The POP Premium
Populism and the cross-section of stock returns

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Abstract

We construct a Populism Index (POP) from over one million Wall Street Journal articles from 1984 to 2024 using large language models to quantify populism-related sentiment in U.S. media. Firm's exposure to changes in populist sentiment is a priced risk in the cross-section of equity returns: stocks with low POP betas earn significantly higher returns, yielding an annualized excess return of about 8%, unexplained by standard risk factors. The premium exists before the 2016 surge in populism, persists under both Republican and Democratic administrations, highlighting that populism represents a distinct, state-dependent source of systematic risk in equity markets.

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1 Introduction

We introduce a new measure of populist sentiment in U.S. media and examine its implications for the cross-section of stock returns. Using large language model (LLM) to analyze over 1 million articles from The Wall Street Journal (WSJ) over the period 1984–2024, we construct a Populism Index (POP) that quantifies the presence and intensity of populism-related narratives in financial and political coverage. The index tracks rhetoric, leaders, policies, and movements associated with populism, capturing the frequency of such content. We show that firms' exposure to changes in populist sentiment, measured by their POP beta, is a priced characteristic in equity markets. Firms whose returns comove negatively with increases in populism earn higher ex-post average returns, yielding a POP premium of 0.62% per month, or about 8% per year, that remains highly significant after controlling for Fama–French factors, momentum, and q-factor. A \$1 investment in the long–low, short–high POP-beta portfolio in 1986 would have grown to roughly \$30 by 2024, even after risk adjustment.

Our methodology builds on, but substantially extends, the Bag-of-Words (BoW) approaches developed by Bonikowski and Gidron (2016) and Filippou et al. (2020). Traditional BoW methods classify text based on the raw frequency of pre-specified terms such as "elite" or "people", disregarding context, grammar, and meaning. While this approach offers a transparent baseline, it may overlook context-dependent nuances, as the same term can reflect populism in one setting but not in another. In contrast, the LLM-based POP index leverages contextual interpretation and structured prompting to identify populism-related content along four dimensions, producing a more comprehensive and semantically consistent measure of populist sentiment. The LLM output provides intensity scores, confidence levels, and reference sentences for each classification, ensuring transparency and interpretability at scale.

To connect our method more closely to the existing literature, we also construct a new dictionary-based index derived from the LLM's own textual attributions. To construct the new dictionary, we apply a Term Frequency–Inverse Document Frequency (TF-IDF) approach that quantifies the distinctiveness of words used in news articles with populism-related vs non-populism related content. The method assigns higher weight to terms that occur frequently within populist narrative but remain rare in the overall corpus, enabling us to identify language that persistently characterizes populism across time. This process yields both enduring markers ("tax cuts") and time-dependent policy references ("tariffs") that acquire populist connotations only after specific political events. We activate each term dynamically, only after its first occurrence in clearly populist contexts, thus reducing look-ahead bias and improving temporal precision. The correlation between our LLM-based POP and the new Bag-of-Words (BoW) measure that we develop exceeds 0.90, indicating that the two indices track each other closely, with the LLM index extending coverage beyond the scope of static dictionaries.

The construction of our new BoW measure reveals that terms commonly associated with modern populist rhetoric, such as "fake news," and "America First," have only a limited influence on the magnitude of the POP premium, reflecting their relatively sparse occurrence in news coverage. Instead, accurately capturing the intensity of populism-related content requires a deeper understanding of the linguistic and contextual cues surrounding each article, underscoring the importance of using a language model that interprets meaning beyond the mere frequency of specific terms.

We then examine how populist sentiment is priced in the cross-section of returns. Sorting stocks by their exposure to the POP index, we find that the POP premium—the return spread between low- and high-POP-beta portfolios—is positive, economically large, and strongly statistically significant. The premium persists across alternative specifications, including equal-weighted portfolios, decile sorts, and different lag structures for returns and

factors. It remains significant after controlling for size, value, profitability, investment, momentum, reversal, volatility, illiquidity, political risk (Hassan et al., 2019), geopolitical risk (Caldara and Iacoviello, 2022), presidential economic policy approval index (Chen et al., 2023), and war discourse index (Hirshleifer et al., 2025).

After controlling for the five-factor model of Fama and French (2015), the risk-adjusted alpha of the POP premium reaches 0.61% per month, suggesting that the effect is not subsumed by known sources of systematic risk. When we replicate the analysis using earlier dictionary versions, the POP premium is positive but not statistically significant, indicating that traditional bag-of-words methods capture less cross-sectional variation in returns than the evolving vocabulary derived from the LLM.

A central concern with text-based indices is measurement error, particularly look-ahead bias, hallucination, and overfitting in large language models. We address these issues through several robustness exercises. First, we mask all personal names and dates in the corpus to prevent the model from associating populism with specific individuals or electoral events ex post. Second, we re-estimate the index using confidence-weighted classifications, and third, we reconstruct it using the LLM's own "populism-as-risk" scores, which capture the extent to which news coverage explicitly frames populist developments as sources of political or policy risk. Across all specifications, the POP premium remains positive and statistically significant, with spreads that are consistently between 0.5% and 0.8% per month.

The POP premium is not a recent phenomenon confined to the post-2016 surge in populism-related coverage. When we split the sample into pre-2017 and post-2017 periods, the premium remains positive and statistically significant in both subsamples, indicating that investors priced populist sentiment well before the recent acceleration of populism in the media. Moreover, the premium persists under both Republican and Democratic administrations, with slightly larger magnitudes observed during Republican presidencies. These patterns suggest that the pricing of populist sentiment reflects deeper, nonpartisan economic

forces rather than shifts tied to specific political cycles.

We further examine whether the POP premium is driven by the rise of technology or AI-related stocks, whose prominence overlaps with the post-2016 increase in populism-related coverage. Controlling for returns on the iShares U.S. Technology ETF or excluding the seven largest U.S. technology firms (Apple, Microsoft, Amazon, NVIDIA, Tesla, Alphabet, and Meta) leaves the POP premium virtually unchanged. These results indicate that populist sentiment captures firm-level risks orthogonal to sectoral or technological trends.

The interpretation of the POP premium offers additional insight. We show that firms with higher POP betas are more closely aligned with the party that exhibits the strongest populist rhetoric: their employees direct a larger share of their campaign contributions toward the more populist party. These firms may benefit from ties to the populist agenda and therefore may serve as a hedge against populist risk in cross-sectional portfolios. This hedging channel is stronger when the more populist party controls the administration, which we interpret as proximity to the party in power reinforcing the link between political alignment and populism exposure. Hence, a low β_{POP} portfolio earns higher returns not because these firms are safer, but because they lack the political connections that insulate high β_{POP} firms when populism rises. This mechanism differs from standard risk-aversion channels and suggests that populism represents a state-dependent source of systematic risk that traditional factor models do not capture.

Literature Review. Our paper is related to several strands of the economics, finance, and political science literatures. The first set of studies defines and measures populism as a political phenomenon. Early attempts, such as Bonikowski and Gidron (2016), describe populism as a discourse opposing the virtuous people to a corrupt elite and introduce dictionary-based approaches to quantify it in political speech. Filippou et al. (2020) extend this work to social-media contexts, constructing a U.S. Aggregate Populist Rhetoric Index that captures

the rise of "Populism 2.0." Pástor and Veronesi (2021) link populism to anti-globalization movements, emphasizing its macroeconomic roots in inequality and trade imbalances. Building on these foundations, our paper develops a new populism index using LLM techniques applied to WSJ articles. The POP index inherits the conceptual definition of populism as the conflict between "the people" and "the elite," while refining earlier dictionary-based measures through inductive learning from textual patterns that the LLM identifies as populist. This approach increases the temporal coverage and contextual precision of the index and aligns its fluctuations with major episodes of globalization backlash described in Pástor and Veronesi (2021).

A second strand of related work advances text-based measurement of political and economic risk. Hassan et al. (2019) pioneer the identification of firm-level political risk by parsing earnings-call transcripts, and later studies extend their framework to separate risk from sentiment (Hassan et al., 2024) and discuss limitations such as hindsight bias in machine learning (Hassan et al., 2025). Bybee (2023) applies LLM to historical news to infer macroeconomic beliefs, demonstrating that it can extract expectations and causal narratives from text. Jha et al. (2021) use text-based measure and show that sentiment toward finance responds heterogeneously to disasters, declining after uninsured risks like epidemics but rising after insured risks like droughts. Our methodology follows these advances by prompting GPT-4o-mini to evaluate over one million WSJ articles, quantifying populist intensity, risk type, and confidence scores, while masking identifying information to mitigate hindsight bias.

Another related paper is Grotteria (2024), who documents a 6–8% annual premium for high-lobbying firms and rationalizes it through a model in which lobbying generates political-contracting risk. Our paper differs along two dimensions. First, the two papers focus on different forms of corporate political engagement: Grotteria (2024) centers on direct lobbying expenditures, while we center on campaign donations as the channel through which firm

returns acquire exposure to populist sentiment. The political science literature has shown these activities to be largely disconnected. Indeed, Furnas et al. (2025) document that only 6.3% of politically active organizations engaged in both lobbying and PAC contributions over 1998–2018. This separation is reflected in our respective samples: the Grotteria (2024) analysis covers roughly 1,700 unique lobbying firms, while our cross-section spans the broad CRSP/Compustat universe, most of which never lobby. Second, the underlying economic logic differs: in the Grotteria (2024) framework, lobbying itself manifests political-contracting risk and commands a positive premium, while in ours, donations to the more populist party reflect coalitional alignment that hedges populism risk, generating lower expected returns for more aligned firms. The two channels are thus complementary, capturing distinct dimensions of political risk.

Loughran and McDonald (2011) establish the challenge of accurately measuring financial tone with external dictionaries and create the preeminent dictionary benchmark based on a bag-of-words approach, whose inherent limitations in capturing contextual meaning the LLM method seeks to supersede. Building on this foundation, Garcia et al. (2023) document the value of advanced machine learning techniques to automatically derive empirically successful sentiment dictionaries, marking an important step beyond static word lists toward automated content coloring and setting the stage for the contextual processing capabilities of LLM. Our analysis relates closely to this evolution, as we emphasize the role of contextual processing as a necessary progression from static word lists to the advanced interpretive capabilities offered by LLM.

Finally, our work connects to the asset pricing literature on political and sentiment risk, including Chen et al. (2023) on presidential approval, Hassan et al. (2019) on political risk, Caldara and Iacoviello (2022) on geopolitical risk, Hirshleifer et al. (2025) on war risk, and Bali et al. (2017) on uncertainty betas. Sheng et al. (2024) document differences in stock returns between firms dominated by Democratic investors and those dominated by

Republican investors during the COVID pandemic. Shen et al. (2017) find that the cross-sectional pricing of macro-factors is sentiment-contingent, following a two-regime pattern where the positive risk-return relation holds only after low-sentiment periods. We show that the POP premium, the return differential between low and high POP beta firms, remains robust after controlling for these factors, persists across political cycles, and behaves more like a systematic sentiment-risk component than a transient anomaly.

Organization of the paper. The rest of the paper is organized as follows. Section 2 describes the construction of the populism index and the new dictionary POP BoW3. Section 3 presents the asset-pricing tests and robustness analyses, including controls for AI-related exposures. Section 4 investigates some of the economic drivers of our result. Section 5 concludes.

2 Data and Methodology

2.1 Data

Media Sources. We construct the U.S. populism index using a media corpus that comprises all full articles published in The Wall Street Journal (WSJ) from Jan 1984 to Dec 2024, totaling over 1.1 million articles. As one of the largest newspapers in the world, the WSJ is widely utilized in the literature to study U.S. economic and political issues (Bybee et al., 2024, 2023; Caldara and Iacoviello, 2022; Goldman et al., 2024; Hong et al., 2025; Liu and Matthies, 2022).

The WSJ publishes an average of approximately 2,252 articles per month, with over 1.5 million terms (See Figure A.1 in Internet Appendix A.2). WSJ provides rich textual data, enabling the model to better capture the linguistic patterns of populism. This offers strong support for the subsequent construction and validation of the populism index. However, it

can be observed that the number of WSJ articles shows rapid decreases (e.g., in 1994) or increases (e.g., in 2000).

Financial and Macroeconomic Data. The sample in this paper includes all common stocks listed on the NYSE, Amex, and Nasdaq from January 1986 to December 2024. Stocks with prices below $1 at the portfolio formation date are excluded to mitigate liquidity concerns related to penny stocks. To address survivorship bias, stock returns are adjusted for delisting following the methodology of Shumway (1997). Return and price data are obtained from the Center for Research in Security Prices (CRSP), and accounting information is drawn from Compustat.

The excess market return and the Fama-French three factors, the Fama-French five factors, and the momentum factor are from Kenneth French's data library. The q-factors are sourced from Hou et al. (2015). As in Fama and French (1992), the size (SIZE) is computed as the natural logarithm of the product of the price per share and the number of shares outstanding. The logarithm of book-to-market equity ratio (BM) is calculated as the book value of stockholder equity plus deferred taxes and investment tax credit (if available) minus the book value of preferred stock at the end of the last fiscal year, scaled by the market value of equity at the end of December of last calendar year. Firms with negative book values are excluded from the analysis. We match the annual BM information in year $t-1$ to monthly returns from July of year t to June of year $t+1$. Consistent with Hou et al. (2015), the annual growth rate of total assets (I/A) is measured by the change in book assets divided by its lagged counterpart. The quarterly operating profitability (ROE) is measured by income before extraordinary items divided by one-quarter-lagged book equity. Following Jegadeesh and Titman (1993), momentum (MOM) is defined as the cumulative return of a stock over a period of 11 months ending one month prior to the portfolio formation. In line with Jegadeesh (1990), short-term reversal (STR) is defined as the stock return over the prior month. Following Ang et al. (2006), the monthly idiosyncratic volatility of a stock (IVOL)

is computed as the standard deviation of the daily stock idiosyncratic returns relative to the Fama-French three-factor model. As in Amihud (2002), we measure the ill-liquidity of a stock (ILLIQ) as the ratio of the daily absolute stock return to the daily dollar trading volume averaged within the month. A stock is required to have at least 15 valid daily returns to calculate the IVOL and ILLIQ. Following Chen et al. (2021), we estimate β_{BW} using 60-month rolling regressions of excess stock returns on changes and lagged changes of the Baker and Wurgler (2006) sentiment index. We follow Bali et al. (2017) and compute β_{UNC} using 60-month rolling regressions of excess stock returns on the economic uncertainty index of Jurado et al. (2015) together with market, size, book-to-market, momentum, liquidity, investment, and profitability factors, with the requirement of at least 24-month non-missing data.

We control for a set of macroeconomic variables when estimating the populism beta. Specifically, we include the effective federal funds rate (series DFF), the coincident economic activity index (series USPHCI), the total monetary base (series BOGMBASE), and the total nonfarm payroll employment (series PAYEMS). These macroeconomic series are obtained from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis.[1]

Lastly, we consider four alternative political risk-related variables. We construct an economy-wide political risk index (PRisk) from WSJ articles using the dictionary-based method proposed by Hassan et al. (2019). The geopolitical risk index (GPR) in Caldara and Iacoviello (2022) is sourced from Matteo Iacoviello's webiste. The presidential economic approval rating index (PEAR) in Chen et al. (2023) is sourced from Zilin Chen's website. The war discourse index (War) in Hirshleifer et al. (2025) is sourced from Kuntara Pukthuanthong's website.

[1]In the robustness test, we consider the 132 macroeconomic variables in McCracken and Ng (2016) and examine their correlations with the populism index we propose.

Political Affiliation. To measure firm-level political affiliation, we obtain records of individual contributions to political campaign committees from the Federal Election Commission (FEC) over the period 1984–2024. We match the self-reported employer names in the FEC records to firms in CRSP and Compustat following the fuzzy string matching procedure described in Internet Appendix C. The regional election returns are obtained from the MIT Election Data and Science Lab.

2.2 Measures of Populist Sentiment

Benchmark. We employ GPT-4o-mini as the primary language model for large-scale financial news analysis. GPT-4o-mini is appropriate for this study for three main reasons. First, long-context handling. Each WSJ article can span several hundred to several thousand tokens. With support for up to 128,000 tokens, GPT-4o-mini can process entire articles without truncation, thereby preserving the full narrative structure essential for accurate detection and classification of populist elements. Second, alignment with structured prompting. The model exhibits reliable performance in adhering to complex, multi-step instructions such as Chain-of-Thought (CoT) prompting, which is central to our analytical framework for extracting nuanced indicators across multiple dimensions of populism. Third, cost and throughput efficiency. Given the scale of this task, potentially involving the processing of over one million news articles, GPT-4o-mini's low per-token cost and computational efficiency make it a practical choice for maintaining project scalability without compromising analytical depth.

Our methodology for measuring populist sentiment spans four key dimensions: populist leaders, movements, policies, and rhetoric. This choice is motivated by the extant literature. Mudde (2004), Müller (2017), and Funke et al. (2023) define populism as a political style centered on the purported conflict between the "people" and the "elite". The significant impact of populist leaders is empirically documented by Funke et al. (2023), who linked their

presence to markedly lower GDP growth across 60 countries. Mudde (2007); Van Kessel (2015); Wiesehomeier (2017); and Bonikowski and Gidron (2016) analyze party documents, speeches, and manifestos to assess whether political parties and leaders are populist. Among these, the criteria for judging populism are reflected not only in rhetoric but also in concrete policies. For instance, Van Kessel (2015) shows that populist parties often attract voters through anti-establishment and anti-elite rhetoric, and notes that their policy proposals typically involve opposition to globalization, immigration control, and an emphasis on national sovereignty. In addition, populists may trigger populist movements, such as the Tea Party movement, the Occupy Wall Street movement, and the Capitol riot.

Using news texts from WSJ, we leverage LLM to identify the presence and intensity of each populist dimension, as well as assess the level of populism risk associated with each instance.[2] Additionally, we prompt the model to generate confidence scores for its findings and provide key reference sentences from the original text, which helps mitigate potential hallucinations. Throughout our analysis, we document the robustness of our findings to different confidence score thresholds. To further enhance accuracy, we also include specific examples and important notes to guide the model's output, ensuring a higher level of precision in identifying populist content. We reported the detailed prompts that we used in Table A.1 of Internet Appendix A.1.

We measure the level of populism using the proportion of populist-related articles. We assign to each article a weight based on the average score of Populist Intensity across the four dimensions. Specifically:

$$\text{POP}_t \;=\; \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\sum_{d=1}^{4}\text{Intensity}_{i,d,t}^{\text{POP}} \Big/ \sum_{d=1}^{4}\text{Intensity Presence}_{i,d,t}^{\text{POP}}\right), \tag{1}$$

where t denotes the month, POP_t represents the U.S. populism level in the month t; N_t

[2]Table E.10 presents examples of populist risk that are identified by the LLM in the Wall Street Journal articles, such as trade protectionism and fracture of global supply chains, political interference with the Fed's independence, and tax and budget deficit.

is the total number of news articles published in the month t; $\text{Intensity}_{i,d,t}^{\text{POP}}$ denotes the populist intensity score of news article i in month t for dimension d; $\text{Intensity Presence}_{i,d,t}^{\text{POP}}$ is a dummy variable indicating whether a populism dimension d is mentioned in the news article i in month t.

Bag of Words approach. We compare the index constructed using LLM with a Bag of Words (henceforth "BoW") approach. This methodology classifies text according to the presence of specific keywords; it abstracts from grammar and sentence structure, focusing instead on the frequency and timing of terms that are indicative of populist coverage.

Two dictionaries of populist terms have already been developed. The first, which we refer to as POP BoW1, was constructed by Bonikowski and Gidron (2016) using U.S. presidential campaign speeches from 1952 to 1996. It emphasizes broad rhetorical markers of populism. The second, POP BoW2, was introduced by Filippou et al. (2020) and extends POP BoW1 by incorporating terms related to economic policies and political debates. While both dictionaries are valuable, they also have limitations: POP BoW1 is restricted in temporal scope and primarily rhetorical, whereas POP BoW2 adds policy-related terms that may not consistently capture populist themes across different contexts and time periods.

