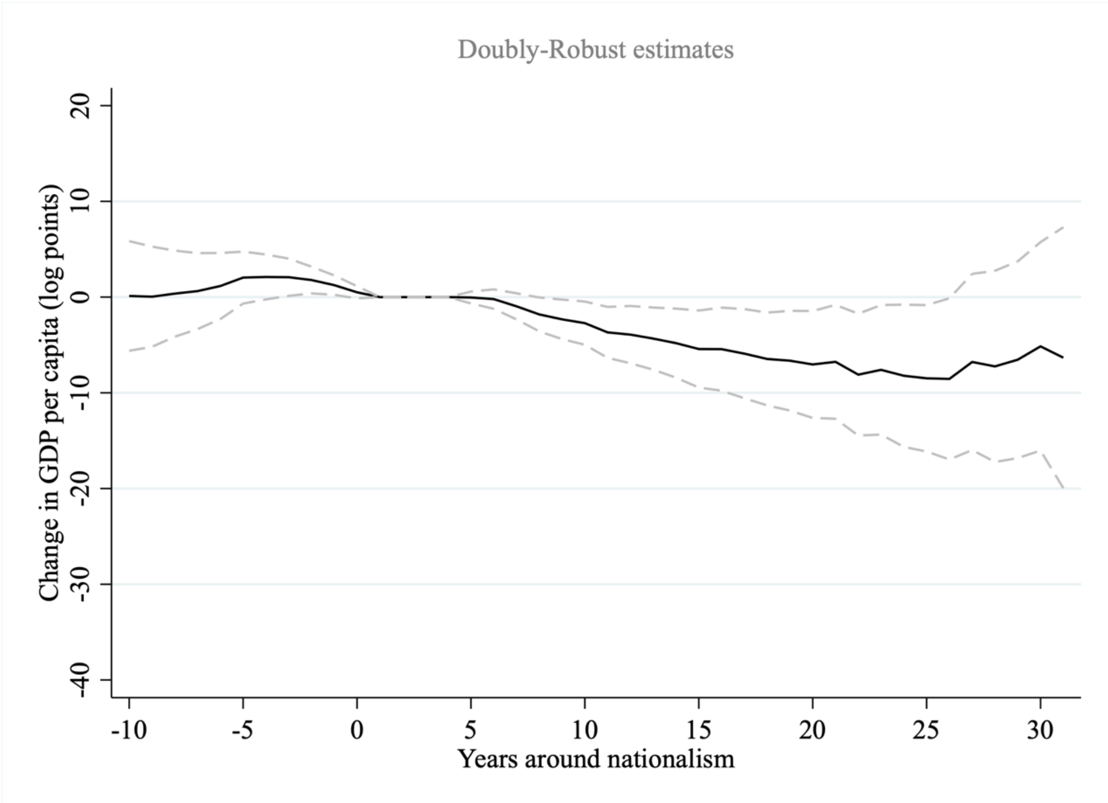
For implementation, three different approaches are considered based on three seminal works, i.e., adjusted-regression estimator (Jordà, 2005; Kline, 2011), inverse reweighted propensity score estimator (Angrist and Kuersteiner, 2011; Angrist et al., 2018), and doubly-robust estimator (Imbens and Wooldridge, 2009). We adopt a dynamic rolling window approach spanning 45 years, partitioned into a 10-year pre-nationalism phase and a 30-year post-nationalism phase. As illustrated in Fig. 4, our dynamic estimates reveal a pronounced decline in GDP per capita immediately after nationalist rhetoric emerges, with projected growth trajectories remaining consistent across various estimation techniques.



(a) Adjusted-regression estimator.



(b) Inverse reweighted propensity score estimator.



(c) Doubly-robust estimator.

Fig. 4. Semiparametric estimates of the dynamic effects of nationalism on GDP

per capita [log-transformed].

Notes: This figure presents semiparametric estimates illustrating the impact of nationalism on log-transformed GDP per capita. The solid curve reflects the mean estimated effect of transitioning to nationalism on GDP per capita, while the dashed bands denote the associated 95% confidence interval. The horizontal axis represents time in years relative to the onset of nationalism. The estimates are derived using a regression framework that models counterfactual trajectories under the assumption of linear GDP evolution absent nationalism. This allows us to net out baseline growth trends and isolate the effect attributable to nationalist shifts.