In this paper, we introduce POP BoW3, which builds on these earlier resources while addressing some of their potential shortcomings. The construction of POP BoW3 involves four steps. First, we employ a LLM to classify news articles into two categories—populist and non-populist—based on whether any of the four populist dimensions is referenced in the text. Second, we compute the Term Frequency-Inverse Document Frequency (TF-IDF) scores for all uni-grams, bi-grams, and tri-grams annually and by category, then calculate the TF-IDF score difference between populist and non-populist articles for each n-gram. The TF-IDF method quantifies the relative importance of each n-gram by considering both its prevalence within specific document categories and its rarity across the entire corpus. If N represents the total number of articles in the sample category, df_i the number of articles

containing at least one occurrence of the ith word, $tf_{i,j}$ the raw count of the ith in the jth article, and α_j the average word count in the article j, then the TF-IDF score of the ith in the jth article is measured as

$$\text{TF-IDF}_{i,j} = \begin{cases} \dfrac{1+\log(tf_{i,j})}{1+\log(\alpha_j)} \log \dfrac{N}{df_i}, & \text{if } tf_{i,j} \geq 1. \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

N-grams with larger score differences are considered to hold greater relative importance. The mean TF-IDF score for each n-gram is then calculated separately for the populist and non-populist article categories. Third, for each presidential term, we average the TF-IDF score differences across all n-grams and rank the top 40 n-grams with the highest average values. The results are presented in Table E.2. Finally, we remove terms that appearing in more than 4% of all WSJ articles and exclude presidents' names, country names, and other proper nouns. For each remaining term, we apply a one-month lag relative to the start of the presidential term before including it in the dictionary, thereby mitigating the risk of look-ahead bias.

The advantages of POP BoW3 are twofold. It expands the scope of populist coverage by capturing both traditional and newly salient terms identified through LLM-assisted analysis, and it introduces temporal precision by activating terms only when they historically function as markers of populism. A detailed account of all terms included in POP BoW1, POP BoW2, and POP BoW3, along with their time restrictions where relevant, is provided in Table E.1.

3 Populist sentiment and the Cross-Section of Stock Returns

3.1 Populist sentiment: descriptive statistics

Table 1 reports the summary statistics and pairwise correlation of all indices. On average, the WSJ publishes 2,252 news articles per month, with a minimum of 1,323 articles and a maximum of 3,193 articles.[3] The mean of POP index is 0.125, indicating that on average about 12.5% of news articles in The Wall Street Journal contain populist-related content.[4] The correlation of POP with POP BoW1, POP BoW2, and POP BoW3 are -0.002, 0.319 and 0.880, suggesting that as the populism dictionary is refined, the correlation between LLM-based and dictionary-based measurements progressively strengthens.

The correlation of POP index with GPR, PRisk, and PEAR are -0.104, 0.375, -0.195, respectively, suggesting that populism captures distinct information compared to geopolitical risk, political risk, and presidential economic approval rating. Populism is often associated with political division, movements, and conflicts, and therefore positively correlates with political risk. During our sample, populism is unlikely to promote warfare, military actions, or other geopolitical conflicts; instead, it may trigger geopolitical economic actions, such as tariffs, trade protectionism, and financial sanctions. In contrast, when geopolitical risks increase, the public's attention to internal national conflicts tends to decrease, which leads to a negative correlation with geopolitical risks.

Panel A of Figure 1 shows that the POP index closely tracks populist events in the U.S., yet exhibits distinct time-series dynamics relative to alternative POP indices constructed via bag-of-words approaches using existing dictionaries, with the notable exception of the POP BoW3 index, with which it moves in close alignment. In addition, Panel B of Figure 1

[3]See Internet Appendix A.2 for a description of the sections of each newspaper that were used in the construction of the index.

[4]Restricting to articles with LLM confidence scores above 80% (85%), the mean POP index is 0.09 (0.02).

Table 1: Summary Statistics and Pairwise Correlation of Indices

Panel A: Summary statistics

	Mean	Median	Min	Max	SD
Articles	2250.15	2277	1323	3193	415.94
Terms	1,257,201	1,254,098	596,197	2,036,800	390,265.99
POP	0.125	0.112	0.052	0.271	0.045
POP BoW1	0.057	0.053	0.025	0.161	0.017
POP BoW2	0.090	0.087	0.042	0.197	0.023
POP BoW3	0.121	0.109	0.058	0.295	0.039
GPR	82.552	77.420	28.030	303.590	30.743
PRisk	245.202	235.251	61.770	655.947	82.659
War	0.103	0.102	0.042	0.177	0.021
PEAR	46.375	45.735	17.500	77.000	11.493

Panel B: Pairwise correlation

	POP	POP BoW1	POP BoW2	POP BoW3	GPR	PRisk	War
POP BoW1	-0.002						
POP BoW2	0.319	0.756					
POP BoW3	0.880	-0.024	0.319				
GPR	-0.104	0.102	0.029	-0.128			
PRisk	0.375	-0.005	0.036	0.311	-0.058		
War	0.058	-0.126	-0.230	0.016	0.594	0.174	
PEAR	-0.195	-0.159	-0.122	-0.126	-0.171	-0.176	-0.216

This table reports summary statistics of the WSJ articles, terms, populism indices, and other political risk indices. The mean, median, minimum (Min), maximum (Max), and standard deviation (SD) of each indices are shown in Panel A, and their pairwise correlations are presented in Panel B. Articles denotes the monthly count of Wall Street Journal news articles. Terms denotes the monthly count of Wall Street Journal news terms. POP represents the U.S. Populism Index measured using large language models. POP BoW1, POP BoW2, and POP BoW3 represent the U.S. Populism Indices measured based on populism dictionary V1 (Bonikowski and Gidron (2016)), dictionary V2 (Filippou et al. (2020)), and the newly developed dictionary (this study), respectively. "GPR" is the Geopolitical Risk Index, with data sourced from Caldara and Iacoviello (2022). "PRisk" is the Political Risk Index, which is derived from Wall Street Journal articles using the dictionary-based method proposed by Hassan et al. (2019). "War" is the war discourse index, with the data sourced from Hirshleifer et al. (2025). "PEAR" is the Presidential Economic Approval Rating Index, with data sourced from Chen et al. (2023). The sample period is 1984:01-2024:12 with the exception of the "War", which covers the period from January 1984 to October 2019.

highlights clear differences between the POP, GPR, PEAR, and PRisk indices derived from news texts. The GPR index and War index rises markedly during major geopolitical events such as the 9/11 terrorist attacks, the Gulf War, and the Russia–Ukraine conflict. The PEAR index features an upward trend during the administrations of Bill Clinton and the initial tenure of Barack Obama, while showing a decrease during the administrations of George H.W. Bush and George W. Bush. The PRisk index, in contrast, increases substantially

following the 2008 financial crisis, consistent with the firm-level evidence reported by Hassan et al. (2019). After 2016, however, populism intensified sharply. The political risk index we construct following the dictionary-based method of Hassan et al. (2019) declines during much of Trump's first term, even as our populism index remains persistently elevated. This divergence is consistent with the interpretation that traditional dictionary-based measures of political risk capture a dimension of risk that is distinct from populism.

3.2 The POP premium

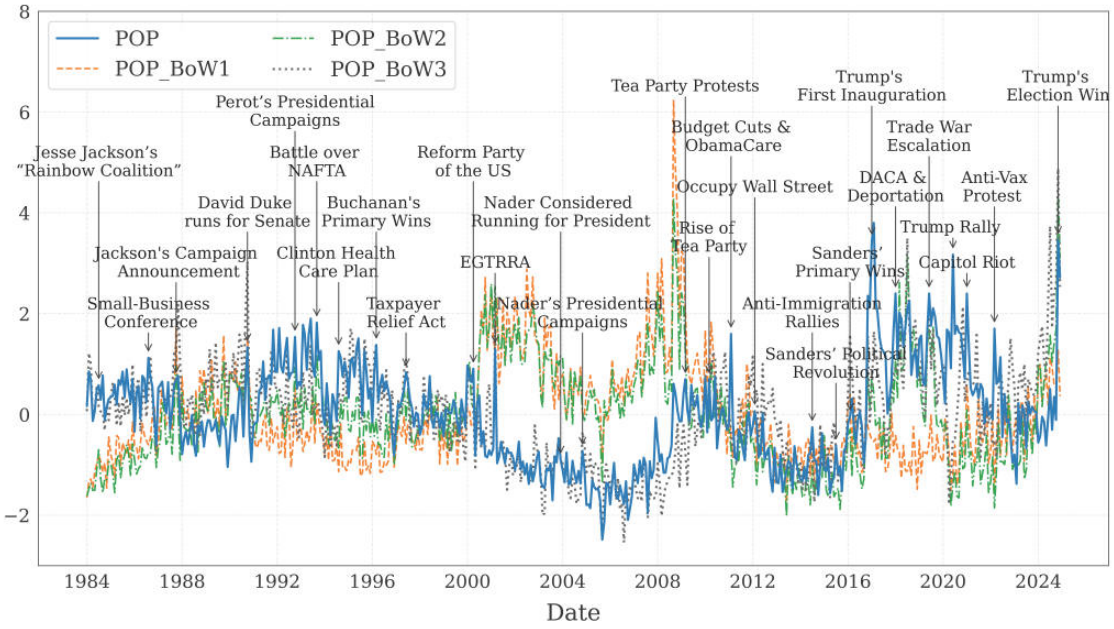
POP beta. Following Chen et al. (2023), we measure a firm's exposure to populism using the U.S. Populism Beta (POP beta), which captures the sensitivity of its stock return to changes in the populism index. Because the U.S. populism index is likely correlated with broader economic conditions (Heinisch et al., 2017; Guriev and Papaioannou, 2022), we estimate the POP beta while controlling for a set of macroeconomic variables. For each stock and each month beginning in January 1984, we estimate the following time-series regression using a 60-month rolling window, requiring at least 24 valid observations:

$$R_{i,t} = \alpha_i + \beta_{i,0} \cdot \Delta\text{POP}_t + \beta_{i,1} \cdot \Delta\text{POP}_{t-1} + \beta_{i,\text{Macro}} \cdot \text{Macro}_t + \varepsilon_{i,t}, \tag{3}$$

where $R_{i,t}$ is the excess return of stock i in month t, and ΔPOP_t represents the change in the POP index from month $t-1$ to month t. Macro_t consists of the change in the effective federal funds rate, the log change in the Coincident Economic Activity Index, the log change in the total monetary base, the log change in total nonfarm employees, and the stock market return[5]. The regression includes the lagged change ΔPOP_t to accommodate the nonsynchronicity between the timing of the POP index and return measurement. Following Dimson (1979), the POP beta (β_{POP}) is defined as $\beta_i = \beta_{i,0} + \beta_{i,1}$.

[5]Controlling for additional macro variables with the highest absolute correlations with the change in populism index does not quantitatively change the main results

Panel A: POP indices based on LLM and dictionaries



Panel B: POP index and other political risk indices

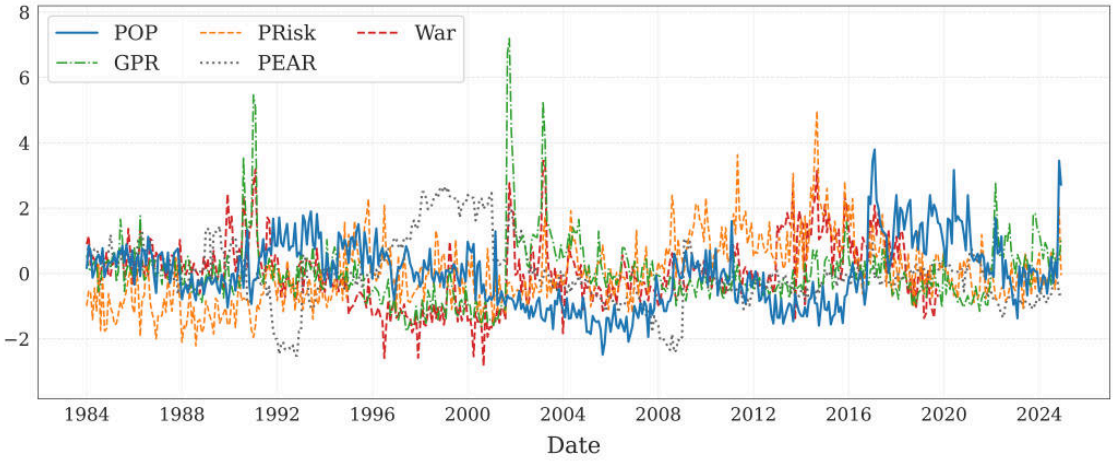


Fig. 1 - The POP indices and comparative measures

This figure plots the time series of standardized U.S. populism and political risk indices. Panel A displays the standardized values of four U.S. Populism Indices: POP (measured using large language models, this study), POP BoW1 (based on Bonikowski and Gidron (2016)), POP BoW2 (based on Filippou et al. (2020)), and POP BoW3 (based on the new dictionary developed in this study). Panel B plots the standardized values of POP alongside four political risk indices: the Geopolitical Risk Index (GPR, Caldara and Iacoviello 2022), the Political Risk Index (PRisk, Hassan et al. 2019), the War Discourse Index (War, Hirshleifer et al. 2025), and the Presidential Economic Approval Rating Index (PEAR, Chen et al. 2023). The sample period is 1984:01–2024:12 with the exception of the "War", which covers the period from January 1984 to October 2019.

Benchmark Results. At the beginning of each month from Jan 1984 to Dec 2024, we form quintile portfolios by sorting firms into five groups based on their POP beta from the prior month. Quintile 1 (5) contains stocks with the lowest (highest) POP beta. We value-weight the stocks in these portfolios and rebalance them monthly. The POP beta spread portfolio (P1 - P5) refers to the strategy of buying stocks in quintile 1 and selling stocks in quintile 5.[6]

Table 2 presents the main results. Note that on average the POP beta of the stocks in quintile 1 (5) is strongly negative (positive). The average monthly excess return of the POP beta portfolios declines from 1.06% in quintile 1 to 0.44% in quintile 5, yielding a spread of 0.62% (t-stats = 4.00). We estimate risk-adjusted returns using four factor models: the Fama and French (1992) three-factor model (FF3), the FF3 augmented with the momentum factor (FF3&Mom), the Fama and French (2015) five-factor model (FF5), and the q-factor model of Hou et al. (2015) (HXZ). None of these models fully account for the return spread across POP beta portfolios. For example, when adjusted using the FF5 model, the spread is 0.61% (t-stats = 4.28).

The results indicate an economically and statistically significant excess return associated with investing in firms that exhibit negative exposure to populism. The average excess return monotonically declines as populism exposure increases, suggesting that our measure captures a distinctive and priced source of risk. The pattern of returns implies that investors require higher compensation for bearing the risks associated with firms that tend to get hurt when populist sentiment rises, consistent with the interpretation that the POP factor reflects a novel dimension of systematic risk rather than a statistical anomaly.

Robustness. To address potential look-ahead bias and hallucination in large language models,

[6]The results are robust to switching from quintiles to deciles, to using equally weighted average, to using different choice of lags for the Newey-West standard error. The associated results are in Table D.1 and Figure D.1.

Table 2: POP Premium

	Avg POP beta	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
P1	-3.60	1.06	0.32	0.32	0.36	0.45
		(4.28)	(3.60)	(3.44)	(3.97)	(4.66)
P2	-0.91	0.74	0.05	0.04	-0.03	-0.03
		(3.81)	(1.08)	(0.83)	(-0.62)	(-0.54)
P3	-0.02	0.73	0.05	0.04	-0.03	-0.06
		(3.88)	(1.27)	(1.07)	(-0.86)	(-1.43)
P4	0.88	0.65	-0.08	-0.05	-0.10	-0.14
		(3.33)	(-1.60)	(-0.94)	(-1.87)	(-2.41)
P5	3.72	0.44	-0.41	-0.37	-0.25	-0.33
		(1.69)	(-4.85)	(-4.42)	(-3.30)	(-4.02)
P1-P5		0.62	0.73	0.69	0.61	0.79
		(4.00)	(4.92)	(4.59)	(4.28)	(5.23)

This table reports monthly average excess returns and alphas (in %) of POP beta quintile portfolios, where P1 (P5) refers to the portfolio with low (high) POP beta, and P1-P5 refers to the strategy that buys P1 and sells P5. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

we conduct several robustness checks. First, following Breitung and Müller (2025) and Jha et al. (2024), we mask personal names and dates to mitigate forward-looking bias. Specifically, we remove all references to presidential and vice-presidential candidates (as listed in Table E.6) and all explicit dates appearing in the text. As shown in Table E.6, several prominent figures that might be associated with populist movements have participated in U.S. presidential elections since 1984, including Ross Perot (1992 and 1996), Pat Buchanan (2000), and Donald Trump (2016, 2020, and 2024). If such identifiers were not masked, the model could directly associate these names or years with well-known populist campaigns, artificially inflating measured populist content. In addition, we remove all examples from the prompt (while keeping all other settings unchanged) to prevent that our prompts may unintentionally reveal contextual information.

Second, following Audrino et al. (2024), we reconstruct the populism index by incorpo-

Table 3: POP Premium: Robustness

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
POP Mask	0.57	0.67	0.63	0.64	0.77
	(3.24)	(4.26)	(4.08)	(3.71)	(4.64)
POP Confidence	0.60	0.70	0.67	0.59	0.77
	(3.94)	(4.92)	(4.65)	(4.15)	(5.16)
POP Risk	0.50	0.53	0.52	0.55	0.71
	(3.69)	(4.44)	(4.46)	(4.18)	(5.14)

This table reports the monthly average excess returns and alphas (in %) of POP beta portfolios from the strategy of buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5). Row "POP Mask" presents the results after masking candidate names and dates. Row "POP Confidence" reports the results of using confidence score weights to adjust for the low-certainty predictions, while Row "POP Risk" shows the results of substituting populist intensity with a risk score when estimating the POP index. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

rating confidence-score weights to downweight predictions with low certainty.

$$\text{POP Confidence}_t \;=\; \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\frac{\sum_{d=1}^{4}\text{Intensity}_{i,d,t}^{\text{POP}}\cdot\text{Confidence}_{i,d,t}^{\text{POP}}}{\sum_{d=1}^{4}\text{Intensity Presence}_{i,d,t}^{\text{POP}}}\right). \tag{4}$$

Third, we replace populist intensity with the model's risk score when constructing the populism index, interpreting this measure as a proxy for the extent to which the media view populist developments as political risk.

$$\text{POP Risk}_t \;=\; \frac{1}{N_t}\sum_{i=1}^{N_t}\left(\sum_{d=1}^{4}\text{Risk}_{i,d,t}^{\text{POP}}\,/\sum_{d=1}^{4}\text{Risk Presence}_{i,d,t}^{\text{POP}}\right). \tag{5}$$

Table 3 reports the corresponding excess returns, showing that the POP premium remains statistically significant. The reason of this result lies in the strong correlation across the benchmark populism index and all the refinements that we considered (see Figure B.1 in Internet Appendix B).

Furthermore, we also eliminate the impact of potential hallucinations by removing LLM measurement results with low confidence levels. Given that an article may involve multiple

dimensions of populism, we measure the average confidence level of each article according to

$$\text{Confidence}_{i,t}^{\text{POP}} = \frac{\sum_{d=1}^{4} \text{Confidence}_{i,d,t}^{\text{POP}} \cdot \text{Intensity Presence}_{i,d,t}^{\text{POP}}}{\sum_{d=1}^{4} \text{Intensity Presence}_{i,d,t}^{\text{POP}}} \tag{6}$$

On average, the confidence of each article identified by our methodology as containing populism-related content is greater than 0.6, and over 75% of identified articles have confidence levels falling within the 70%-80% range. In contrast, fewer than 15% of populist articles exhibit confidence levels exceeding 85%. Motivated by this observation, we reconstruct the populism index by limiting the analysis to articles whose confidence scores exceed varying thresholds (CT ranging from 70% to 85%), as defined in Equation 7. We then re-estimate our models to assess the robustness of the findings.

$$\text{POP } CT_t = \frac{1}{N_t} \sum_{i=1}^{N_t} \frac{\sum_{d=1}^{4} \text{Intensity}_{i,d,t}^{\text{POP}}}{\sum_{d=1}^{4} \text{Intensity Presence}_{i,d,t}^{\text{POP}}} \cdot \mathbb{I}(\text{Confidence}_{i,t}^{\text{POP}} \geq CT), \tag{7}$$

where, $\mathbb{I}(\cdot)$ denotes an indicator function that evaluates to 1 if the condition inside the parentheses is true, and to 0 otherwise.

Table 4: POP Premium: Confidence Threshold

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
POP 70%	0.61	0.71	0.68	0.60	0.78
	(3.93)	(4.91)	(4.64)	(4.31)	(5.25)
POP 75%	0.64	0.72	0.70	0.70	0.88
	(4.04)	(5.16)	(4.95)	(4.87)	(5.69)
POP 80%	0.60	0.64	0.62	0.65	0.81
	(3.59)	(4.66)	(4.35)	(4.55)	(5.65)
POP 85%	0.25	0.31	0.30	0.14	0.25
	(1.69)	(2.11)	(2.10)	(0.96)	(1.69)

This table reports the monthly average excess returns and alphas (in %) of POP beta portfolios from the strategy of buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5). The sample of populist news articles is filtered based on the confidence level of the LLM classification. The POP index is then reconstructed using only articles that meet the specified confidence thresholds of $70\%, 75\%, 80\%$, and 85%, respectively. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

Table 5: POP Premium: AI Stocks Impact

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
Control AI-ETF	0.52	0.48	0.44	0.32	0.48
	(3.12)	(2.82)	(2.65)	(1.92)	(2.85)
Ex. Big Tech	0.52	0.63	0.56	0.50	0.63
	(3.98)	(4.83)	(4.25)	(3.84)	(4.63)

This table reports the monthly average excess returns and alphas (in %) of POP beta portfolios from the strategy of buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5). Row "Control AI-ETF" presents results after controlling for the return of the iShares U.S. Technology ETF. Row "Ex. Big Tech" shows results after excluding seven major U.S. technology stocks (Apple, NVIDIA, Microsoft, Amazon, Tesla, Alphabet, and Meta). All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. Panel A uses the sample period from 2002:05 to 2024:12, and Panel B from 1986:01 to 2024:12.

Figure B.2 in Internet Appendix B plots the POP measures based on different confidence levels, all of which exhibit a high correlation with the benchmark measure. Table 4 presents the results under different confidence thresholds. When the confidence level is set at 75%, the POP premium achieves its highest statistical significance. However, when the confidence threshold is raised to 85%, both the economic magnitude and statistical significance of the POP premium decline noticeably. This occurs because while a moderately higher confidence threshold helps prune potentially misclassified cases, an excessively high threshold substantially reduces the sample size of articles identified as containing populism-related content.

To mitigate potential confounding effects from the rise of technology or AI-related firms, which constitute a non-trivial part of our sample, we conduct two robustness checks controlling for AI-related factors. In Panel A of Table 5, we estimate the POP beta while controlling for the returns of the iShares U.S. Technology ETF. The iShares U.S. Technology ETF had total assets under management of $21,488 million, ranking it as the largest ETF by asset size as of October 2025. Panel B further shows the results after excluding seven major technology stocks (Apple, NVIDIA, Microsoft, Amazon, Tesla, Alphabet, and Meta). In both cases, the POP premium remains statistically significant, indicating that our findings are not driven by exposures to the technology sector or leading AI-focused firms.

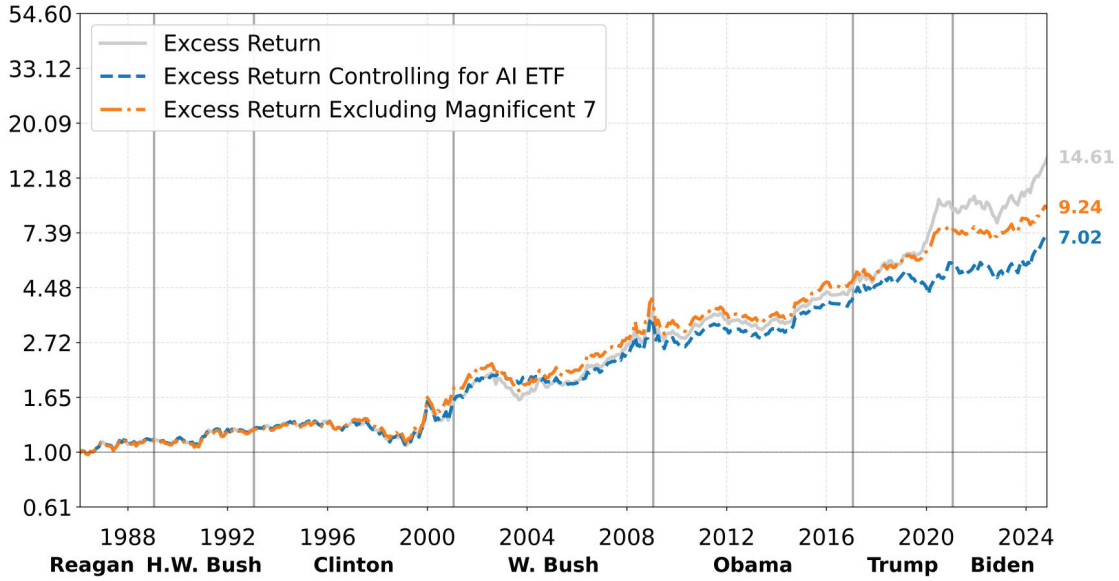


Fig. 2 - POP premium: cumulative return

This figure presents the log cumulative return of the POP beta spread portfolio, and the cumulative return adjusted for exposures to AI stocks. The series in the figure are expressed in U.S. dollars for intuitive interpretation. The sample period is 1986:01-2024:12.

Performance. In this subsection, we assess the economic value of trading on the POP premium by examining the performance of the POP beta spread portfolio. Figure 2 plots the log cumulative returns of the POP premium portfolio. Over the sample period from January 1986 to December 2024, an investor would earn a profit of $14.61, with no evidence of substantial drawdowns. We also find that the cumulative return of the POP premium portfolio diminishes after controlling for AI-related exposures, yet the investment strategy's effectiveness persists.

Figure 3 presents the excess returns and alphas of the POP beta spread portfolio up to 12 months after portfolio formation. The results show that the POP premium remains persistent and statistically significant for up to seven months following formation. Moreover, the premium does not exhibit any reversal within the subsequent 12 months, suggesting that it is unlikely to arise from temporary price pressures or liquidity-induced trading.

Comparison with the Bag-of-Words Methodology. In Table 6, we present portfolio results

based on the BoW methodology for constructing the POP index. The POP premium is not statistically significant when the index is constructed using existing dictionaries BoW1 (Bonikowski and Gidron, 2016) or BoW2 (Filippou et al., 2020). However, the POP beta spread and its corresponding t-statistics are higher when we employ the POP BoW2 dictionary. The final row of Table 6 presents the results for the POP beta estimated using POP BoW3, showing a statistically significant POP premium. Nonetheless, the magnitude of this premium is smaller than the baseline estimate in Table 2. This suggests that traditional BoW methods capture less cross-sectional variation in returns than the evolving vocabulary derived from the LLM. The difference arises because LLMs provide a more nuanced assessment of populism-related content than traditional BoW approaches, which by construction cannot account for linguistic or contextual variation. This results in an alternative measure of populist sentiment that offers a superior ability to capture firms' exposure to this source of risk. In Table E.7, we report examples of articles that contain few, if any, traditional populist terms but are nevertheless classified by the LLM as exhibiting high levels of populism-related content due to its ability to interpret contextual meaning.

To mitigate look-ahead bias, we introduce a lag ranging from one to six months following the start of a president's tenure before admitting a new term into the BoW3 dictionary. As shown in Table 7, this adjustment does not alter our conclusions regarding the POP premium.

We further investigate the contribution of individual terms by reconstructing the POP BoW3 index, each time excluding one populist term from or adding one populist term to the lexicon. Figure 4 presents the excess returns and alphas of the resulting POP beta spread portfolios. The label "All" corresponds to the baseline case without any exclusions or addition. Our analysis shows that most individual terms have little effect on the magnitude of the POP premium. Keywords such as "social security," "supreme court," and "legislation" exhibit greater influence on the level of the POP premium, reflecting their higher prevalence in populist articles. In contrast, commonly used modern populist rhetoric terms—such as

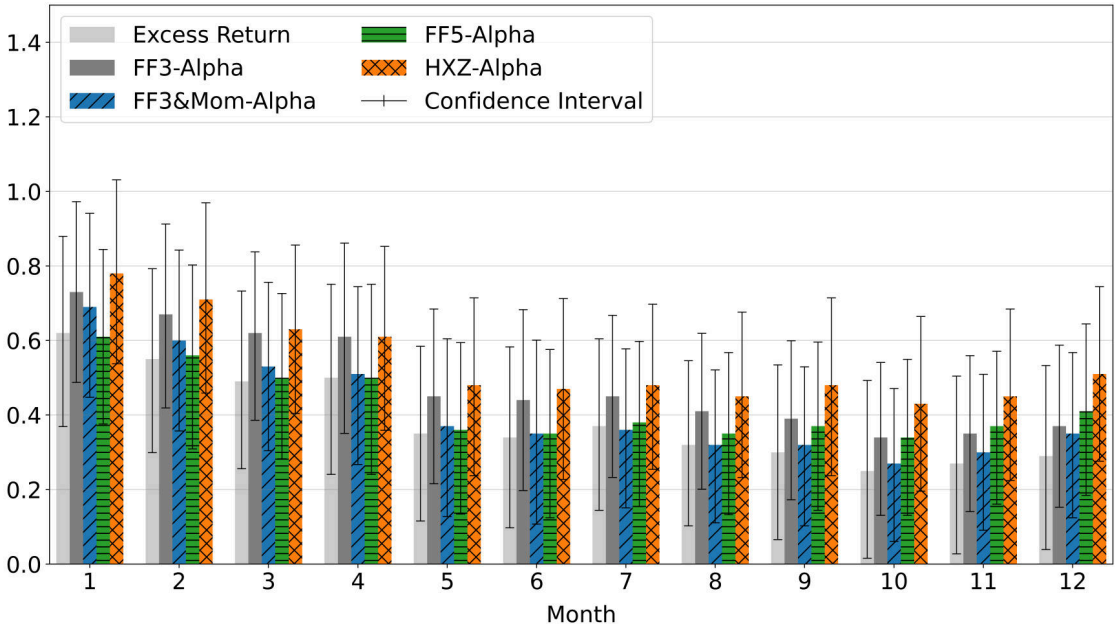


Fig. 3 - POP premium after portfolio formation

This figure plots the excess return and alphas of the POP beta spread portfolio up to 12 months after formation. Bars represent point estimates, and vertical lines indicate the 90% confidence intervals. The sample period is 1986:01-2024:12.

Table 6: POP Premium: Bag-of-Words Method

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
POP BoW1	0.11	0.16	0.07	0.06	0.06
	(0.81)	(1.12)	(-0.44)	(0.33)	(0.42)
POP BoW2	0.16	0.24	0.13	0.10	0.15
	(1.14)	(1.63)	(0.90)	(0.57)	(1.05)
POP BoW3	0.43	0.43	0.44	0.57	0.64
	(2.77)	(2.91)	(2.81)	(3.41)	(3.73)

This table reports the monthly average excess returns and alphas (in %) of POP beta portfolios from the strategy of buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5). We use Bag-of-Words methodology (instead of the LLM method) to construct the POP index. BoW1 dictionary is from Bonikowski and Gidron (2016), BoW2 dictionary is from Filippou et al. (2020), and BoW3 dictionary is developed in this study. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

"fake news," "America First," and "Make America Great Again"—have only a marginal impact on the magnitude of the POP premium, consistent with their relatively limited occurrence in news coverage, as reported in Table E.3.

Table 7: POP Premium: Lagged BoW3 Dictionary Inclusion

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
1	0.43	0.43	0.44	0.57	0.64
	(2.77)	(2.91)	(2.81)	(3.41)	(3.73)
2	0.38	0.39	0.40	0.55	0.61
	(2.33)	(2.52)	(2.41)	(3.03)	(3.28)
3	0.36	0.35	0.36	0.51	0.57
	(2.25)	(2.36)	(2.23)	(2.92)	(3.11)
4	0.40	0.39	0.39	0.54	0.59
	(2.49)	(2.58)	(2.42)	(3.01)	(3.18)
5	0.38	0.37	0.37	0.52	0.57
	(2.41)	(2.42)	(2.26)	(2.97)	(3.08)
6	0.43	0.43	0.43	0.58	0.63
	(2.67)	(2.76)	(2.58)	(3.19)	(3.33)

This table reports the monthly average excess returns and alphas (in %) of POP beta portfolios from the strategy of buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5), based on different POP BoW3 measures. We introduce a lag ranging from one to six months following the start of a president's tenure before admitting term into the BoW3 dictionary, and subsequently re-estimate the POP BoW3 index. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

Controlling for Existing Indices. In this subsection, we further isolate the distinct information in the POP beta by controlling for established political and geopolitical risk measures. Specifically, we calculate the POP beta by including the geopolitical risk index of Caldara and Iacoviello (2022), the political risk index of Hassan et al. (2019), the war discourse index of Hirshleifer et al. (2025), and the presidential economic approval rating of Chen et al. (2023). For each stock and each month since January 1984, we estimate this specification using a 60-month rolling window, requiring a minimum of 24 observations:

$$\begin{aligned} R_{i,t} &= \alpha_i + \beta_{i,0} \cdot \Delta\text{POP}_t + \beta_{i,1} \cdot \Delta\text{POP}_{t-1} + \beta_{i,P0} \cdot \Delta\text{Political}_{i,t} + \beta_{i,P1} \cdot \Delta\text{Political}_{i,t-1} \\ &\quad + \beta_{i,\text{Macro}} \cdot \text{Macro}_t + \varepsilon_{i,t}, \end{aligned} \tag{8}$$

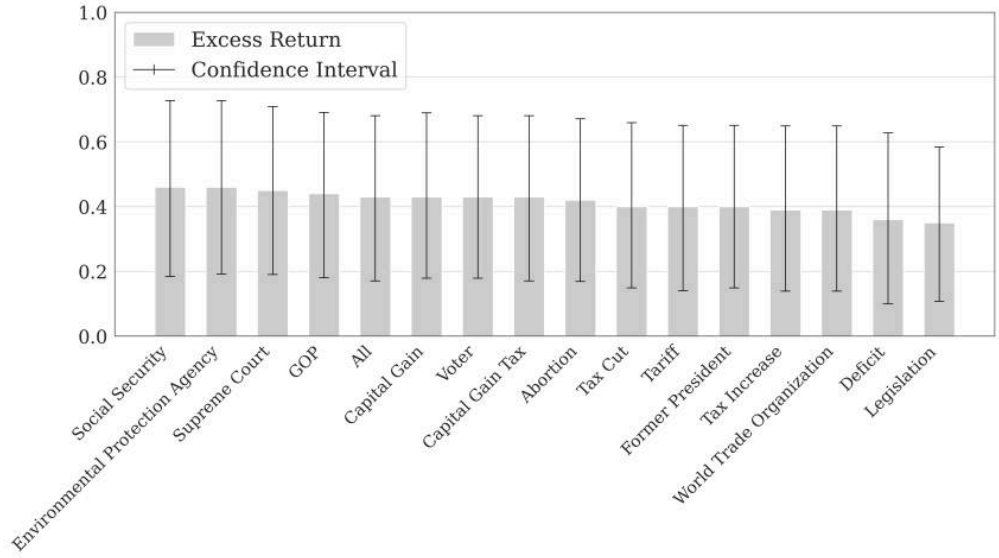
As shown in Table 8, the POP premium remains both statistically significant and economically meaningful after being orthogonalized against these existing political risk factors.

We also conduct a series of portfolio double sorts to verify that the POP premium is not subsumed by other known return predictors. We first sort all stocks into terciles based on a given control characteristic. Subsequently, within each characteristic-based tercile, we perform an independent sort into quintiles based on POP beta. This allows us to construct and evaluate the POP beta spread portfolio conditional on the level of the other firm characteristic. As reported in Table 9, the POP premium remains both economically large and statistically significant after controlling for exposures to political risks (β_{GPR}, β_{PRisk}, β_{PEAR}, β_{War}), three firm characteristics (BM, INV, OP) from Fama and French (2015), limits-to-arbitrage (IVOL), and illiquidity (ILLIQ). Panel E presents the sole exception, revealing a significantly stronger POP premium among larger firms. These results reinforce that the POP premium captures a distinct dimension of firm risk not reflected by existing political risk indices or common asset pricing characteristics.

Subsample Analysis. To assess whether the POP premium is a general phenomenon rather than one unique to the Trump administration, we divide the sample into pre- and post-2017 periods. Table 10 reports the average monthly returns and alphas for the P1–P5 POP beta spread portfolio in these subperiods. Results in Panel A (LLM-based POP) and Panel D (BoW3-based POP) confirm that a significant POP premium existed prior to Donald Trump's presidency. Furthermore, with the exception of Panel B (BoW1), the premium is generally stronger in the post-2017 period. The attenuated result in Panel B is likely attributable to the Bonikowski and Gidron (2016) dictionary's reliance on pre-1992 narratives, which may not adequately capture the evolution of U.S. populism in the 21st century.

Next, we examine whether the POP premium is confounded by the partisan cycle, given that populist rhetoric is not exclusive to either major party. Historically, the Know Nothings Party emerged under Democrat James K. Polk, while the Greenback Party arose under Republican Ulysses S. Grant. More recently, the Tea Party and Occupy Wall Street move-

Panel A: POP premium: exclude terms from BoW3 dictionary



Panel B: POP premium: add terms to BoW3 dictionary

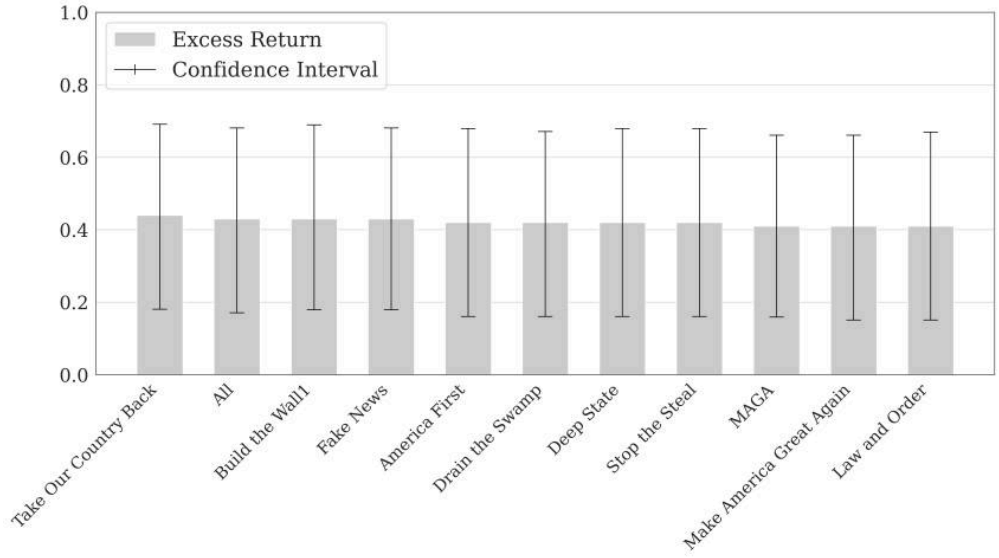


Fig. 4 - POP premium: change BoW3 lexicon

This figure plots the excess returns of the POP beta spread portfolio when individual populist terms are excluded from (Panel A) or added to (Panel B) the BoW3 dictionary. The x-axis shows the excluded terms or the added term to the BoW3 lexicon, with 'All' indicating the baseline model. The sample period is 1986:01-2024:12.

ments both originated during the Democratic administration of Barack Obama, preceding the presidency of Republican Donald Trump. Figure 5 displays the point estimates and the 90% confidence band of the POP premium across different administrations. The premium

Table 8: POP Premium: Control for Political Risk

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
Control GPR	0.53	0.63	0.59	0.53	0.69
	(3.61)	(4.45)	(4.21)	(3.64)	(4.67)
Control PRisk	0.49	0.59	0.52	0.47	0.62
	(3.33)	(4.04)	(3.71)	(3.13)	(4.19)
Control PEAR	0.54	0.65	0.62	0.56	0.70
	(3.33)	(4.47)	(4.27)	(4.01)	(4.55)
Control War	0.56	0.65	0.64	0.54	0.72
	(3.68)	(4.59)	(4.29)	(4.07)	(5.05)
Control All	0.48	0.60	0.55	0.49	0.63
	(3.39)	(4.45)	(4.18)	(3.63)	(4.54)

This table reports the monthly average excess returns and alphas (in %) of POP beta portfolios from the strategy of buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5). The POP beta is estimated following Equation 8. Row "Control GPR" controls for the geopolitical risk index (Caldara and Iacoviello (2022)), row "Control PRisk" controls for the political risk (Hassan et al. (2019)), row "Control PEAR" controls for the presidential economic approval rating index (Chen et al. (2023)), row "Control War" controls for the war discourse index (Hirshleifer et al. (2025)), and row "Control All" controls for all four indices. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

is statistically significant under both Democratic and Republican presidencies. The magnitude is generally larger during Republican administrations, with the three highest premiums occurring under Donald Trump, Joe Biden, and George W. Bush.