Table 4 presents the averaged cumulative average treatment effects (ATE) derived from three specifications. The results indicate that the dynamic ATEs tend to become markedly significant approximately a decade (i.e., in an accumulative manner) after countries display nationalist tendencies. However, the timing and magnitude of these effects vary across models. For instance, the cumulative impact of nationalism on GDP per capita attains statistical significance around five years 'post-treatment.' Moreover, when nationalism manifests through overtly racist rhetoric, the ensuing repercussions tend to intensify in the subsequent years. Despite the cumulative ATEs losing statistical significance in all specifications beyond this point, the detrimental influence on economic growth amplifies, suggesting a lasting adverse trajectory initiated by nationalist signaling. Once again, the doubly-robust estimator in Panel C of Table 5 reaffirms no discernible downturn in GDP is observed before nationalism, and the economic losses from nationalism stabilized around 14 percent after two decades of adoption.

Table 4

Semiparametric estimates of the effects of nationalism on GDP per capita [log-transformed]: ATEs

	(1) -5 ~ -1 Years	(2) 0 ~ 4 Years	(3) 5 ~ 9 Years	(4) 10 ~ 14 Years	(5) 15 ~ 19 Years	(6) 20 ~ 24 Years	(7) 25 ~ 29 Years
	Panel A: Adjusted regression estimator						
ATE	1.7706	0.0980	-1.0825	-3.9190	-5.9737	-7.4167	-7.3586
95% Lower	-0.0991	-0.0299	-2.4421	-6.8668	-10.5873	-13.8355	-16.5047
95% Upper	3.6402	0.2258	0.2771	-0.9711	-1.3600	-0.9980	1.7875
	Panel B: Inverse reweighted propensity score estimator						
ATE	2.0967	0.0984	-1.0997	-3.9544	-5.9776	-7.5068	-7.4614
95% Lower	0.0747	-0.0840	-2.4641	-6.8953	-10.5857	-13.9384	-16.5767
95% Upper	4.1187	0.2809	0.2647	-1.0135	-1.3696	-1.0753	1.6539
	Panel C: Doubly-robust estimator						
ATE	1.7706	0.0980	-1.0825	-3.9190	-5.9737	-7.4167	-7.3586
95% Lower	-0.0991	-0.0299	-2.4421	-6.8668	-10.5873	-13.8355	-16.5047
95% Upper	3.6402	0.2258	0.2771	-0.9711	-1.3600	-0.9980	1.7875

Notes: This table reports semiparametric estimates assessing the effects of nationalism on GDP per capita [log-transformed] across multiple time intervals, as denoted by the column headers. The estimates reflect the average impact on treated units. Panel A applies an adjusted regression estimator to construct counterfactuals for countries exhibiting nationalism. Panel B uses an inverse reweighted propensity score estimator to derive alternative estimates. Panel C implements a doubly-robust methodology that synthesizes regression adjustment and propensity-based reweighting. The 95% confidence intervals are displayed under each respective estimate and are shown beneath each coefficient.

4.3 Two-stage least squares (2SLS)

As visualized in Fig. 2, nationalism has reemerged as a potent force. This resurgence is characterized by regional waves, where nationalist sentiments and movements gain momentum within specific geographical areas, often influenced by shared cultural and other socio-economic factors. For example, in China, the state has strategically employed nationalism to consolidate power and legitimize its policies. Under President Xi Jinping, nationalist narratives emphasizing historical grievances and national rejuvenation have been amplified, particularly in trade tensions with the US. This state-led nationalism unifies the populace and reinforces the Communist Party's authority. Despite the indirect connections, another example by Guriev and Papaioannou (2022), despite the indirect connections, illustrates how populist movements influence each other across borders, especially in democratic societies[14].

Motivated by these insights, we leverage regional waves of nationalist resurgence and ideological retrenchment as a quasi-exogenous source of variation in political orientation. In Fig. 6, we document the propagation of nationalism by computing, for each of the seven regions defined in Section 2.3, the share of states exhibiting strong nationalist positioning among those initially aligned with transnational or cosmopolitan ideologies. We then track the evolution of this share over time relative to the year in which the first observable nationalist shift occurred in that region (excluding the first mover to avoid spurious upward bias). Following the onset of nationalism in an area, the share of states embracing similar ideological realignments converges rapidly toward levels seen elsewhere, providing compelling evidence for the existence of regionally diffused nationalism waves.

[14] Guriev and Papaioannou (2022) primarily focused on populism, not nationalism. However, they acknowledged overlap between the two and discussed how populist rhetoric often draws upon nationalist themes. They described "competitive populism," where political actors mimic the strategies of successful populist leaders in other countries.