Furthermore, we examine how the POP beta spread portfolio performs across the four years of a presidential term. Existing literature documents distinct return patterns over the political cycle: Belo et al. (2013) find that government spending exposure predicts returns more strongly in the second and third years, while Addoum and Kumar (2016) show that stock prices are most sensitive to political climate changes in the first and fourth years. Chen et al. (2023) demonstrate that the low PEAR beta premium persists throughout the term but is strongest in the first three years. In contrast to these patterns, Figure 6 reveals that the POP premium intensifies during the last two years of a president's tenure. We posit that during this pre-election period, candidates from both parties are more likely to adopt populist positions, thereby stimulating populist sentiment and amplifying the premium.

Table 9: Double Sort

	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$		$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
Panel A: Double sort on β_{GPR} and β_{POP}			Panel B: Double sort on β_{PRisk} and β_{POP}		
Low	0.75	0.90	Low	0.53	0.67
	(4.37)	(5.41)		(3.08)	(3.87)
High	0.60	0.78	High	0.48	0.67
	(2.88)	(4.04)		(2.46)	(3.18)
High-Low	-0.15	-0.11	High-Low	-0.05	-0.01
	(-0.66)	(-0.52)		(-0.24)	(-0.03)
Panel C: Double sort on β_{PEAR} and β_{POP}			Panel D: Double sort on β_{War} and β_{POP}		
Low	0.46	0.68	Low	0.46	0.61
	(2.85)	(3.80)		(3.05)	(4.39)
High	0.43	0.52	High	0.69	0.82
	(2.35)	(3.03)		(3.10)	(3.67)
High-Low	-0.03	-0.16	High-Low	0.23	0.21
	(-0.15)	(-0.68)		(0.93)	(0.84)
Panel E: Double sort on SIZE and β_{POP}			Panel F: Double sort on BM and β_{POP}		
Low	0.28	0.31	Low	0.52	0.63
	(2.88)	(3.10)		(3.12)	(3.69)
High	0.63	0.84	High	0.47	0.67
	(4.03)	(4.97)		(2.12)	(3.13)
High-Low	0.36	0.52	High-Low	-0.05	0.05
	(2.36)	(3.24)		(-0.22)	(0.19)
Panel G: Double sort on INV and β_{POP}			Panel H: Double sort on OP and β_{POP}		
Low	0.51	0.67	Low	0.54	0.64
	(3.01)	(3.96)		(3.11)	(3.59)
High	0.62	0.76	High	0.58	0.77
	(3.40)	(4.07)		(3.26)	(3.89)
High-Low	0.11	0.09	High-Low	0.04	0.13
	(0.59)	(0.49)		(0.21)	(0.60)
Panel I: Double sort on IVOL and β_{POP}			Panel J: Double sort on ILLIQ and β_{POP}		
Low	0.65	0.81	Low	0.41	0.56
	(3.28)	(3.73)		(3.62)	(4.88)
High	0.55	0.77	High	0.27	0.33
	(3.11)	(3.75)		(2.75)	(3.08)
High-Low	-0.09	-0.04	High-Low	-0.14	-0.22
	(-0.40)	(-0.14)		(-1.27)	(-2.12)

This table reports the monthly Fama and French (2015) alphas and Hou et al. (2015) alphas of β_{POP} spread portfolios that are double-sorted by firm characteristics and POP beta. In each month, all stocks are first sorted into terciles based on their firm characteristics (β_{GPR}, β_{PRisk}, β_{PEAR}, β_{War}, SIZE, BM, INV, OP, IVOL, ILLIQ). Within each tercile, stocks are further sorted into quintiles based on POP beta. All portfolios are value-weighted and rebalanced at a monthly frequency. Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

Table 10: POP Premium: Pre and Post 2017

Panel A: POP

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
Pre-2017	0.44	0.57	0.53	0.46	0.63
	(3.01)	(4.00)	(3.78)	(3.43)	(4.64)
Post-2017	1.35	1.35	1.32	1.21	1.39
	(2.98)	(3.61)	(3.56)	(3.27)	(3.53)

Panel B: POP BoW1

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
Pre-2017	0.18	0.22	0.11	0.12	0.12
	(1.30)	(1.56)	(0.81)	(0.80)	(0.81)
Post-2017	-0.16	-0.05	-0.11	-0.17	-0.14
	(-0.39)	(-0.14)	(-0.29)	(-0.44)	(-0.37)

Panel C: POP BoW2

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
Pre-2017	0.09	0.16	0.05	0.03	0.09
	(0.58)	(1.04)	(0.31)	(0.20)	(0.59)
Post-2017	0.44	0.54	0.48	0.36	0.42
	(1.39)	(1.75)	(1.44)	(1.22)	(1.29)

Panel D: POP BoW3

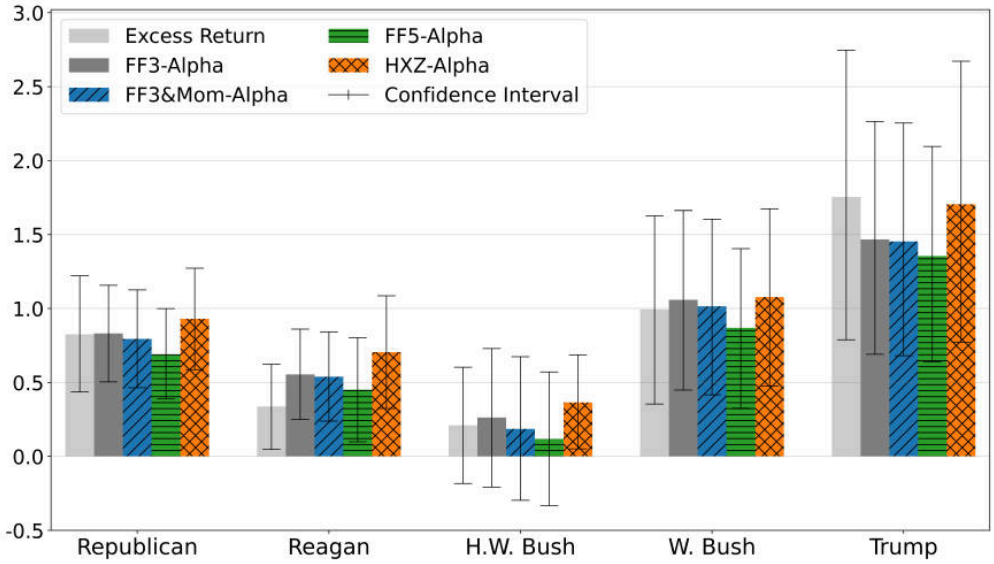
	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
Pre-2017	0.31	0.33	0.35	0.49	0.56
	(2.06)	(2.33)	(2.44)	(3.29)	(3.93)
Post-2017	0.90	0.79	0.80	0.91	0.95
	(1.95)	(2.00)	(2.02)	(2.48)	(2.60)

This table reports the monthly average excess returns and alphas (in %) of POP beta spread portfolios when buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1 - P5), separated into periods before and after 2017. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

In Table D.10, we show that fixing portfolio compositions at the start of each presidential term attenuates the results, suggesting that the reallocation of firms across portfolios over the presidential cycle plays an important role in driving the premium we document.

Fama-MacBeth regressions. So far, we have tested the significance of POP beta as a determinant of future returns at the portfolio level. A potential concern with portfolio-based analysis is that aggregation discards substantial information from the cross-section and complicates

Panel A: POP premium: Republican presidencies



Panel B: POP premium: Democratic presidencies

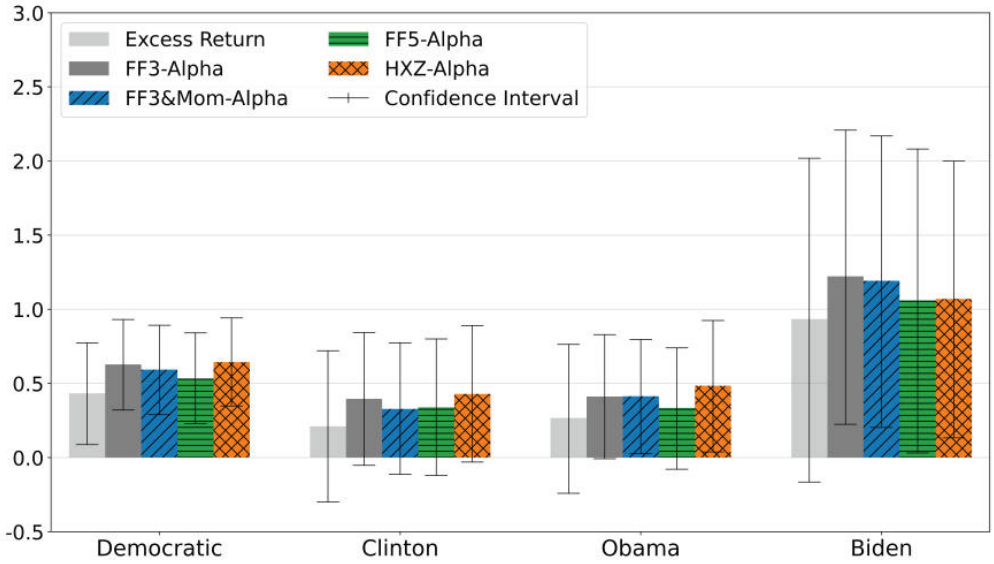


Fig. 5 - POP premium under Democratic and Republican presidencies

This figure plots the excess return and alphas of the POP beta spread portfolio across Republican and Democratic administrations. The sample period is 1986:01-2024:12.

the simultaneous control of multiple factors that may jointly influence POP beta. To address this concern, we employ the two-step Fama and MacBeth (1973) regression framework, in which firms' one-month-ahead excess returns are regressed on POP beta and a comprehensive set of control variables. In the first step, firm-level POP betas (and other factor betas) are estimated via rolling time-series regressions. In the second step, the market prices of

Table 11: Firm Characteristics and β_{POP}

Panel A: Summary statistics

	Mean	Median	Min	Max	P25	P75	Std
β_{POP}	0.17	0.12	-8.24	8.81	-1.27	1.57	2.78
β_{CAPM}	1.14	1.04	-0.25	3.35	0.66	1.52	0.70
β_{BW}	0.01	0.01	-0.69	0.72	-0.11	0.12	0.23
β_{UNC}	0.03	0.01	-1.56	1.84	-0.21	0.25	0.51
β_{GPR}	0.02	0.01	-0.54	0.67	-0.08	0.11	0.19
β_{Prisk}	0.00	0.00	-0.18	0.17	-0.03	0.03	0.06
β_{PEAR}	0.00	0.00	-0.03	0.03	0.00	0.01	0.01
β_{War}	0.10	0.03	-6.92	7.74	-1.12	1.27	2.38
SIZE	5.98	5.88	1.97	10.93	4.52	7.31	1.97
BM	-0.67	-0.57	-3.27	1.16	-1.15	-0.10	0.84
I/A	0.18	0.07	-0.43	2.84	-0.01	0.21	0.45
ROE	0.16	0.20	-2.25	1.82	0.08	0.32	0.47
STR	0.01	0.00	-0.31	0.49	-0.06	0.07	0.13
MOM	0.16	0.08	-0.72	2.48	-0.16	0.35	0.53
IVOL	0.03	0.02	0.01	0.11	0.01	0.03	0.02
ILLIQ	0.28	0.04	0.00	2.70	0.01	0.28	0.54

Panel B: Pairwise correlation

	β_{POP}	β_{CAPM}	β_{BW}	β_{UNC}	β_{GPR}	β_{Prisk}	β_{PEAR}	β_{War}	SIZE	BM	I/A	ROE	STR	MOM	IVOL
β_{CAPM}	0.00														
β_{BW}	0.05	-0.07													
β_{UNC}	-0.01	0.10	0.01												
β_{GPR}	-0.06	0.11	0.01	0.06											
β_{Prisk}	0.16	0.01	0.08	-0.03	0.08										
β_{PEAR}	0.05	0.01	0.02	0.07	0.10	0.02									
β_{War}	-0.05	0.03	0.01	0.03	0.51	0.14	0.03								
SIZE	-0.04	0.00	-0.04	-0.01	-0.03	0.04	-0.06	0.00							
BM	0.00	-0.12	0.07	-0.03	-0.03	0.01	0.03	-0.05	-0.26						
I/A	0.00	0.08	-0.04	0.02	0.03	-0.01	0.00	0.03	0.04	-0.18					
ROE	-0.01	-0.13	0.00	-0.04	-0.05	0.03	-0.04	-0.04	0.30	0.00	0.03				
STR	-0.01	0.00	0.01	0.02	0.00	0.00	-0.01	0.00	0.05	0.02	-0.02	0.01			
MOM	0.00	-0.02	0.03	0.01	-0.01	-0.01	-0.02	-0.02	0.15	0.04	-0.06	0.03	0.27		
IVOL	0.03	0.19	0.02	0.04	0.05	-0.03	0.05	0.02	-0.52	0.01	0.03	-0.32	0.10	-0.10	
ILLIQ	0.02	-0.13	0.05	-0.02	0.00	-0.04	0.05	-0.02	-0.60	0.21	-0.07	-0.15	-0.02	-0.15	0.44

This table reports the summary statistics of β_{POP} and other firm characteristics (in Panel A) and their pairwise correlations (in Panel B). Variables include $\beta_{\text{POP}}, \beta_{\text{CAPM}}, \beta_{\text{BW}}$ (Chen et al., 2021), β_{UNC} (Bali et al., 2017), β_{GPR} (Caldara and Iacoviello, 2022), β_{PRisk} (Hassan et al., 2019), β_{PEAR} (Chen et al., 2023), β_{War} (Hirshleifer et al., 2025), log firm size (SIZE), log book-to-market ratio (BM), annual growth of book assets (I/A), return on book equity (ROE), short-term reversal (STR), price momentum (MOM), idiosyncratic volatility (IVOL), and illiquidity (ILLIQ). The sample period is 1986:01-2024:12. All variables are winsorized at the 1st and 99th percentiles within each month. Both the descriptive statistics and correlation analysis are conducted on a monthly basis, with the final results presented as monthly averages.

risk are recovered by running monthly cross-sectional regressions of realized returns on the estimated betas and control variables. We control for for other firm-specific characteristics, market and sentiment βs, political risk βs, and industry effects. Firm-specific characteristics include log firm size (SIZE), log book-to-market ratio (BM), total asset growth (I/A), return on book equity (ROE), short-term reversal (STR), price momentum (MOM), idiosyncratic volatility (IVOL), and illiquidity (ILLIQ). Market and sentiment βs include $\beta_{\text{CAPM}}, \beta_{\text{BW}}$, and β_{UNC}. Political risk βs include β_{GPR}, β_{PRisk},,β_{PEAR}, and β_{War}. To mitigate the influence of outliers, we winsorize all continuous independent variables at the 1st and 99th percentiles for each month. Table 11 reports the summary statistics and pairwise correlation of other firm characteristics and it shows the modest degree of correlation with our β_{POP}.

Table 12 reports the results of Fama-MacBeth regressions, in which all variables are

standardized to facilitate comparison across specifications. Column 1 shows that POP beta enters with a significantly negative coefficient of –0.161 in the absence of control variables. Economically, the absolute value of t-statistics is proportional to the Sharpe ratio of the POP beta spread portfolio, which equals the annualized Sharpe ratio times the number of years in the sample. So the t-stats of -3.16 suggests that an investor can earn an annualized Sharpe ratio of 0.53 by trading on the POP premium. When we include standard firm characteristics in column 2, the coefficient remains significant at –0.121. Further controlling for other market and sentiment betas in column 3 attenuates the coefficient only slightly to –0.105 (t-stats = –3.05), suggesting that heterogeneous exposure to these economic-related variables do not fully account for the POP premium. In column 4, when we include other political risk betas, the coefficient of POP beta changes to –0.101 (t-stats = –3.09), indicating that political exposures alone cannot explain the premium. Finally in column 5, we run the Fama-MacBeth regression while controlling for the Fama-French 48 industry fixed effects. The regression coefficients for POP beta remain significant, indicating that the POP premium is not an industry-level phenomenon.

4 Economic Determinants of Populism Exposure

In this section, we investigate the economic forces underlying cross-sectional differences in POP betas, with the goal of understanding which firm characteristics make certain firms more sensitive to shifts in populist sentiment than others.

We systematically test whether firms with higher POP betas are more closely aligned with the party that exhibits the strongest populist rhetoric. Firms whose employees direct a larger share of their campaign contributions toward the more populist party have returns that covary positively with increases in populist sentiment. These firms may benefit from ties to the populist agenda and therefore may serve as a hedge against populist risk in cross-

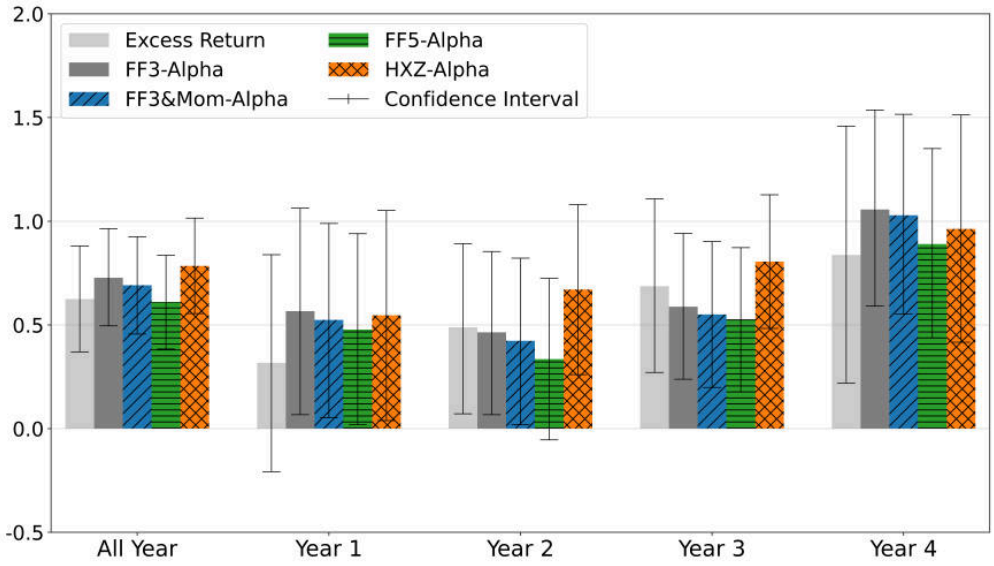


Fig. 6 - POP premium over the presidential term cycle

This figure plots the monthly average excess return and alphas of the POP beta spread portfolio across years of the president's term. The sample period is 1986:06-2024:12

sectional portfolios: investors who hold high-β_{POP} stocks are partially insured against the adverse effects of rising populism. If the more populist party also controls the administration, we would expect this hedging channel to be stronger, as proximity to the party in power reinforces the link between political alignment and populism exposure.

Administration Alignment based on Campaign Contributions. Our empirical analysis relies on two firm-level political alignment measures, both bounded between 0 and 1. The first, Alignment with the Party Exhibiting the Highest Degree of Populist Rhetoric (Align_POP$_{i,t}$), measures the share of a firm's contributions directed toward whichever party displays stronger populist rhetoric in a given election cycle. The second, Alignment with the Current Administration (Align_Adm$_{i,t}$), captures the degree to which a firm's employees direct political contributions toward the incumbent party.

To construct Align_POP$_{i,t}$, we first identify the party with the highest degree of populist rhetoric in each election cycle by analyzing candidates' nomination acceptance speeches using a large language model. Following Duchin et al. (2023), we then use employee cam-

Table 12: Fama-MacBeth Regressions

	[1]	[2]	[3]	[4]	[5]
λ_{POP}	-0.161***	-0.121***	-0.105***	-0.099***	-0.073***
	(-3.16)	(-3.37)	(-3.05)	(-2.99)	(-2.74)
Firm characteristics	No	Yes	Yes	Yes	Yes
Market and sentiment βs	No	No	Yes	Yes	Yes
Political risk βs	No	No	No	Yes	Yes
Industry Effects	No	No	No	No	Yes
Observations	1,580,693	1,580,693	1,580,693	1,580,693	1,580,693
Adj. R^2	0.001	0.002	0.002	0.052	0.085

This table reports the Fama-MacBeth regressions results of one-month-ahead stock excess returns (in %) on POP beta, controlling for other firm-specific characteristics, market and sentiment βs, political risk βs, and industry effects. Firm-specific characteristics include firm size (SIZE), book-to-market ratio (BM), total asset growth (I/A), return on book equity (ROE), short-term reversal (STR), price momentum (MOM), idiosyncratic volatility (IVOL), and illiquidity (ILLIQ). Market and sentiment βs include $\beta_{\text{CAPM}}, \beta_{\text{BW}}$ (Chen et al., 2021), and β_{UNC} (Bali et al., 2017). Political risk βs include β_{GPR} (Caldara and Iacoviello, 2022), β_{PRisk} (Hassan et al., 2019), β_{War} (Hirshleifer et al., 2025), and β_{PEAR} (Chen et al., 2023). In Column 5, we include 48 industry dummies classified following Fama and French (1997). All independent variables are winsorized at the 1st and 99th percentiles and are normalized to have zero mean and standard deviation of one. Intercepts are included in all the regressions but unreported for brevity. Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1986:01-2024:12.

paign contribution records from the Federal Election Commission (FEC) to measure firm's political affiliation. Specifically, for each firm i in month t, we compute Align_POP$_{i,t}$ as the share of its employees' political donations directed toward the party exhibiting stronger populist rhetoric in the most recent presidential election. The donation shares are computed over a rolling 96-month window, subject to a minimum of five individual contributions. For instance, in the 2016 election, in which the Republican Party exhibit a higher degree of populist rhetoric, a firm whose employees directed 65% of their contributions toward Republican committees in January 2017 would receive an Align_POP$_{i,t}$ value of 0.65 for that month. Thus, what varies across election cycles is the party designated as more populist, while the firm-level donation share toward that party is updated monthly.

Similarly, for each firm i in month t, we define Align_Adm$_{i,t}$ as the share of employee political donations directed toward the incumbent administration's party. For instance, since the Republican Party held the presidency from 2017 to 2021, a firm whose employees contributed 80% of their donations to Republican committees in January 2017 would receive an Align_Adm$_{i,t}$ value of 0.80. The full construction details for Align_POP$_{i,t}$ and

$\text{Align_Adm}_{i,t}$ are provided in Internet Appendix C.

Administration Alignment based on Headquarters. We further construct alternative alignment measures based on regional election returns obtained from the MIT Election Data and Science Lab. For each presidential election cycle, we compute a county-level version of $\text{Align_POP}_{i,t}$ as the vote share received by the party with the highest degree of populist rhetoric in the county where the firm is headquartered, and analogously define $\text{Align_Adm}_{i,t}$ as the incumbent party's vote share in the same county.

Portfolio-Level Analysis. We examine the association between POP beta and political alignment at the portfolio level. Portfolio aggregation averages out firm-specific noise in both estimated betas and characteristics, thereby improving the signal-to-noise ratio and yielding more stable inference. Each month, we sort firms into quintiles based on their POP betas and compute value-weighted firm characteristics for each quintile as $X_{p,t} = \sum_{i \in p} w_{i,t-1} X_{i,t}$, where X represents β_{POP}, Align_Adm, Align_POP, and other firm characteristics; i, t, and p index stocks, months, and portfolios, respectively; and $w_{i,t-1}$ is firm i's lagged market capitalization weight within portfolio p. We then run portfolio-level panel regressions of POP beta on political alignment, controlling for other firm characteristics and including time fixed effects, with standard errors clustered at the year-month level:

$$\beta_{\text{POP}\,p,t} = \alpha + \beta\,\text{Align_POP}_{p,t} + \delta\,\text{Align_POP}_{p,t} \times \text{Align_Adm}_{p,t-k} + \gamma\,\text{Controls}_{p,t} + \mu_t + \epsilon_{p,t} \tag{9}$$

When $\delta = 0$, this specification reduces to an unconditional test of the association between POP beta and alignment with the party exhibiting the highest degree of populist rhetoric. When δ is freely estimated, the interaction term captures whether the association strengthens when that party holds the administration. We interact the contemporaneous $\text{Align_POP}_{p,t}$ with the lagged alignment with the incumbent administration $\text{Align_POP}_{p,t-k}$ because political donations take time to manifest in firm-level risk exposure, and the lag structure better

captures contributions made during the campaign period that preceded the current administration. Our baseline specification sets $k = 12$, but the results are robust to alternative choices of k.[7]

Panel A of Table 13 reports results using the five quintile portfolios (Obs $= 5 \times 467 =$ 2,335). The coefficient on Align_POP in column [1] is 0.6, implying that POP beta increases by 0.6 standard deviations for each one-standard-deviation increase in Align_POP. Using donation amounts rather than counts yields a coefficient of 0.439 in column [3], which remains statistically significant. Column [2] and [4] document a positive association between POP beta and the interaction term $\text{Align_POP}_{p,t} \times \text{Align_Adm}_{p,t-k}$ indicating that the unconditional relationship is amplified during periods of more populist administration. When the party exhibiting greater populist rhetoric controls the administration, campaign contributions further raise firms' POP beta, consistent with the interpretation that closer alignment with a populist administration serves as a hedge against the risks associated with populist policies.

To examine whether the relationship between political alignment and POP beta varies by political geography, we distinguish between firms headquartered in "swing" and "safe" states, where a "swing" state is defined as one that supported each party in at least two elections during the sample period.[8] Panel B of Table 13 reports the corresponding estimates. Column [1] and [3] yield significantly positive coefficients for both Align_POP in both the "swing" and the "safe" states. The estimated coefficients are systematically larger for firms from "safe" state, suggesting that political stability amplifies the sensitivity of POP beta to political alignment. Firms operating in safe states, where political preferences are stable and homogeneous, exhibit a more persistent translation of alignment with the populist incumbent

[7]FEC filings are subject to publication delays. In Table D.14, we address this concern by using lagged political alignment measures $\text{Align_POP}_{p,t-k}$ and $\text{Align_Adm}_{p,t-k}$ and find that the potential publication delay does not materially affect our results.

[8]Results are robust to an alternative definition in which a state is classified as a "swing" state if the average absolute two-party vote margin falls below 10 percentage points.

Table 13: POP Beta and Political Alignment

Panel A: Full Sample

	Donation Count		Donation Amount	
	[1]	[2]	[3]	[4]
Align_POP	0.600 ***	0.578 ***	0.439 ***	0.413 ***
	(10.33)	(9.75)	(8.50)	(7.92)
Align_POP × Align_Adm		0.074 **		0.105 ***
		(2.36)		(3.69)
Control	YES	YES	YES	YES
Fixed Effects	Yearmon	Yearmon	Yearmon	Yearmon
Observations	2,335	2,335	2,335	2,335
Adj. R^2	0.354	0.356	0.328	0.332

Panel B: Swing states vs. Safe states

	Donation Count		Donation Amount	
	[1]	[2]	[3]	[4]
Align_POP_Swing	0.261 ***	0.253 ***	0.167 ***	0.160 ***
	(6.94)	(6.62)	(4.81)	(4.39)
Align_POP_Safe	0.352 ***	0.319 ***	0.280 ***	0.260 ***
	(10.42)	(9.76)	(9.22)	(8.67)
Align_POP_Swing × Align_Adm_Swing		0.051 **		0.067 ***
		(2.53)		(3.56)
Align_POP_Safe × Align_Adm_Safe		0.144 ***		0.142 ***
		(6.34)		(5.97)
Control	YES	YES	YES	YES
Fixed Effects	Yearmon	Yearmon	Yearmon	Yearmon
Observations	2,335	2,335	2,335	2,335
Adj. R^2	0.349	0.363	0.329	0.345

This table reports the panel regressions results of POP beta on the Align_POP and its interaction with Align_Adm at the portfolio level. Panel A utilizes full sample of firm-month observations, while Panel B split sample into firms headquartered in swing states and safe states. In both panels, firm-level alignment with the party with stronger populist rhetoric (and the incumbent party) is measured by the share of employee political donation directed toward that party, using donation counts in columns [1] and [2] and donation amounts in columns [3] and [4]. The firm-level measures are then aggregated to portfolio level. All variables are normalized to have zero mean and standard deviation of one. Intercepts are included in all the regressions but unreported for brevity. *t*-statistics based on standard errors clustered by year-month are presented in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1986:01-2024:12.

into populism exposure. The interaction estimates in column [2] and [4] further confirm that political alignment is particularly consequential for POP beta during periods of populist governance.

Robustness. Table D.12 further confirms the robustness of the results of Table 13 to alternative choices of estimation window and minimum donation threshold. In Table D.13, we show that the results are consistent when using county-level election results to construct an alternative political alignment measure.

5 Concluding Remarks

This paper introduces a novel measure of populist sentiment in U.S. media and examines its implications for asset pricing. Using large language model (LLM) to analyze over one million articles from the Wall Street Journal, we construct a Populism Index (POP) that captures the evolving narratives, leaders, movement, and policies associated with populism. Firms' exposures to changes in populist sentiment—their POP betas—are priced in the cross-section of stock returns. Portfolios with negative exposure to populism earn significantly higher average returns, yielding an annualized excess return of about 8%, which remains robust after controlling for standard risk factors. The premium is economically meaningful, persistent over time, and evident across different political administrations, suggesting that populism represents a distinct, state-dependent source of systematic risk in equity markets.

Our findings also show that the LLM-based measure outperforms traditional dictionary approaches by capturing the contextual and semantic nuances of populist language. This methodological improvement allows for a richer understanding of how political content and economic sentiment interact to affect return differentials across firms.

A natural next step for future research is to embed this new dimension of risk into a fully fledged production economy. Developing a structural model in which populist sentiment affects firms' investment and financing decisions, and in which investors require compensation for exposure to populist shocks, would provide deeper understanding of the mechanisms linking political narratives and risk premia in financial markets. More broadly, the results

highlight the potential of text-based approaches to reveal new dimensions of systematic risk and to bridge political economy and financial markets.

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POP Premium: Technical Appendix

A Methodology

A.1 Prompt Design

To systematically identify and quantify populist themes in news coverage, we design structured prompts guiding a large language model (LLM) to analyze Wall Street Journal articles. The prompt instruct the model to focus exclusively on textual content and to return results in JSON format without additional commentary.

The task definition follows the literature on populism, framing it as a political phenomenon opposing "the people" and "the elite." The prompt operationalizes this concept along four dimensions: (i) populist leader, (ii) populist movement, (iii) populist policy, and (iv) populist rhetoric. For each dimension, the LLM evaluates whether the indicator is present in the article (Populist.Presence), the intensity of the populist signal (Populist.Intensity), and whether the article links the phenomenon to risk (Risk.Type). When risk is identified, the model assigns a severity score (Risk.Score), a self-assessed confidence level (Confidence), a concise justification (Rationale), and the supporting text (Source). An example of the expected JSON output is embedded in the prompt to standardize formatting and interpretation across analyses. This design enables structured extraction of populist content, facilitating quantitative text-based measurement aligned with established political economy frameworks.

Table A.1: Prompt Design

You are assisting me in analyzing Wall Street Journal news. Based solely on the content, analyze the following metrics by following a step-by-step reasoning process (Chain-of-Thought, CoT). Please complete the following task and return your analysis only in JSON format without any additional explanations or commentary.

Task: U.S. Populism Analysis

Populism: A political phenomenon characterized by a fundamental opposition between "the people" and "the elite", typically expressed through leadership style, movement, policy choices, and rhetorical strategies. It can be identified along the following four dimensions:

- 1. Populist_leader: A political figure or party who claims to directly represent "the will of the people" against established elites, often rejecting institutional constraints and portraying themselves as the sole legitimate voice of the nation. (e.g., Donald Trump, Ross Perot, Tea Party, People's Party)
- 2. Populist_movement: A political or social mobilization that frames politics as a conflict between "the pure people" and "the corrupt elite". (e.g., Seattle WTO Protests, Tea Party Movement, Occupy Wall Street Movement)
- 3. Populist_policy: Emphasizes income redistribution, nationalism, or resistance to globalization; de-emphasizes risks like inflation, budget deficits, or institutional credibility. (e.g. Trump's tariffs, large tax cuts, expansive welfare promises or subsidies, restrictive immigration policies, attack on judicial/media/academic independence, direct democracy mechanisms)
- 4. Populist_rhetoric: Typically including "us vs. them" framing, anti-elitist and anti-establishment language, simplification of complex issues, nationalistic and protectionist themes. (e.g. The 1% vs. The 99%, forgotten people, American first, bring jobs back, Make America Great Again, MAGA, will of the people, "deep state" narratives)

Analysis Framework

For each indicator :

- Populist_Presence (true/false): Set to true if the indicator is mentioned or implied in the text, otherwise false.
- Populist_Intensity (0 to 1): The intensity of the populist signal in the news.
- Risk_Type (true/false): Set to true if the article links the populist phenomenon to any form of risk, uncertainty, or instability, otherwise false.
- Risk_Score (0 to 1): The perceived severity of the risk or uncertainty mentioned.
- Confidence (0 to 1): A self-assessed score of how confident the model is in the extracted values for this indicator.
- Rationale (<50 words): A concise explanation for assessing the indicator.
- Source (<50 words): The sentences from the raw content that mainly support the assessment.

```
## Output Example ##
{
  "Populist_leader": {
    "Populist_Presence ": true,
    "Populist_Intensity": 0.7,
    "Risk_Type": false,
    "Risk_Score": 0,
    "Confidence": 0.9,
    "Rationale": "The article praises Trump's leadership for restoring national pride and prioritizing American workers.",
    "Source": "Supporters say President Trump is finally putting America first, restoring pride among forgotten workers."
  },
  "Populist_movement": {
    "Populist_Presence ": true,
    "Populist_Intensity": 0.5,
    "Risk_Type": false,
    "Risk_Score": 0,
    "Confidence": 0.8,
    "Rationale": "The article provides background on the Tea Party's mobilization without expressing clear support or criticism.",
    "Source": "Tea Party activists gathered in Washington to demand lower taxes and reduced government spending."
  },
  "Populist_policy": {
    "Populist_Presence ": true,
    "Populist_Intensity": 0.6,
    "Risk_Type": true,
    "Risk_Score": 0.6,
    "Confidence": 0.85,
    "Rationale": "The article neutrally reports on the tariff policy while noting it may hurt global trade in the long run.",
    "Source": "The administration's tariffs have drawn mixed responses, with some economists warning of long-term trade disruptions."
  },
  "Populist_rhetoric": {
    "Populist_Presence ": true,
    "Populist_Intensity": 0.9,
    "Risk_Type": true,
    "Risk_Score": 0.8,
    "Confidence": 0.95,
    "Rationale": "The article condemns Trump's divisive language as fueling distrust in institutions and societal conflict.",
    "Source": "His claim that the media is the enemy of the people has sparked concerns about rising threats against journalists."
  },
```

In Table A.2, we report the LLM inference configuration used in our analysis. We use a two-turn prompt (system task + article text) with deterministic decoding (temperature 0, top-p 1), max context 128k tokens, and default frequency and presence penalties.

Table A.2: LLM Inference Setup

Parameter	Value / Description
Model	gpt-4o-mini (OpenAI)
Prompt Structure	Two-turn message: system prompt (task definition) + user prompt (news content)
Temperature	0– Deterministic output
Max Tokens	128,000 tokens
Top-p	1 (default) – Full sampling space
Frequency Penalty	0 (default) – No repetition penalty
Presence Penalty	0 (default) – No novelty penalty

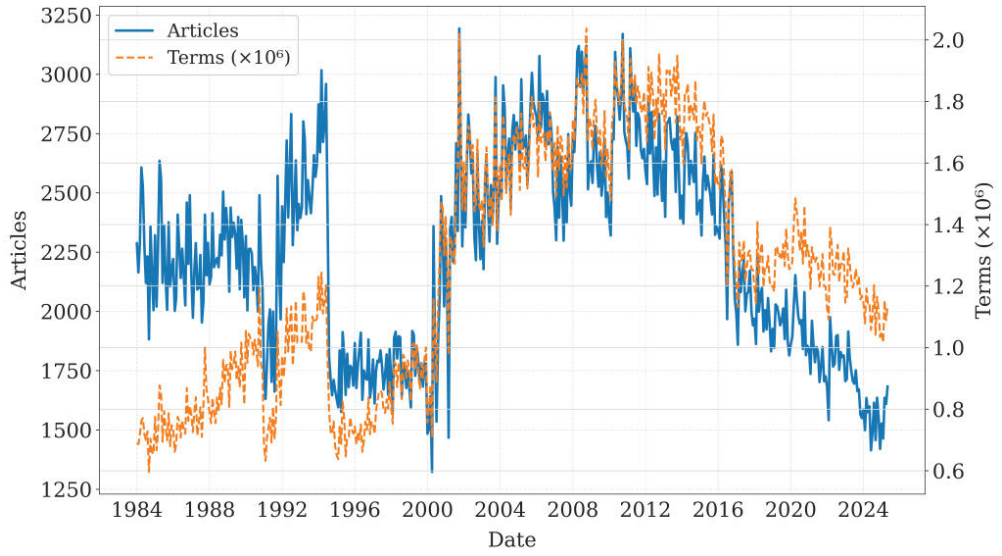

Fig. A.1 - WSJ Article and Terms counts

This figure plots the original article count and the total term counts aggregated over all articles each month from the Factiva database. The sample period is 1984:01-2024:12.

A.2 WSJ: Quantity and Type of Articles

Figure A.1 shows the total number or articles that appeared in the WSJ over the sample that we use in our analysis.

Furthermore, we conduct the following screening process for news articles categorized as populist (as determined by either the LLM or the dictionary method):

1. We exclude international news unrelated to the United States. Specifically, we screened articles by checking whether their titles contain any of the following terms—"World News", "World Brief", "World-Wide", "World Wide", "World Wire", "Business World", "Global View", "World Watch", "Global Finance" — while not containing the terms "US", "U.S", "America", or "American".