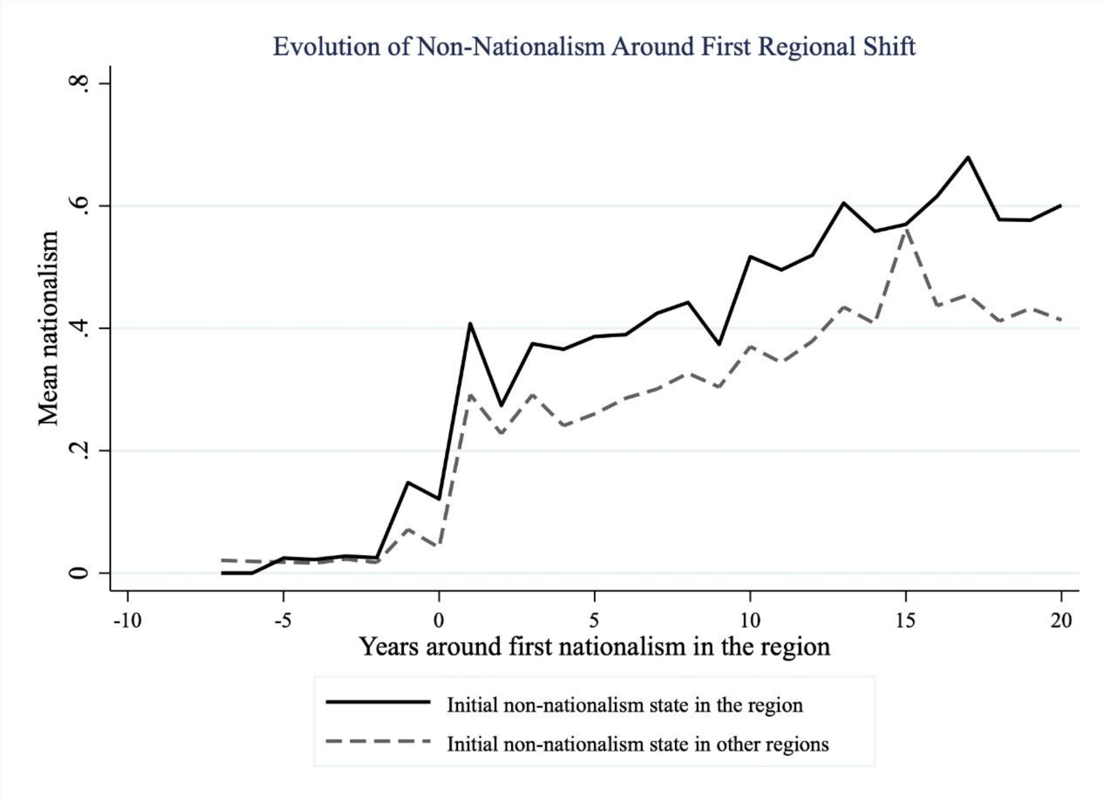


Fig. 5. Regional nationalistic waves.
Notes: This plot tracks the average nationalism levels of countries that were not democratic when their region first experienced a move toward nationalistic behavior and compares them with similar countries in other regions.

To conceptualize the presence of regional nationalistic waves, we first identify the countries potentially affecting the evolution of nationalism within a given country. For each country *i*, let $Nationalism_{it0}$ indicate whether it exhibited nationalist or non-nationalist characteristics at the beginning of the observation period, and let N_i represent its geographic region. We assume that nationalism in country *i* is shaped by nationalism trends in the set of countries $\Omega_i = \{i': i' \neq i, Nationalism_{i't_0} = Nationalism_{it_0}, Nationalism_{i'} = Nationalism_i\}$, which comprises regional neighbors sharing comparable initial political orientations. Therefore, the instrument variable (IV) is,

$$\mathcal{G}_{it} = \frac{1}{|\Omega_i|} \sum_{i' \in \Omega_i} Nationalism_{i't} \tag{4}$$

where $\mathcal{G}_{it}$ denotes the jackknife mean of regional nationalism within the initial regime classification, excluding self-loop.