2. We exclude articles with page-citation tags corresponding to any sections other than A, B, C, or missing tags.

3. We retain articles that have the following type tags: "Corporate/Industrial News", "Economic News", "Political/General News", "Commodity/Financial Market News", "Content Types", while excluding those that contain the tags: "Arts/Entertainment", " Music", "Weather", "Books".

Table A.3: Summary Statistics of WSJ Articles, Terms, and Tokens

	Mean	Median	Min	Max	SD
Articles	2250.15	2277	1323	3193	415.94
Terms	1,257,201	1,254,098	596,197	2,036,800	390,265.99
Tokens	1,617,837	1,583,088	782,962	2,719,988	494,111
AvgTerms	556.22	607.75	292.60	754.20	127.05
AvgTokens	715.25	780.65	386.60	945.90	155.18

This table reports summary statistics of the WSJ articles, terms, and tokens. Articles denotes the monthly count of Wall Street Journal news articles. Terms denotes the monthly count of Wall Street Journal news terms. Tokens denotes the monthly total number of tokens produced by the GPT-4o-mini tokenizer (cl100k_base) for all Wall Street Journal news articles. AvgTerms and AvgTokens denote the average number of white space-delimited terms and GPT-4o-mini tokens per article in a given month, respectively, calculated as the ratio of the monthly total to the monthly article count. The sample period is 1984:01-2024:12.

A.3 Token count per WSJ article

Table A.3 reports summary statistics on token counts per Wall Street Journal article. In our analysis, one token corresponds approximately to one to two words. The average article contains 715 tokens (SD = 155.18), with the monthly average peaking at 945.90 tokens—well below the 128,000-token context window of GPT-4o-mini. These figures confirm that the model's token limit never constitutes a binding constraint in our analysis.

B Alternative Constructions of the Populism index

Figure B.1 compares the benchmark POP with three variants. POP Mask (names and dates masked) tracks the benchmark closely with slightly lower short-run volatility, indicating that explicit entity and time cues are not necessary for the signal. POP Confidence, which weights observations by the model's confidence, dampens transitory noise while preserving turning points. POP Risk replaces intensity with a risk score; it comoves with the benchmark but at a lower average level and with sharper month-to-month movements. Figure B.2 applies confidence cutoffs from 70 to 85 percent. The resulting series overlap tightly and share the same peaks and troughs, showing that reasonable filtering by confidence leaves the time-series pattern largely unchanged.

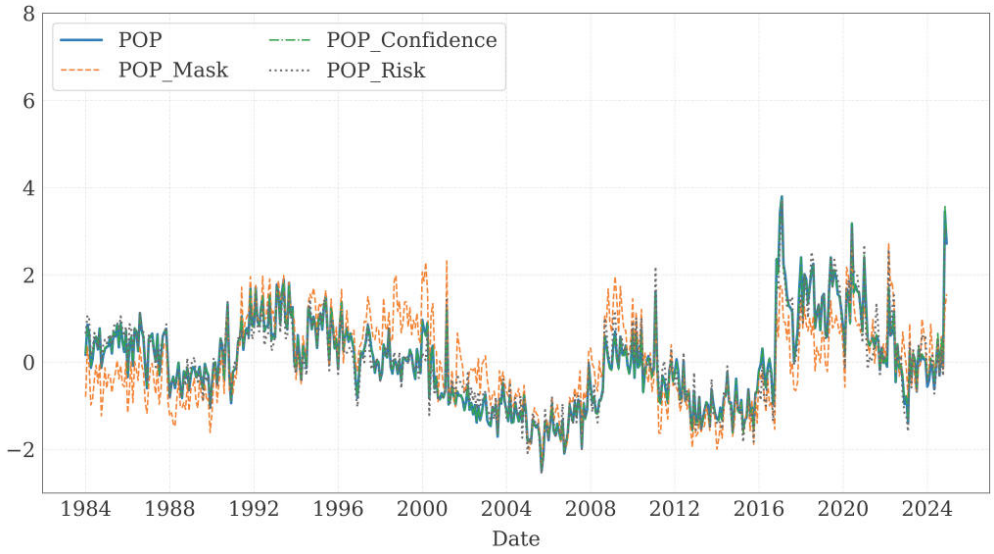

Fig. B.1 - The POP indices: robustness

This figure displays the time series of standardized U.S. populism indices constructed using different methodologies: "POP_Mask" applies masking of candidate names and dates; "POP_Confidence" incorporates confidence-score weighting for predictions; and "POP_Risk" substitutes populist intensity with a model-based risk score. The sample period is 1984:01-2024:12.

Figures B.3, B.4, and B.5 show fitted linear trends to the method and confidence-threshold comparisons. Across BoW constructions, masking, confidence weighting, risk substitution, the estimated trends are positive and of comparable slope. The tight clustering of trend lines across confidence cutoffs indicates that these alternative constructions preserve the main secular pattern in the benchmark series.

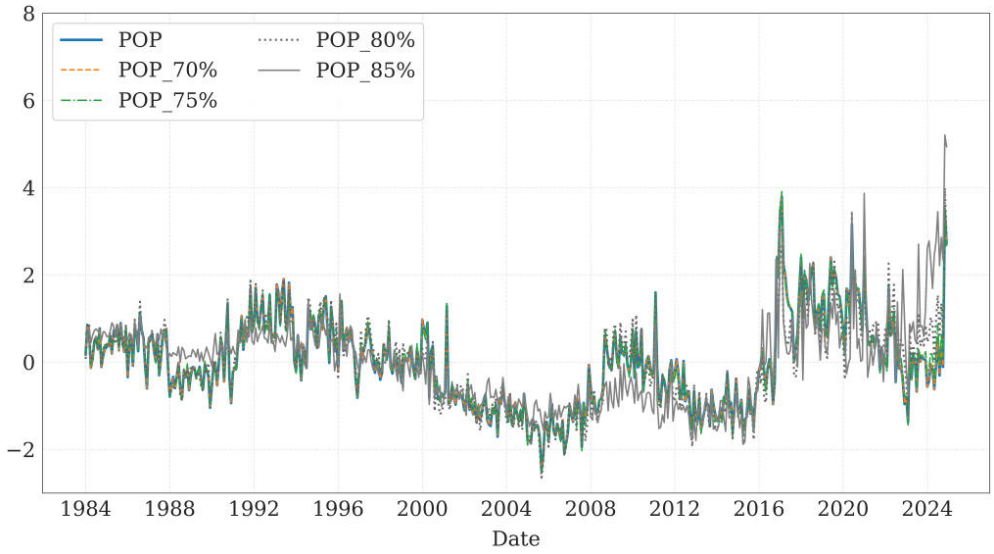

Fig. B.2 - The POP indices: confidence threshold

This figure displays the time series of standardized U.S. populism indices constructed using different LLM classification confidence level. We use news articles that meet the specified confidence thresholds of 70%, 75%, 80%, and 85%, respectively. The sample period is 1984:01-2024:12.

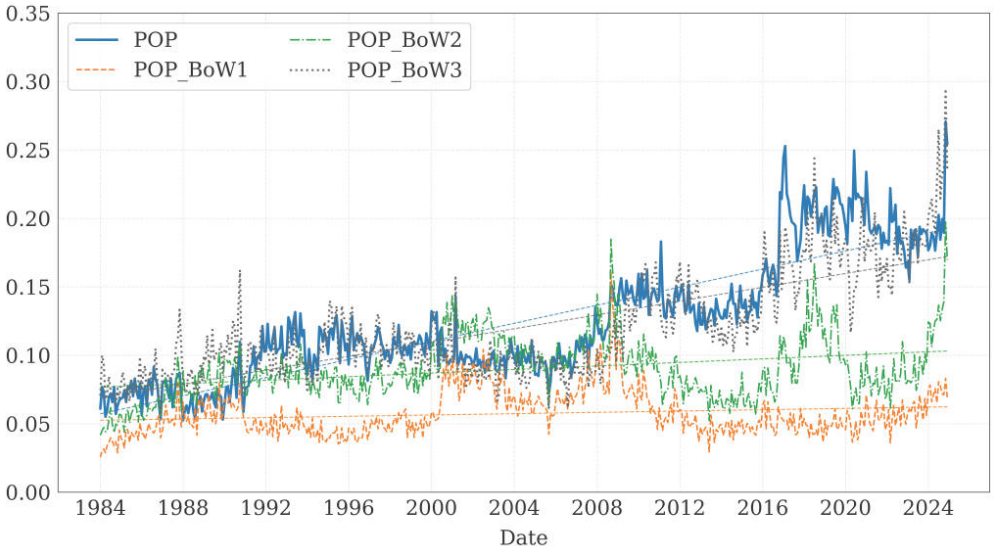

Fig. B.3 - The POP indices and fitted trends: LLM and dictionaries

This figure displays the time series of the original values of four U.S. populism indices with their fitted trends: POP (measured using LLM, this study), POP BoW1 (Bonikowski and Gidron, 2016), POP BoW2 (Filippou et al., 2020), and POP BoW3 (based on the new dictionary developed in this study). The sample period is 1984:01-2024:12.

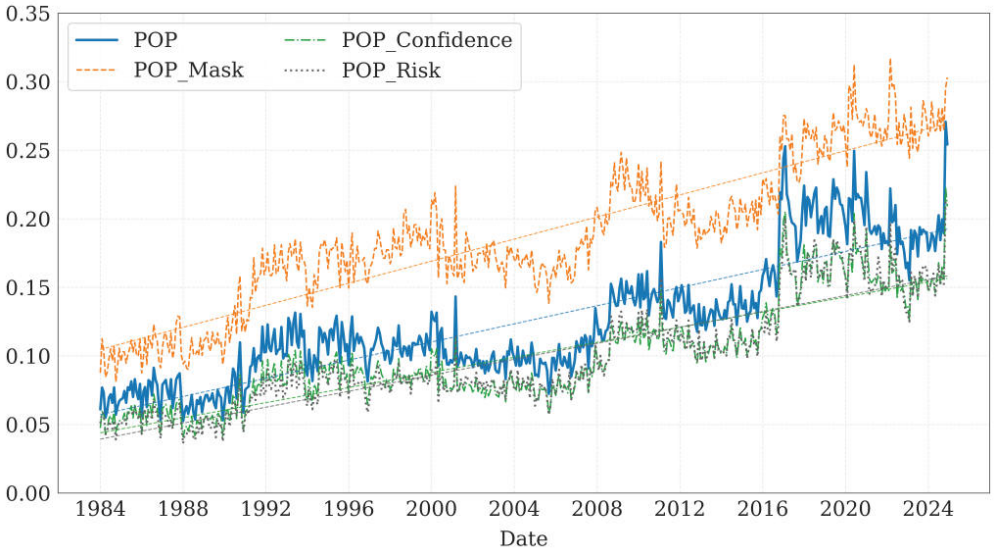

Fig. B.4 - The POP indices and fitted trends: robustness

This figure displays the time series of the original values of U.S. populism indices with their fitted trends constructed using different methodologies: "POP_Mask" applies masking of candidate names and dates; "POP_Confidence" incorporates confidence-score weighting for predictions; and "POP_Risk" substitutes populist intensity with a model-based risk score. The sample period is 1984:01-2024:12.

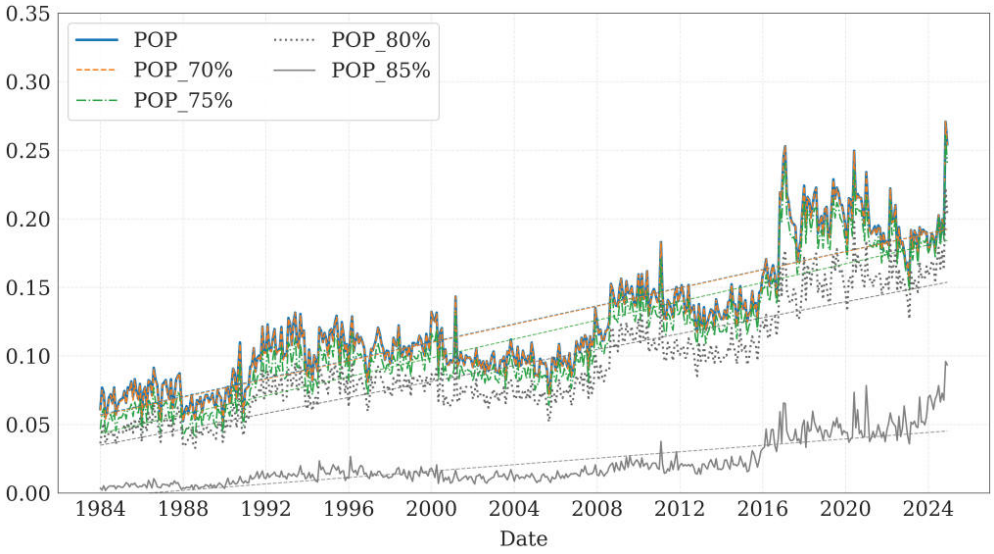

Fig. B.5 - The POP indices and fitted trends: confidence threshold

This figure displays the time series of original values of U.S. populism indices with their fitted trends constructed using different LLM classification confidence level. We use news articles that meet the specified confidence thresholds of 70%, 75%, 80%, and 85%, respectively. The sample period is 1986:01-2024:12.

C Measure of Firm-level Political Alignment

In this section, we provide additional detail on our firm-level political alignment measures. Following Duchin et al. (2023), we construct these measures for each firm-month using individual campaign contribution records from the Federal Election Commission (FEC). The FEC requires political committees to file reports on a regular basis, including monthly filings for active committees and specific filings before and after elections. The construction proceeds in four steps.

Step 1: cleaning the FEC individual contribution data.
We obtain individual contribution records from the FEC bulk data files for the period 1980–2024. Each record contains the contributor's self-reported employer name, the recipient committee identifier, the transaction date, and the transaction amount, among other fields. We impose several filters on the raw data. First, we retain only individual contributions (entity type "IND") and exclude committee-to-committee transfers and other non-individual transactions. Second, we drop records flagged with a memo indicator of "X" as these amounts are already included in other line items and would otherwise be double-counted. Third, we exclude contributions from individuals who report their employer as "Self-Employed", "Retired", "Not Employed", "Homemaker", "Student", or similar designations indicating the absence of a corporate employer. Finally, we drop employer names appearing fewer than five times across the full sample, as these are unlikely to match reliably to public firms.

Step 2: classifying donations by party.
We assign a party label—Democrat (DEM) or Republican (REP)—to each contribution based on the recipient committee's political affiliation, employing a three-step classification procedure. In the first step, we use the committee's self-declared party affiliation from the FEC Committee Master File. In the second step, for committees that do not declare a party affiliation, we infer party from the affiliated candidate's party as recorded in the FEC Candidate Master File and the Candidate-Committee Linkage File. In the third step, for committees that remain unclassified after the first two steps, we examine disbursement patterns using the committee-to-committee transaction files: if 80% or more of a committee's disbursements flow to committees of a single party, we assign that party label to the committee. Contributions to committees that cannot be classified as either DEM or REP after all three steps are excluded from the affiliation calculations.

Step 3: matching FEC employer names to compustat firms.
Because the employer name field in the FEC data is self-reported and unstandardized, we match it to firm names in Compustat using a fuzzy string matching procedure. We first standardize both the FEC employer names and the Compustat company names (conml) by converting all text to lowercase, removing non-alphanumeric characters, replacing common words with abbreviations (e.g., "corporation" to "corp" "international" to "intl", and "technologies" to "tech"), and converting digits to their English spellings to increase their weight in the similarity calculation (e.g., "21st" to "twoonest").

We then compute the bigram similarity score between each standardized FEC employer

name and all standardized Compustat names. For two strings s_1 and $_2$, the bigram similarity is defined as:

$$\text{Bigram Similarity}(s_1, s_2) = \frac{|\text{Common Bigrams}(s_1, s_2)|}{|\text{Bigrams}(s_1)| \times \text{Bigrams}(s_2)|} \tag{A.1}$$

where a bigram is a consecutive pair of characters and common bigrams are counted with multiplicity. For each FEC employer name, we retain only the highest-scoring Compustat match, discarding all matches with a bigram similarity score below 0.75 and manually reviewing matches in the range [0.75,0.85) to verify accuracy.

Step 4: computing firm-Level political affiliation.
Using the matched and party-classified donations, we compute four political affiliation measures for each firm i in month t over a rolling 96-month window (spanning approximately two presidential election cycles). To ensure the reliability of our political affiliation measures, we require a minimum of five individual donations within the measurement window. For firms that do not satisfy this threshold within the baseline eight-year window, we extend the window incrementally by one year at a time, up to a maximum of 16 years, until the minimum donation requirement is met. Firms that remain below the threshold after the maximum extension are excluded from the sample. This approach is motivated by two considerations. First, affiliation estimates based on very few donations are subject to substantial measurement error, as a single contribution could disproportionately determine a firm's measured partisanship. Second, the incremental window extension preserves sample coverage—particularly for smaller firms with less frequent donation activity—thereby mitigating potential sample selection bias.

Let $N_{i,t}^{\text{Dem}}$ and $N_{i,t}^{\text{Rep}}$ denote the number of donations classified as Democrat and Republican, respectively, made by employees of firm i in month t, and let $A_{i,t}^{\text{Dem}}$ and $A_{i,t}^{\text{Rep}}$ denote the corresponding total dollar amounts. We define:

$$\text{Dem_Aff_Num}_{i,t} = \frac{\sum_{\tau=t-95} N_{i,\tau}^{\text{Dem}}}{\sum_{\tau=t-95} N_{i,\tau}^{\text{Dem}} + \sum_{\tau=t-95} N_{i,\tau}^{\text{Rep}}} \tag{A.2}$$

$$\text{Rep_Aff_Num}_{i,t} = \frac{\sum_{\tau=t-95} N_{i,\tau}^{\text{Rep}}}{\sum_{\tau=t-95} N_{i,\tau}^{\text{Dem}} + \sum_{\tau=t-95} N_{i,\tau}^{\text{Rep}}} \tag{A.3}$$

$$\text{Dem_Aff_Amt}_{i,t} = \frac{\sum_{\tau=t-95} A_{i,\tau}^{\text{Dem}}}{\sum_{\tau=t-95} A_{i,\tau}^{\text{Dem}} + \sum_{\tau=t-95} A_{i,\tau}^{\text{Rep}}} \tag{A.4}$$

$$\text{Rep_Aff_Amt}_{i,t} = \frac{\sum_{\tau=t-95} A_{i,\tau}^{\text{Rep}}}{\sum_{\tau=t-95} A_{i,\tau}^{\text{Dem}} + \sum_{\tau=t-95} A_{i,\tau}^{\text{Rep}}} \tag{A.5}$$

$\text{Dem_Aff_Num}_{i,t}$ and $\text{Rep_Aff_Num}_{i,t}$ capture the share of employee political donations directed toward Democratic and Republican committees, respectively, weighting each do-

nation equally. Dem_Aff_Amt$_{i,t}$ and Rep_Aff_Amt$_{i,t}$ captures the corresponding share weighted by dollar amount.

Importantly, the winning party in a given election cycle does not necessarily exhibit the stronger populist orientation. For instance, in the 2020 presidential election, the Republican candidate Donald Trump demonstrated a markedly higher degree of populism than the Democratic candidate Joe Biden. To identify the more populist party in each election cycle, we analyze the text of presidential candidates' nomination acceptance speeches using a large language model (Gemini 3). Our prompt design is presented in Table C.1.

Table C.1: Prompt Design for Convention Speeches

You are assisting me in analyzing Convention Speeches of Address Accepting the Presidential Nomination. Based solely on the content, analyze the "Populism" metric by following a step-by-step reasoning process (Chain-of-Thought). These are the speeches of two candidates in a presidential election. Please comprehensively judge which speech has a higher populist level based on the following three dimensions. It is necessary to distinguish the populist levels in the two candidates' speeches. Please return your analysis only in JSON format without any additional explanations or commentary.

Task: U.S. Populism Analysis

Populism: A political phenomenon characterized by a fundamental opposition between "the people" and "the elite", typically expressed through leadership style, movement, policy choices, and rhetorical strategies. It can be identified along the following three dimensions:

- 1. Populist_leader: A political figure or party who claims to directly represent "the will of the people" against established elites, often rejecting institutional constraints and portraying themselves as the sole legitimate voice of the nation. (e.g., Donald Trump, Ross Perot, Tea Party, People's Party)
- 2. Populist_policy: Emphasizes income redistribution, nationalism, or resistance to globalization; de-emphasizes risks like inflation, budget deficits, or institutional credibility. (e.g. Trump's tariffs, large tax cuts, expansive welfare promises or subsidies, restrictive immigration policies, attack on judicial/media/academic independence, direct democracy mechanisms)
- 3. Populist_rhetoric: Typically including "us vs. them" framing, anti-elitist and anti-establishment language, simplification of complex issues, nationalistic and protectionist themes. (e.g. The 1% vs. The 99%, forgotten people, American first, bring jobs back, Make America Great Again, MAGA, will of the people, "deep state" narratives)

Analysis Framework

For each indicator :

- Populist_Intensity (0 to 1): The intensity of the populist signal in the news.
- Confidence (0 to 1): A self-assessed score of how confident the model is in the extracted values for this indicator.
- Rationale (<50 words): A concise explanation for assessing the indicator.
- Source (<50 words): The sentences from the raw content that mainly support the assessment.

Table C.2 reports the resulting populism scores for each election. A notable pattern emerges: the candidate with the higher populism score won the election in most cases. The exceptions are the 1996, 2000, 2004, and 2020 elections, in which the candidate with the lower populism score prevailed. This suggests a generally strong, though not absolute, relationship between the populist tone of a candidate's rhetoric and electoral success over this period.

Based on these results, we construct two political alignment variables: Align_POP and Align_Adm. Align_POP is defined as the share of a firm's campaign contributions directed toward the party with the highest degree of populist rhetoric in the last election cycle. For example, in the 2020 election, the Republican Party was identified as the more populist-leaning party. If firm i's political affiliation toward the Republican candidate is 35% in month t (month t is between 2021 and 2025), then firms i is assigned an Align_POP$_{i,t}$ value

Table C.2: Populism Scores of Major-Party Presidential Candidates (1984–2024)

Election Year	Ruling Party	Higher Populism	Rep Candidate	Rep Score	Dem Candidate	Dem Score
1984	Rep	Rep	Ronald Reagan	0.78	Walter Mondale	0.63
1988	Rep	Rep	George H.W. Bush	0.78	Michael Dukakis	0.62
1992	Dem	Dem	George H.W. Bush	0.68	Bill Clinton	0.85
1996	Dem	Rep	Bob Dole	0.83	Bill Clinton	0.65
2000	Rep	Dem	George W. Bush	0.67	Al Gore	0.85
2004	Rep	Dem	George W. Bush	0.70	John F. Kerry	0.82
2008	Dem	Dem	John McCain	0.65	Barack Obama	0.80
2012	Dem	Dem	Mitt Romney	0.60	Barack Obama	0.75
2016	Rep	Rep	Donald J. Trump	0.98	Hillary Clinton	0.67
2020	Dem	Rep	Donald J. Trump	0.93	Joe Biden	0.70
2024	Rep	Rep	Donald J. Trump	0.93	Kamala Harris	0.43

This table presents comparative populism scores derived from the acceptance speeches of Republican and Democratic presidential candidates in each election from 1984 to 2024. Scores range from 0 to 1, with higher values reflecting stronger populist tones in the speech.

of 0.35 for that month.

$$\text{Align_POP}_{i,t} = \begin{cases} \text{Dem_Aff}_{i,t}, & \text{if party with higher populism score = Dem} \\ \text{Rep_Aff}_{i,t}, & \text{if party with higher populism score = Rep} \end{cases} \tag{A.6}$$

where $\text{Dem_Aff}_{i,t}$ denotes either $\text{Dem_Aff_Num}_{i,t}$ or $\text{Dem_Aff_Amt}_{i,t}$, and $\text{Rep_Aff}_{i,t}$ denotes either $\text{Rep_Aff_Num}_{i,t}$ or $\text{Rep_Aff_Amt}_{i,t}$.

Align_Adm is defined as the share of a firm's campaign contribution directed toward the incumbent party:

$$\text{Align_Adm}_{i,t} = \begin{cases} \text{Dem_Aff}_{i,t}, & \text{if incumbent administration = Dem} \\ \text{Rep_Aff}_{i,t}, & \text{if incumbent administration = Rep} \end{cases} \tag{A.7}$$

Our sample universe comprises approximately 1.58 million firm-month observations. Table C.3 reports summary statistics for our two baseline political alignment measures, Align_POP and Align_Adm, along with the reduction in sample size imposed by our chosen estimation window and minimum donation threshold.

As a robustness check, we construct an alternative measure of political alignment based on regional election returns obtained from the MIT Election Data and Science Lab. For each presidential term cycle, we compute Align_Adm for every county as the vote share of the prevailing party in that region. For instance, between 2017 and 2021, in which the Republican Party won the presidency, if county A cast 65% of its two-party votes for the Republican candidate, then firms headquartered in county A are assigned an Align_Adm value of 0.65 for the 2017–2021 period. Analogously, we construct the regional Align_POP measure as the vote share received by party with higher populist rhetoric in each region. In the 2017 election,

Table C.3: Summary Statistics of Political Alignment Variables

	Obs	Min	P25	Mean	P50	P75	Max	SD
Panel A: Donation count								
Align_POP	836,701	0.000	0.117	0.446	0.400	0.769	1.000	0.346
Align_Adm	836,701	0.000	0.175	0.510	0.518	0.842	1.000	0.350
Panel B: Donation amount								
Align_POP	836,701	0.000	0.106	0.463	0.427	0.815	1.000	0.360
Align_Adm	836,701	0.000	0.147	0.506	0.512	0.867	1.000	0.362

This table reports summary statistics—mean, median, minimum, maximum, selected percentiles, and standard deviation— for the political alignment measures Align_Adm and Align_POP. Panel A constructs these measures using campaign donation counts; Panel B uses campaign donation amounts. All statistics are computed at the firm-month level and averaged across firms and months. The sample spans 1986:01 to 2024:12.

for example, if county A cast 35% of its two-party votes for the Republican candidate—the more populist-leaning party that cycle—then firms headquartered in county A are assigned an Align_POP value of 0.35 for the 2017–2021 period. We merge firm-level data with county-level election returns using a ZIP-to-FIPS crosswalk; for ZIP codes spanning multiple counties, we assign the ZIP code to the county with the highest BUS_RATIO.

D Additional Results and Robustness

This appendix presents a comprehensive set of robustness checks to assess the stability of our main findings under alternative econometric specifications and empirical designs. Across all exercises, the estimated POP premium and the cross-sectional pricing of populism exposure remain robust to variations in model specification, sample filtering, and portfolio construction. The evidence consistently supports the interpretation that the populism factor captures an independent and economically meaningful source of systematic risk.

Table D.1 examines alternative portfolio weighting and sorting schemes. Panel A reports average excess returns and alphas under equal-weighted (rather than value-weighted) portfolio formation, while Panel B presents results from sorting stocks into deciles (instead of quintiles) based on POP beta. The economic magnitude and statistical significance of the POP premium remain unaffected by these alterations.

Table D.2 reports results from grouping stocks by the sign and statistical significance of their POP beta. We classify firms into three categories: those with statistically significant positive, statistically significant negative, and statistically insignificant POP betas. The POP premium of the long–short portfolio that buys negative POP beta stocks and sells positive POP beta stocks remains economically and statistically significant across all specifications, further reinforcing the baseline findings.

Table D.3 presents portfolio-level results after excluding firms from specific industries. The pricing results continue to hold, further confirming their robustness.

Table D.1: POP premium: Equal Weighted Portfolios and Decile Portfolios

Panel A: quintile portfolios + equal weighted

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
P1	0.81	0.01	0.13	0.11	0.27
	(2.52)	(0.15)	(1.39)	(1.31)	(2.99)
P5	0.50	-0.30	-0.18	-0.16	-0.04
	(1.62)	(-3.57)	(-2.00)	(-1.82)	(-0.43)
P1-P5	0.31	0.32	0.31	0.27	0.31
	(3.54)	(3.92)	(3.85)	(3.43)	(3.59)

Panel B: decile portfolios + value weighted

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
P1	0.92	0.12	0.15	0.25	0.33
	(3.41)	(1.11)	(1.31)	(2.33)	(2.94)
P10	0.36	-0.53	-0.46	-0.33	-0.33
	(1.18)	(-4.37)	(-3.87)	(-3.20)	(-3.20)
P1-P10	0.56	0.65	0.61	0.55	0.66
	(3.26)	(3.61)	(3.30)	(3.42)	(3.89)

This table reports monthly average excess returns and alphas (in %) of POP beta spread portfolios. In Panel A, the stocks are sorted into quintiles based on POP beta and all portfolios are equal-weighted. In Panel B, the stocks are sorted into deciles based on POP beta and all portfolios are value-weighted. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses in Panels A and B. The sample period is 1986:01-2024:12.

Table D.4 reports the average excess returns and risk-adjusted alphas of industry-neutral portfolios. Within each Fama-French 12-industry group (Panel A) and each Fama-French 48-industry group (Panel B), we independently sort stocks into quintile portfolios based on POP beta and then construct aggregate quintile portfolios by pooling the corresponding within-industry quintiles. The results confirm that POP beta retains significant cross-sectional pricing power after controlling for industry membership.

Figure D.1 plots the t-statistics of the POP premium under different lag-length choices in the Newey and West (1987) adjustment. The statistical significance of the premium is unaffected by the selection of lag length.

In constructing the POP BoW3 index, we remove terms that appear in more than 4% of all WSJ articles from the vocabulary. Table D.5 reports summary statistics and pairwise correlations for alternative POP indices under different pruning thresholds. Retaining all terms inflates the populism dictionary and misclassifies a larger share of articles as populist. This empirical trade-off reduces Type I error at the cost of substantially higher Type II error. Indeed, Panel A of Table D.5 shows that without pruning, about 67.7% of WSJ articles are identified as populist—an implausibly high proportion. Lowering the threshold from 4% to 3% increases the share of populist-related articles, but the resulting index remains highly correlated with our benchmark.

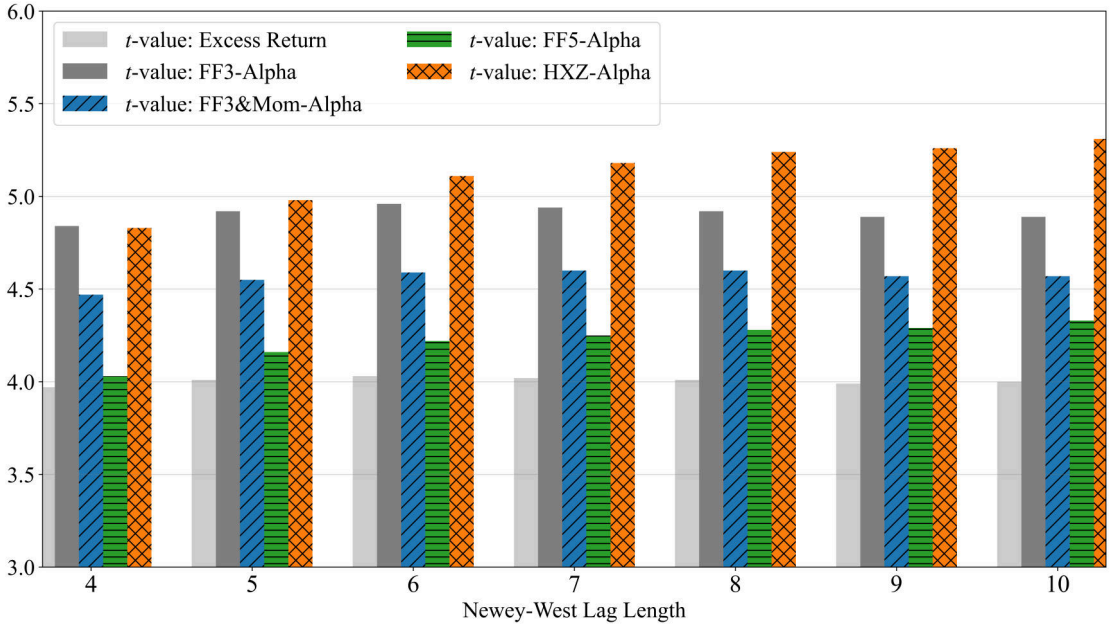

Fig. D.1 - t-stats for POP premium: across Newey-West Lag Lengths

This figure plots the t-statistics for the POP premium across different specifications of the Newey and West (1987) adjustment, using lag lengths from 4 to 10. The sample period is 1986:01-2024:12.

Table D.6 confirms that the POP premium is robust to alternative pruning thresholds (3% to 5%). By contrast, the excess returns and alphas of the POP beta spread portfolio become statistically insignificant when all vocabulary is retained.

Table D.7 presents summary statistics and pairwise correlations after expanding the BoW3 dictionary with terms from Filippou et al. (2020) or modern populist rhetoric. Adding rhetoric terms only marginally alters the POP BoW3 index, and the resulting series remains highly correlated with the benchmark—consistent with the limited occurrence of such phrases in WSJ articles. Incorporating the Filippou et al. (2020) vocabulary raises the average POP index value and yields an alternative index with a correlation of about 0.65 to POP BoW3.

Table D.8 further shows that expanding the BoW3 dictionary via either the Filippou et al. (2020) lexicon or populist rhetoric terms does not materially affect the magnitude or significance of the POP premium.

We employ GPT-4o-mini as the primary language model for financial news analysis. Given that GPT-4o-mini's training data extends through October 2023, we conduct an additional robustness check using the subsample spanning November 2023 to December 2024 to verify that our findings hold in the post-training-cutoff period. As reported in Table D.9, the estimated POP premium is larger over this subsample and remains statistically significant at the 10% level. The reduced t-statistic relative to the benchmark case likely reflects the shorter sample length rather than any attenuation of the underlying economic effect.

To assess the role of turnover, we impose a restriction that fixes portfolio composi-

tion at the start of a presidential term. We consider two variants: one in which weights are set at the beginning of a president's first term and held fixed throughout the entire presidency—irrespective of whether the president serves two consecutive terms—and one in which weights are reset at the outset of each term. As reported in Table D.10, fixing portfolio weights substantially attenuates both the excess returns and alphas of the long-short portfolio. Specifically, the excess returns in Panel A and B and the Fama-French five-factor alpha in Panel B are no longer significant at the 10% level. These results indicate that the POP premium is largely attributable to the dynamic rebalancing of portfolio positions based on time-varying POP beta estimates, rather than to the static firm characteristics captured at portfolio formation.

To distinguish the populism premium from the lobby premium documented in Grotteria (2024), we identify firms that have engaged in lobbying activities over the period 1999—2019 using the same data from LobbyView. In total, we identify 1,693 unique lobbying firms, with lobbying observations amounting to approximately 120,000, representing less than 10% of our baseline sample. Panel A of Table D.11 reports the POP premium after excluding all lobbying firms, for both the full sample period and the 1999–2019 subperiod. Panel B restricts the sample to lobbying firms only. The POP premium remains large and statistically significant in both panels, confirming that the populism premium and the lobby premium capture two distinct dimensions of political risk and that our channel is complementary to that of Grotteria (2024).

Table D.12 examines the robustness of the association between POP beta and political alignment to alternative estimation window and minimum donation threshold specifications. Panel A reproduces our benchmark result. Panel B reduces the minimum donation threshold from 5 to 1, Panel C raises it to 10, and Panel D disables the extended search window of 192 months. Panel E shortens the baseline estimation window for political affiliation from 96 to 60 months. Across all specifications, the economic magnitude and statistical significance of the results remain stable.

Table D.13 shows that our main results are robust to using an alternative political alignment measure based on regional election returns: the positive and statistically significant association between POP beta and alignment with party with the highest populist rhetoric is preserved, and stronger when the more populist party holds office and for firms headquartered in "safe" regions.

The FEC requires most committees to file quarterly, while national party committees must file monthly. In addition, all committees are required to submit a year-end report to the FEC by January of the following year. To account for potential publication delays in FEC filings, Table D.14 reports results using lagged alignment with the party exhibiting the highest populist rhetoric $\text{Align_POP}_{p,t-k}$ and lagged alignment with the incumbent party $\text{Align_Adm}_{p,t-k}$. We find that our results are not materially affected by potential publication delays.

Table D.2: POP Premium: Statistically Significant β_{POP}

Panel A: $\beta_{\Delta POP_t} + \beta_{\Delta POP_{t-1}}$ significant

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$	N
Neg	1.02	0.34	0.30	0.23	0.30	105
	(4.77)	(2.42)	(2.00)	(1.65)	(2.04)	
NS	0.75	0.03	0.04	0.01	0.01	3788
	(3.71)	(2.62)	(3.35)	(0.90)	(0.70)	
Pos	0.44	-0.35	-0.34	-0.31	-0.41	141
	(1.82)	(-3.37)	(-3.23)	(-2.89)	(-3.64)	
Neg-Pos	0.58	0.69	0.64	0.53	0.71	
	(3.08)	(3.54)	(3.24)	(2.74)	(3.45)	

Panel B: $\beta_{\Delta POP_t}$ or $\beta_{\Delta POP_{t-1}}$ significant

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$	N
Neg	0.93	0.25	0.23	0.14	0.22	209
	(4.59)	(2.58)	(2.28)	(1.52)	(2.32)	
NS	0.74	0.02	0.03	0.01	0.00	3565
	(3.63)	(1.35)	(2.10)	(0.44)	(-0.02)	
Pos	0.49	-0.28	-0.26	-0.27	-0.33	260
	(2.15)	(-3.39)	(-3.24)	(-2.98)	(-3.80)	
Neg-Pos	0.44	0.53	0.49	0.41	0.55	
	(2.92)	(3.62)	(3.31)	(2.76)	(3.71)	

Panel C: $\beta_{\Delta POP_t}$ significant

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$	N
Neg	0.99	0.27	0.28	0.16	0.27	111
	(4.72)	(2.29)	(2.13)	(1.42)	(1.99)	
NS	0.73	0.01	0.01	-0.01	-0.02	3777
	(3.61)	(0.56)	(1.10)	(-0.78)	(-1.47)	
Pos	0.51	-0.20	-0.18	-0.18	-0.24	147
	(2.06)	(-1.83)	(-1.52)	(-1.54)	(-1.87)	
Neg-Pos	0.47	0.48	0.46	0.34	0.51	
	(2.57)	(2.52)	(2.21)	(1.84)	(2.31)	

Panel D: $\beta_{\Delta POP_{t-1}}$ significant

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$	N
Neg	0.94	0.27	0.26	0.19	0.22	111
	(4.39)	(2.05)	(1.88)	(1.42)	(1.83)	
NS	0.75	0.02	0.03	0.00	0.00	3790
	(3.66)	(2.28)	(3.03)	(0.41)	(0.38)	
Pos	0.51	-0.31	-0.29	-0.30	-0.37	134
	(2.15)	(-2.79)	(-2.59)	(-2.48)	(-3.08)	
Neg-Pos	0.43	0.58	0.55	0.49	0.59	
	(2.33)	(3.07)	(2.81)	(2.32)	(3.04)	

This table reports monthly average excess returns and alphas (in %) for portfolios sorted by the sign and significance of POP betas from Equation 3. Portfolios are classified as "Neg" or "Pos" if the POP beta is significantly negative or positive at the 5% level, respectively, and "NS" otherwise. Panel A uses the significance of $\beta_{\Delta POP_t} + \beta_{\Delta POP_{t-1}}$; Panel B uses either $\beta_{\Delta POP_t}$ or $\beta_{\Delta POP_{t-1}}$; Panel C (D) uses $\beta_{\Delta POP_t}$ ($\beta_{\Delta POP_{t-1}}$) alone. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. N refers to the average number of samples within a portfolio, that is, the number of companies in the portfolio each month. The sample period is 1986:01-2024:12.