Our 2SLS model is regulated in the following form through a dynamic manner:

$$y_{it} = \beta Nationalism_{it} + \sum_{k=1}^{p} \tau_k y_{it-k} + l_i + \mu_t + \varepsilon_{it}$$
$$Nationalism_{it} = \sum_{k=1}^{q} \psi_j \mathcal{G}_{it-k} + \sum_{k=1}^{p} \tau_k y_{it-k} + \eta_i + \alpha_t + \xi_{it} \tag{5}$$

Eq. (5) mirrors the earlier dynamic panel specification, with the distinction that nationalism is now treated as endogenous and instrumented using lagged values of $\mathcal{G}_{it}$. The core identifying condition in this context is formalized as:

Assumption 3 [Strict exclusion condition]:
$E[\varepsilon_{it} \mid y_{it-1}, \dots, y_{it0}, \mathcal{G}_{it-1}, \dots, \mathcal{G}_{it0}, l_i, \mu_t] = 0$ for all $y_{it-1}, \dots, y_{it0}$ *and* $\mathcal{G}_{it-1}, \dots, \mathcal{G}_{it0}$ and l_i and μ_t and for all i and $t \geq t_0$.

This exclusion restriction is particularly credible in political institutions, where shifts in democratic governance often evolve slowly and are shaped by historical path dependencies rather than immediate macroeconomic fluctuations. For instance, prior electoral cycles or past democratic breakdowns may influence current levels of nationalist governance without directly impinging on contemporaneous economic performance, except through their effect on the current political regime. Accordingly, these lagged variables provide a source of exogenous variation relevant to explaining nationalism and plausibly unrelated to unobserved shocks in the growth equation[15].

Panel B of Table 5 presents the first-stage results underlying our 2SLS estimates. The large F-statistics for the excluded instruments suggest that regional nationalism waves strongly and statistically significantly influence a country's nationalistic status within that region. Temporally, the most pronounced effect arises from the first tree waves, though the fourth lag has less explanatory power. The relatively stronger impact of nationalism on GDP per capita identified through our 2SLS method may stem from two primary factors: first, an inherent downward bias in earlier estimates caused by unobserved time-varying confounders, and second, attenuation bias arising from potential measurement errors in the nationalism index. By incorporating multiple lagged values of IVs as instruments, our specification permits a Hansen-style overidentification test, which does not reject the validity of the instrument set, thereby mitigating concerns of model misspecification.

Columns 1 and 2 display the estimates by controlling for IV's first and fourth

[15] Our IV strategy isolates the component of nationalism that is exogenous to current growth shocks, enabling us to retrieve consistent estimates of its causal effect on economic performance. This dynamic IV framework thus corrects for simultaneity bias and omitted variable concerns that would otherwise invalidate inference in conventional fixed-effects or lagged dependent variable models. The validity of our approach hinges on Assumption 3, which ensures that historical political trajectories serve as valid instruments by excluding the possibility that they exert direct influence on growth beyond their role in shaping contemporary nationalist dynamics.

lag, respectively. In columns 3 through 7, we conduct robustness checks by augmenting our baseline specification with dynamic covariates that might otherwise compromise the exclusion restriction. The principal concern is the presence of contemporaneous economic or political disturbances – often regionally clustered – that could jointly influence shifts toward nationalist policy frameworks and concurrent growth, thereby confounding the estimated causal pathway. These estimates serve as supplementary analyses in Table 3, where each selected regressor is first detrended using regional patterns before inclusion in the 2SLS specification. The results consistently reveal negative coefficients on nationalism.

Table 5
Effect of nationalism on GDP per capita [log-transformed], 2SLS

			Regional trade trends	Regional unrest trends	Regional debt trends	Regional financial trends	Regional population trends
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: 2SLS second-stage regression results						
Nationalism	-8.2900**	-3.9932*	-3.6785*	-4.0106*	-4.0180*	-3.8510*	-4.9691**
	[3.3815]	[2.2073]	[2.1822]	[2.2146]	[2.2164]	[2.1985]	[2.1915]
Long-run effect of nationalism	-121.8182***	-61.7840**	-56.9751*	-62.1021**	-62.4025**	-59.5574**	-74.8300***
	[44.0661]	[29.1731]	[29.4507]	[29.2507]	[29.4533]	[29.5562]	[28.1383]
Effect of nationalism after 20 years	-110.9010***	-55.3295**	-50.8841*	-55.5835**	-55.8319**	-53.3017*	-67.4250***
	[40.6656]	[27.0764]	[27.1069]	[27.1437]	[27.3108]	[27.3034]	[26.0018]
Persistence of GDP process	0.9319***	0.9354***	0.9354***	0.9354***	0.9356***	0.9353***	0.9336***
	[0.0138]	[0.0126]	[0.0126]	[0.0125]	[0.0125]	[0.0127]	[0.0145]
Exc. Instruments F-stat.	20.835	13.656	13.159	13.577	13.577	13.555	12.862
p-value, Hansen J-stat.	/	0.1697	0.1739	0.1671	0.1565	0.1690	0.1812
	Panel B: 2SLS first-stage regression results						
Regional nationalism wave t-1	102.1670***	67.3076***	63.7660***	67.2791***	67.1996***	67.0778***	66.0993***
	[22.3847]	[20.0118]	[21.8730]	[20.0549]	[20.0672]	[20.0323]	[20.0557]
Regional nationalism wave t-2		84.1881***	86.5089***	84.1736***	84.4782***	83.9758***	83.4269***
		[15.8929]	[18.4376]	[15.9051]	[15.8726]	[15.8868]	[16.0922]
Regional nationalism wave t-3		39.9345***	45.7184***	39.9492***	39.8217***	39.7535***	39.5399***
		[15.2012]	[16.9850]	[15.2032]	[15.1941]	[15.2044]	[15.1574]
Regional nationalism wave t-4		5.3387	12.9864	5.3176	4.8221	5.2828	5.7130

		[13.2698]	[14.5044]	[13.2730]	[13.2438]	[13.2657]	[13.2486]
N	5761	5761	3883	5761	5761	5761	5761
Cross-Sectional Obs.	193	193	144	193	193	193	193

Notes: *, **, *** signify the significance level of 10%, 5%, and 1%, respectively. Standard errors, reported in parentheses, are corrected for potential heteroskedasticity and autocorrelation within countries. This table reports 2SLS estimates assessing the impact of nationalism on GDP per capita. Panel A displays the second stage estimation of the 2SLS results, where nationalism is instrumented using up to four lags of regional nationalism trends. This panel also includes the p-values from Hansen's overidentification test, evaluating the validity of the excluded instruments. Panel B outlines the associated first-stage regressions, including the F-statistic corresponding to the excluded instruments, thereby gauging their strength in predicting the endogenous regressor. All specifications incorporate a comprehensive set of country and year-fixed effects and four lagged values of the dependent variable (GDP per capita) to mitigate concerns about dynamic endogeneity. Additionally, each regression controls for the covariates indicated in the respective column headers, which are further detailed in the main text. Heteroskedasticity- and autocorrelation-robust standard errors, clustered at the country level, are reported in parentheses.

5. Further tests

While conventional economic research has extensively examined the influence of institutions, trade liberalization, and governance on environmental performance, the ideological dimension, specifically nationalism, has received scant empirical scrutiny as a determinant of cross-national disparities in carbon emissions. We shift the analytical lens toward assessing whether nationalism exerts a measurable effect on a country's carbon footprint. We posit that nationalism, despite its complex political implications, may exert an emission-reducing influence primarily through its dampening impact on economic growth. This proposition aligns with our baseline findings, which consistently demonstrate the contractionary effects of nationalism on output. In this context, the hypothesis is not paradoxical: the environmental benefits stem not from targeted green policies but as an indirect consequence of slowed economic momentum. Such a mechanism resonates with early-stage interpretations of the Environmental Kuznets Curve (EKC), which suggest that during initial development phases, accelerated output is typically accompanied by environmental deterioration, a dynamic that nationalism, by impeding growth, may inadvertently counteract.

In a decentralized economy, pollution grows faster because environmental harm is not adequately regulated. Also, technological progress does not always increase fast enough to offset the damage, and its growth rate may be similar in both efficient and market-driven paths (Byrne, 1997). However, we also admit the positive effect of nationalism on emissions. For example, nationalism may increase emissions by fostering protectionist trade policies, discouraging environmental multilateralism, and promoting inward-looking industrial strategies that reduce access to green technologies and delay decarbonization. Nationalist governments may prioritize energy security through domestic fossil fuels over global climate obligations, weakening regulatory ambition (Rodrik, 2021). Empirical evidence by Dechezleprêtre et al. (2013) explicitly opined that inward-looking policies can reduce the diffusion of environmental innovations across borders, leading to persistent inefficiencies in energy use.

Yet, under specific institutional settings, nationalism may be associated with lower emissions, particularly if it manifests as support for national self-sufficiency in clean energy or environmental protection as a form of cultural or territorial preservation. Nationalist rhetoric can, in some contexts, support environmental conservatism at the domestic level, such as the defense of local land and resources against foreign exploitation (Torras and Boyce, 1998). Moreover, nations with strong public institutions may channel nationalist preferences into green industrial policy, mainly when environmental integrity symbolizes national pride.

To assess the relationship between nationalism and carbon emissions, we employ emissions data from the World Bank's World Development Indicators, as reported in Table 6. Column 1 reveals a significant negative association between nationalism and CO_2 emissions [log-transformed]. This inverse relationship remains robust when emissions intensity is used as the dependent variable in column 2, indicating consistency across alternative emission metrics. Notably, across both specifications, the coefficient on the lagged terms suggests strong temporal persistence in emissions, regardless of how emissions are proxied. Although the long-run effect of nationalism on emissions is quantitatively modest, particularly under projections spanning two decades, it consistently reflects a negative sign. To further validate these patterns, we conduct disaggregated analyses by emission source, including fugitive emissions and sector-specific emissions. These sectoral regressions yield no evidence that nationalism systematically curbs emissions across all sectors. Nonetheless, comparative results suggest that nationalism may be more consequential in reducing emissions within the building, industrial, and transportation domains than in sectors such as agriculture, waste, or fugitive emissions. Our estimates partially align with recent findings suggesting that early impacts of the green transition, driven by decarbonization priorities, are most evident in sectors such as housing, transport, and energy (Rodríguez-Pose and Bartalucci, 2024). Therefore, given the moderating role of nationalism on aggregate emissions, the sector-specific analysis remains robust, revealing differentiated mitigation patterns—most notably in buildings, industry, and transportation—despite the effects being notable yet statistically insignificant.

Table 6
The carbon footprint effect of nationalism.

	CO_2 [Log]	CO_2/GDP [Log]	Fugitive [Log]	Agriculture [Log]	Waste [Log]	Building [Log]	Industry [Log]	Transport [Log]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nationalism	-0.0111**	-0.0103*	0.0235	0.0009	0.0002	-0.0078	-0.0001	-0.0011
	[0.0056]	[0.0058]	[0.0232]	[0.0217]	[0.0102]	[0.0135]	[0.0086]	[0.0058]
Long-run effect of nationalism	-0.0979**	-0.0785*	0.1540	0.0044	0.0034	-0.0633	-0.0005	-0.0092
	[0.0488]	[0.0440]	[0.1474]	[0.1020]	[0.1572]	[0.1086]	[0.0667]	[0.0470]
Effect of nationalism after 20 years	-0.0841**	-0.0719*	0.1501	0.0042	0.0025	-0.0568	-0.0004	-0.0086
	[0.0416]	[0.0401]	[0.1439]	[0.0994]	[0.1166]	[0.0977]	[0.0615]	[0.0440]
Persistence of emissions	0.8865***	0.8683***	0.8477***	0.7873***	0.9354***	0.8771***	0.8717***	0.8765***
	[0.0142]	[0.0103]	[0.0194]	[0.0252]	[0.0174]	[0.0095]	[0.0192]	[0.0145]
N	5585	5202	3827	2797	2573	5460	5485	5469
Cross-Section Obs.	190	181	140	104	87	182	183	182

Notes: *, **, *** signify the significance level of 10%, 5%, and 1%, respectively. Standard errors, reported in parentheses, are corrected for potential heteroskedasticity and autocorrelation within countries. This table reports 2SLS estimates assessing the impact of nationalism on GDP per capita. This table shows the effects of nationalism on GDP per capita (log-transformed). The results are computed through a fixed effects method, which compares changes within each country over time. The dependent variables in Table 6 include CO_2, emissions intensity, emissions from fugitives, agriculture, waste, building, industrial process, and transport. All emissions have been log-transformed. All regressions include country- and year-fixed effects and four lagged GDP per capita values.

We deepen the analysis by exploring how the responsiveness of CO_2 emissions to nationalism and economic growth varies across countries with differing pollution intensities. Given prior evidence that nationalism exerts a mitigating influence on emissions, a theoretically grounded extension is to test whether this effect is more potent in economies historically characterized by high pollution levels, where the marginal abatement benefit may be greater due to concave environmental damage functions and stronger public support for environmental nationalism. To operationalize this, we interact nationalism with initial pollution levels measured via CO_2 emissions from 1979 to 1981, identifying high-intensive countries above the 75th percentile (Acemoglu et al., 2018). Columns 1–4 of Table 7 show that while the interaction term remains statistically insignificant in Column 4, the earlier specifications (columns 1-3) reveal increasingly negative and significant coefficients. This dynamic pattern supports the theoretical expectation that the marginal effectiveness of nationalism in curbing emissions is stronger in initially dirtier economies – consistent with models where abatement efforts yield higher returns in high-emission environments due to convex marginal damages or targeted institutional pressure.

Turning to the role of income, columns 5-8 examine whether economic growth exerts symmetric effects on emissions across the pollution distribution. The interaction between log GDP per capita and historical CO_2 levels consistently yields negative and robust coefficients, suggesting that the emissions elasticity of income is non-monotonic. This aligns with the EKC hypothesis (Grossman and Krueger, 1995), which posits an inverted-U relationship between income and environmental degradation, particularly when marginal damages and political demand for environmental quality rise with accumulated pollution. The evidence also supports dynamic adjustment models in which countries with higher legacy emissions face steeper marginal environmental costs, leading to endogenous policy responses or technological adaptations that dampen the emissions-growth linkage. In this sense, the findings illustrate that the environmental impact of income growth is historically path-dependent and conditioned by prior emissions intensity (Aklin and Urpelainen, 2013).

Table 7
Environmental effects of nationalism and growth.

	interaction between nationalism and CO_2 emissions				Internation between GDP per capita and CO_2 emissions			
	1979	1980	1981	Lagged	1979	1980	1981	Lagged
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Nationalism	-0.0295***	-0.0306***	-0.0301***	-0.0199***	-0.0160***	-0.0161***	-0.0160***	-0.0157***
	[0.0074]	[0.0073]	[0.0072]	[0.0071]	[0.0058]	[0.0058]	[0.0058]	[0.0057]
Nationalism × CO_2	-0.0039	-0.0044*	-0.0043*	0.0004				
	[0.0026]	[0.0026]	[0.0025]	[0.0029]	-0.0002***	-0.0002***	-0.0002***	-0.0002***
GDP per capita [log-transformed] × CO_2					[0.0000]	[0.0000]	[0.0000]	[0.0000]
Long-run effect of nationalism	-0.3235***	-0.3348***	-0.3296***	-0.2175***	-0.1313***	-0.1316***	-0.1319***	-0.1278***
	[0.0705]	[0.0703]	[0.0696]	[0.0794]	[0.0462]	[0.0463]	[0.0467]	[0.0457]
Effect of nationalism after 20 years	-0.2513***	-0.2604***	-0.2562***	-0.1690***	-0.1183***	-0.1185***	-0.1186***	-0.1149***
	[0.0543]	[0.0538]	[0.0532]	[0.0598]	[0.0413]	[0.0415]	[0.0417]	[0.0407]
Persistence of GDP process	0.9087***	0.9085***	0.9086***	0.9083***	0.8782***	0.8780***	0.8786***	0.8770***
	[0.0126]	[0.0126]	[0.0126]	[0.0124]	[0.0139]	[0.0139]	[0.0139]	[0.0142]
N	6014	6014	6014	6197	5499	5499	5499	5662
Cross-Sectional Obs.	194	194	194	204	181	181	181	190

Notes: *, **, *** signify the significance level of 10%, 5%, and 1%, respectively. Standard errors, reported in parentheses, are corrected for potential heteroskedasticity and autocorrelation within countries. The results are computed through a fixed effects method, which compares changes within each country over time. The dependent variables in Table 6 include CO_2, which has been log-transformed. All regressions include country- and year-fixed effects and four lagged GDP per capita values.

Finally, we investigate how nationalism modulates the environmental consequences of economic growth. In addition, we examine whether the emission-mitigating potential of nationalism rests upon income conditions. Table 8 presents the dynamic and heterogeneous influence of nationalism on carbon dioxide emissions, wherein GDP per capita in selected low-income groups (25th percentile). Columns 2 through 4 detail the interactions of nationalism with GDP levels from 1979, 1980, and 1981, respectively, capturing the temporal evolution of this relationship.

In column 1, the interaction term between nationalism and log-transformed GDP per capita is positive and significant at 5%. This indicates that as GDP per capita increases, the adverse effect of nationalism on CO_2 emissions diminishes slightly. However, the interaction terms are uniformly insignificant across columns 2 through 4. These results indicate that, within this low-income range, the moderating effect of economic development on nationalism's influence on emissions is nonexistent. In other words, nationalism's ability to reduce emissions does not meaningfully vary with GDP differences among poorer countries. The near-zero and statistically insignificant interaction coefficients underscore a stable nationalism effect across this income bracket.

Across all specifications, the long-run effects of nationalism remain significantly negative, indicating a persistent emissions-reducing role over time. Even after two decades, the cumulative impact of nationalism on emissions remains substantial—especially in slower-growing or less-developed contexts. This pattern supports the notion that nationalist regimes, while economically restrictive, may unintentionally curtail emissions by dampening growth-intensive, carbon-heavy activities. However, this outcome is highly contingent on both the pace of economic growth and a country's stage of development.

Table 8
Heterogenous environmental effects of nationalism and growth on emissions.

		1979	1980	1981
	(1)	(2)	(3)	(4)
Nationalism	-0.0962***	-0.0189***	-0.0202***	-0.0201***
	[0.0344]	[0.0061]	[0.0061]	[0.0061]
Nationalism × GDP per capita [log-transformed]	0.0001**	0.0000	0.0000	0.0000
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Long-run effect of nationalism	-1.0151***	-0.2105***	-0.2298***	-0.2288***
	[0.3523]	[0.0677]	[0.0702]	[0.0702]
Effect of nationalism after 20 years	-0.8291***	-0.1657***	-0.1791***	-0.1783***
	[0.2885]	[0.0520]	[0.0531]	[0.0531]
Persistence of GDP process	0.9053***	0.9102***	0.9122***	0.9122***
	[0.0105]	[0.0116]	[0.0111]	[0.0111]
N	5662	5095	5157	5157
Cross-Sectional Obs.	190	167	169	169

Notes: *, **, *** signify the significance level of 10%, 5%, and 1%, respectively. Standard errors, reported in parentheses, are corrected for potential heteroskedasticity and autocorrelation within countries. The results are computed through a fixed effects method, which compares changes within each country over time. The dependent variables in Table 6 include CO_2, which has been log-transformed. All regressions include country- and year-fixed effects and four lagged GDP per capita values.

6. Conclusions

While economists have qualitatively explored nationalism's influence on various socioeconomic outcomes, its definitive impact on economic growth remains insufficiently examined—notable exceptions being Born et al. (2019); Mylonas and Tudor (2021). We contribute original empirical evidence demonstrating that nationalism exerts a detrimental effect on global economic growth. Our analytical approach is distinctive, as it innovatively integrates social network theory to model nationalism, a methodology largely absent in current literature. Empirically, we employ a dynamic linear OLS framework that incorporates lagged GDP per capita terms to account for the temporal persistence of growth dynamics. Our findings are consistent and robust across multiple validation techniques.

Quantitatively, baseline results indicate that a country's embrace of nationalist rhetoric corresponds with an approximate 12% decline in long-term GDP over the subsequent two decades. Additionally, we observe democratization and nationalist shifts occurring in geographically clustered waves, whereby recent similar transitions within its region influence a country's likelihood of adopting or abandoning nationalism. Leveraging this spatial diffusion as an instrumental variable for nationalism, we further confirm nationalism's adverse effect on economic output.

Our analysis also uncovers a novel dimension: nationalism facilitates reductions in both total carbon emissions and emissions intensity, though the magnitude of this mitigation varies markedly across sectors. Notably, sectors central to low-carbon commitments, i.e., building, industry, and transport, exhibit significant emissions declines linked to nationalist policies, suggesting targeted environmental benefits despite sectoral heterogeneity.

We also assess how nationalism's emissions-reducing impact interacts with a country's income level. The data reveal that nationalism's dampening effect on carbon emissions slightly diminishes as GDP rises overall; however, this moderating relationship lacks significance within lower-income nations. This suggests that nationalism's environmental influence is most stable and pronounced in less affluent contexts, where fluctuations in economic development exert minimal interference.

In line with these conclusions, policymakers should recognize the trade-offs embedded in nationalist-driven agendas. To mitigate economic stagnation, governments might consider fostering regional cooperation and democratic resilience, given the observed contagion effects of nationalism across neighboring countries. Strengthening democratic institutions could help balance nationalistic tendencies with sustainable economic development.

On the environmental front, nationalism's role in lowering emissions in building, industry, and transport sectors suggests an opportunity to leverage nationalist narratives for advancing targeted low-carbon initiatives. However, these efforts should be carefully calibrated to avoid economic drawbacks, particularly in lower-income countries where environmental gains are more stable, but economic vulnerabilities remain high.

Finally, tailored strategies that account for income-level differences are essential. In lower-income nations, reinforcing nationalism's environmental benefits through complementary economic policies can help sustain emissions mitigation without exacerbating growth challenges. In higher-income contexts, alternative mechanisms beyond nationalism may be required to maintain environmental progress without compromising economic performance.

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