Table D.3: POP Premium: Excluding Individual Industries

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
NoDur	0.61	0.71	0.70	0.61	0.79
	(3.92)	(5.05)	(4.81)	(4.30)	(5.40)
Durbl	0.63	0.73	0.69	0.60	0.78
	(3.97)	(4.84)	(4.54)	(4.19)	(5.14)
Manuf	0.64	0.73	0.70	0.62	0.80
	(3.98)	(4.80)	(4.47)	(4.20)	(5.19)
Enrgy	0.54	0.62	0.62	0.54	0.70
	(3.59)	(4.42)	(4.31)	(3.93)	(4.75)
Chems	0.63	0.74	0.71	0.62	0.79
	(4.08)	(4.96)	(4.64)	(4.34)	(5.35)
BusEq	0.51	0.60	0.53	0.46	0.61
	(3.76)	(4.43)	(4.09)	(3.93)	(4.56)
Telcm	0.59	0.70	0.67	0.61	0.78
	(3.68)	(4.63)	(4.32)	(4.04)	(4.86)
Utils	0.64	0.74	0.70	0.62	0.79
	(4.00)	(4.70)	(4.36)	(4.19)	(5.03)
Shops	0.64	0.74	0.70	0.61	0.80
	(4.07)	(4.94)	(4.60)	(4.35)	(5.21)
Hlth	0.69	0.81	0.77	0.68	0.85
	(4.32)	(5.43)	(5.03)	(4.73)	(5.64)
Money	0.57	0.64	0.61	0.58	0.72
	(3.51)	(4.02)	(3.84)	(3.70)	(4.76)
Other	0.58	0.69	0.64	0.55	0.72
	(3.71)	(4.77)	(4.44)	(3.82)	(4.75)

This table reports monthly average excess return and alphas (in %) of the strategy that buys portfolio with low POP beta and sells portfolio with high POP beta (P1-P5), after excluding firms in one industry at a time and then re-constructing the test portfolios. Each row corresponds to the exclusion of a specific Fama-French industry: Consumer Nondurables, Consumer Durables, Manufacturing, Energy Extraction and Products, Chemicals and Allied Products, Business Equipment, Telephone and Television Transmission, Utilities, Wholesale and Retail, Healthcare, Finance, and Other. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

Table D.4: POP premium: Industry-Neutral Portfolio Sorts

Panel A: Fama-French 12-industry

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
P1	0.90	0.15	0.16	0.20	0.27
	(3.74)	(2.02)	(2.03)	(2.74)	(3.54)
P5	0.45	-0.36	-0.32	-0.24	-0.30
	(1.85)	(-5.24)	(-4.65)	(-3.41)	(-4.11)
P1-P5	0.45	0.51	0.48	0.44	0.57
	(3.71)	(4.26)	(3.97)	(3.59)	(4.63)

Panel B: Fama-French 48-industry

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
P1	0.93	0.19	0.19	0.20	0.24
	(4.04)	(2.73)	(2.80)	(2.80)	(3.52)
P5	0.50	-0.28	-0.25	-0.15	-0.21
	(2.11)	(-4.06)	(-3.59)	(-2.48)	(-3.02)
P1-P5	0.43	0.47	0.44	0.35	0.45
	(3.84)	(4.14)	(3.89)	(3.08)	(3.92)

This table reports the monthly average excess returns and alphas (in %) of POP beta spread portfolios when buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5) We construct industry-neutral portfolios as follows. Within each Fama-French 12-industry group (Panel A) and each Fama-French 48-industry group (Panel B), stocks are sorted into quintile portfolios based on POP beta. The P1 and P5 portfolios are then constructed by pooling the corresponding quintile portfolios across all industries. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

Table D.5: Summary Statistics and Pairwise Correlation of Indices: BoW 3 Pruning

Panel A: Summary statistics

	Mean	Median	Min	Max	SD
POP	0.125	0.112	0.052	0.271	0.045
POP BoW3	0.121	0.109	0.058	0.295	0.039
No prune	0.677	0.697	0.491	0.802	0.066
Prune 3%	0.156	0.152	0.058	0.313	0.051
Prune 5%	0.077	0.071	0.011	0.238	0.037

Panel B: Pairwise correlation

	POP	POP BoW3	No prune	Prune 3%
POP BoW3	0.880			
No prune	0.231	0.170		
Prune 3%	0.849	0.911	0.155	
Prune 5%	0.923	0.934	0.075	0.902

This table presents summary statistics and pairwise correlations for POP indices constructed using the BoW3 dictionary under different pruning thresholds for common terms in WSJ articles. POP denotes the U.S. populism index derived from language models, while POP BoW3 refers to the index based on the newly developed dictionary in this study. Our baseline specification removes terms appearing in more than 4% of all WSJ articles. We also report alternative pruning thresholds: "No prune" retains all terms; "Prune 3%" ("Prune 5%") removes terms occurring in more than 3% (5%) of articles. The sample period is 1986:01-2024:12.

Table D.6: POP Premium: BoW 3 Pruning

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
No trim	0.19	0.21	0.20	0.11	0.17
	(1.38)	(1.45)	(1.32)	(0.68)	(1.03)
Trim 3%	0.32	0.33	0.37	0.38	0.47
	(2.00)	(2.07)	(2.30)	(2.24)	(2.67)
Trim 5%	0.43	0.45	0.45	0.50	0.60
	(2.93)	(3.27)	(3.20)	(3.21)	(3.70)

This table reports the monthly average excess returns and alphas (in %) of POP beta portfolios from the strategy of buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5). We employ the Bag-of-Words methodology developed in this study to construct the POP index but use different pruning thresholds. Our baseline specification (BoW3) removes terms appearing in more than 4% of all WSJ articles. Row "No prune" retains all terms, while row "Prune 3%" and row "Prune 5%" removes terms occurring in more than 3% and 5% of articles, respectively. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

Table D.7: Summary Statistics and Pairwise Correlation of Indices: Expand BoW3

Panel A: Summary statistics

	Mean	Median	Min	Max	SD
POP	0.125	0.112	0.052	0.271	0.045
POP BoW2	0.090	0.087	0.042	0.197	0.023
POP BoW3	0.121	0.109	0.058	0.295	0.039
BoW3+BoW2	0.182	0.177	0.099	0.353	0.037
BoW3+rhetoric	0.122	0.109	0.058	0.300	0.040

Panel B: Pairwise correlation

	POP	POP BoW2	POP BoW3	BoW3+BoW2
POP BoW2	0.319			
POP BoW3	0.880	0.319		
BoW3+BoW2	0.806	0.647	0.898	
BoW3+rhetoric	0.888	0.324	0.999	0.898

This table presents summary statistics and pairwise correlations for POP indices constructed using LLM and different Bag-of-Words dictionaries. POP denotes the U.S. populism index derived from language models, POP BoW2 refers to the index based on Filippou et al. (2020) dictionary, while POP BoW3 refers to the index based on the newly developed dictionary in this study. We also report alternative dictionaries: "BoW3+BoW2" combines terms in BoW 3 and BoW 2; "BoW3+rhetoric" adds terms commonly associated with modern populist rhetoric, such as "fake news" and "America First", to the BoW 3 dictionary. The sample period is 1986:01-2024:12.

Table D.8: POP Premium: Expand BoW3

	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
BoW3+BoW2	0.34	0.39	0.41	0.47	0.61
	(2.18)	(2.66)	(2.68)	(2.97)	(3.78)
BoW3+rhetoric	0.41	0.41	0.43	0.56	0.64
	(2.54)	(2.69)	(2.63)	(3.19)	(3.54)

This table reports the monthly average excess returns and alphas (in %) of POP beta portfolios from the strategy of buying the lowest POP beta portfolios and selling the highest POP beta portfolios (P1-P5). We employ the Bag-of-Words methodology developed in this study to construct the POP index but expand the vocabulary of BoW 3. Row "BoW 3+BoW 2" combines terms in BoW 3 and BoW 2, while row "BoW 3+rhetoric" adds terms commonly associated with modern populist rhetoric, such as "fake news" and "America First", to the BoW 3 dictionary. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

Table D.9: POP Premium in the Post-Training-Cutoff Period

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
P1	3.75	1.25	1.30	1.21	1.14
	(5.32)	(1.44)	(1.54)	(1.14)	(1.45)
P5	0.93	-1.23	-1.28	-1.19	-1.16
	(1.14)	(-1.66)	(-1.50)	(-1.79)	(-1.33)
P1-P5	2.81	2.48	2.58	2.40	2.30
	(4.31)	(2.42)	(2.32)	(1.69)	(1.70)

This table reports monthly average excess returns and alphas (in %) of POP beta quintile portfolios, where P1 (P5) refers to the portfolio with low (high) POP beta, and P1 - P5 refers to the strategy that buys P1 and sells P5. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 2 are presented in parentheses. The sample period is 2023:11-2024:12.

Table D.10: POP premium: Term-Fixed Portfolio Composition

Panel A: Portfolio formation per presidency

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
P1	0.86	0.12	0.12	0.16	0.19
	(3.78)	(1.57)	(1.70)	(2.06)	(2.44)
P5	0.63	-0.25	-0.17	-0.12	-0.19
	(2.44)	(-2.88)	(-2.08)	(-1.54)	(-1.95)
P1-P5	0.23	0.37	0.29	0.28	0.38
	(1.55)	(2.60)	(2.18)	(2.06)	(2.49)

Panel B: Portfolio formation per presidency term

	Excess	α_{FF3}	$\alpha_{\text{FF3\&Mom}}$	α_{FF5}	α_{HXZ}
P1	0.87	0.15	0.16	0.16	0.20
	(4.01)	(2.01)	(2.04)	(2.09)	(2.42)
P5	0.68	-0.20	-0.16	-0.02	-0.09
	(2.54)	(-2.10)	(-1.77)	(-0.19)	(-1.01)
P1-P5	0.19	0.35	0.31	0.18	0.29
	(1.30)	(2.38)	(2.15)	(1.23)	(1.86)

This table reports monthly average excess returns and alphas (in %) of POP beta quintile portfolios, where P1 (P5) refers to the portfolio with low (high) POP beta, and P1-P5 refers to the strategy that buys P1 and sells P5. In Panel A, portfolio composition is fixed at the beginning of a president's first term and held constant throughout the entire presidency, regardless of whether the president serves two consecutive terms. In Panel B, portfolio composition is reset at the start of each presidential term. All portfolios are value-weighted and rebalanced at a monthly frequency. Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses. The sample period is 1986:01-2024:12.

Table D.11: POP premium: Lobbying Firms

Panel A: Exclude lobbying firms					
	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
Full sample period	0.60	0.65	0.62	0.54	0.67
	(4.17)	(4.13)	(3.78)	(3.76)	(4.11)
Sub-sample period	0.73	0.82	0.79	0.60	0.80
	(3.85)	(3.89)	(3.49)	(2.89)	(3.63)

Panel B: Lobbying firms only					
	Excess	$\boldsymbol{\alpha}_{\text{FF3}}$	$\boldsymbol{\alpha}_{\text{FF3\&Mom}}$	$\boldsymbol{\alpha}_{\text{FF5}}$	$\boldsymbol{\alpha}_{\text{HXZ}}$
Full sample period	0.67	0.83	0.78	0.64	0.91
	(3.07)	(4.74)	(4.42)	(3.34)	(5.15)
Sub-sample period	0.52	0.63	0.60	0.51	0.71
	(2.97)	(3.84)	(3.80)	(3.11)	(4.45)

This table reports monthly average excess return and alphas (in %) of the strategy that buys portfolio with low POP beta and sells portfolio with high POP beta (P1-P5). Panel A excludes all firms that have engaged in lobbying activities, as identified in Grotteria (2024). Panel B restricts the sample to lobbying firms only. The full sample period is 1986:01–2024:12. The sub-sample period is 1999:01–2019:12, which corresponds to the sample period studied in Grotteria (2024). Factor models include Fama and French (1992) three-factor model (FF3), FF3 plus momentum factor (FF3&Mom), Fama and French (2015) five-factor model (FF5), and Hou et al. (2015) q-factor model (HXZ). Newey and West (1987) adjusted t-statistics with a lag length of 8 are presented in parentheses.

Table D.12: POP Beta and Political Alignment: Robustness

	Donation Count		Donation Amount	
	[1]	[2]	[3]	[4]
Panel A: base window=96, extended window=192, min donations=5				
Align_POP	0.600 ***	0.578 ***	0.439 ***	0.413 ***
	(10.33)	(9.75)	(8.50)	(7.92)
Align_POP × Align_Adm		0.074 **		0.105 ***
		(2.36)		(3.69)
Adj. R^2	0.354	0.356	0.328	0.332
Panel B: base window=96, extended window=192, min donations=1				
Align_POP	0.594 ***	0.559 ***	0.416 ***	0.383 ***
	(9.87)	(9.17)	(7.86)	(7.25)
Align_POP × Align_Adm		0.119 ***		0.135 ***
		(3.67)		(4.72)
Adj. R^2	0.353	0.356	0.326	0.332
Panel C: base window=96, extended window=192, min donations=10				
Align_POP	0.643 ***	0.629 ***	0.494 ***	0.481 ***
	(10.38)	(10.11)	(8.82)	(8.69)
Align_POP × Align_Adm		0.072 **		0.114 ***
		(2.36)		(3.9)
Adj. R^2	0.352	0.353	0.326	0.331
Panel D: base window=96, extended window=96, min donations=5				
Align_POP	0.633 ***	0.608 ***	0.477 ***	0.449 ***
	(10.54)	(10.02)	(8.83)	(8.32)
Align_POP × Align_Adm		0.091 ***		0.124 ***
		(2.9)		(4.34)
Adj. R^2	0.369	0.371	0.341	0.347
Panel E: base window=60, extended window=192, min donations=5				
Align_POP	0.599 ***	0.576 ***	0.423 ***	0.396 ***
	(10.18)	(9.60)	(8.34)	(7.75)
Align_POP × Align_Adm		0.087 ***		0.117 ***
		(2.74)		(4.29)
Adj. R^2	0.352	0.353	0.324	0.329
Control	YES	YES	YES	YES
Fixed Effects	Yearmon	Yearmon	Yearmon	Yearmon
Observations	2,335	2,335	2,335	2,335

This table reports the panel regressions results of POP beta on the Align_POP and its interaction with Align_Adm at the portfolio level. Panel A to E employ different specifications of estimation window and minimal donation threshold. In both panels, firm-level alignment with the party with stronger populist rhetoric (and the incumbent party) is measured by the share of employee political donation directed toward that party, using donation counts in columns [1] and [2] and donation amounts in columns [3] and [4]. The firm-level measures are then aggregated to portfolio level. All variables are normalized to have zero mean and standard deviation of one. Intercepts are included in all the regressions but unreported for brevity. t-statistics based on standard errors clustered by year-month are presented in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1986:01-2024:12.

Table D.13: POP Beta and Political Alignment: Firm Headquarter

	[1]	[2]	[3]	[4]
Align_POP	0.978 ***	0.921 ***		
	(9.13)	(8.52)		
Align_POP × Align_Adm		0.371 ***		
		(6.21)		
Align_POP_Swing			0.506 ***	0.431 ***
			(7.67)	(5.96)
Align_POP_Safe			0.692 ***	0.608 ***
			(9.47)	(8.05)
Align_POP_Swing × Align_Adm_Swing				0.095 ***
				(4.46)
Align_POP_Safe × Align_Adm_Safe				0.134 ***
				(6.35)
Control	YES	YES	YES	YES
Fixed Effects	Yearmon	Yearmon	Yearmon	Yearmon
Observations	2,335	2,335	2,335	2,335
Adj. R^2	0.354	0.368	0.358	0.372

This table reports the panel regressions results of POP beta on the Align_POP and its interaction with Align_Adm at the portfolio level. Column [1] and [2] utilizes full sample of firm-month observations, while Column [3] and [4] split sample into firms headquartered in swing states and safe states. In both panels, firm-level alignment with the party with stronger populist rhetoric (and the incumbent party) is measured by the share of regional election votes toward that party, using firm's headquarter county. The firm-level measures are then aggregated to portfolio level. All variables are normalized to have zero mean and standard deviation of one. Intercepts are included in all the regressions but unreported for brevity. t-statistics based on standard errors clustered by year-month are presented in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1986:01-2024:12.

Table D.14: POP Beta and Political Alignment: FEC Publication Delay

Panel A: Full Sample				
	Donation Count		Donation Amount	
	[1]	[2]	[3]	[4]
Align_POP	0.563 ***	0.530 ***	0.427 ***	0.394 ***
	(9.60)	(8.74)	(7.98)	(7.22)
Align_POP × Align_Adm		0.103 ***		0.113 ***
		(3.15)		(3.59)
Control	YES	YES	YES	YES
Fixed Effects	Yearmon	Yearmon	Yearmon	Yearmon
Observations	2,335	2,335	2,335	2,335
Adj. R^2	0.329	0.332	0.306	0.310

Panel B: Swing states vs. Safe states				
	Donation Count		Donation Amount	
	[1]	[2]	[3]	[4]
Align_POP_Swing	0.251 ***	0.231 ***	0.168 ***	0.148 ***
	(6.41)	(5.75)	(4.57)	(3.84)
Align_POP_Safe	0.332 ***	0.292 ***	0.266 ***	0.239 ***
	(9.65)	(8.62)	(8.43)	(7.62)
Align_POP_Swing × Align_Adm_Swing		0.064 ***		0.078 ***
		(3.08)		(3.75)
Align_POP_Safe × Align_Adm_Safe		0.157 ***		0.148 ***
		(6.31)		(5.60)
Control	YES	YES	YES	YES
Fixed Effects	Yearmon	Yearmon	Yearmon	Yearmon
Observations	2,335	2,335	2,335	2,335
Adj. R^2	0.324	0.340	0.305	0.322

This table reports panel regressions results of POP beta on the $\text{Align_POP}_{p,t-k}$ and its interaction with $\text{Align_Adm}_{p,t-k}$ at the portfolio level, where $k = 12$. Both political alignment measures are lagged by 12 months to account for potential publication delays in FEC filings. Panel A utilizes full sample of firm-month observations, while Panel B split sample into firms headquartered in swing states and safe states. In both panels, firm-level alignment with the party with stronger populist rhetoric (and the incumbent party) is measured by the share of employee political donation directed toward that party, using donation counts in columns [1] and [2] and donation amounts in columns [3] and [4]. The firm-level measures are then aggregated to portfolio level. All variables are normalized to have zero mean and standard deviation of one. Intercepts are included in all the regressions but unreported for brevity. t-statistics based on standard errors clustered by year-month are presented in parentheses. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is 1986:01-2024:12.

E Illustrative Examples of Populism Related Articles and Vocabularies

This appendix provides complementary evidence on the construction and validation of the Populism Index (POP) and on the robustness of its linguistic and empirical foundations. The analyses reported here illustrate how the text-based measures capture meaningful variation in populist language and verify that the results are not driven by idiosyncratic features of the dataset or by a particular modeling choice.

Table E.1 lists representative examples of populism-related words and expressions identified by the LLM, while Table E.2 reports the most frequently recurring vocabularies across political cycles, highlighting how the LLM isolates persistent stylistic and rhetorical markers of populist discourse. Table E.3 summarizes the frequency and prevalence of modern populist rhetoric in WSJ articles between 1984 and 2024. The low frequency of these specific populist rhetoric terms underscores the need for a more robust and context-sensitive approach to identifying populist sentiment, one that moves beyond rhetoric terms counting to capture the substantive content. Table E.4 traces the evolution of populism in the United States over time. Table E.5 catalogs major populist events between 1984 and 2024. Table E.6 summarizes U.S. presidential election results over the same period. Table E.7 provides examples of Wall Street Journal articles classified as populist by the LLM, illustrating how the model captures populist sentiment in context. Table D8 presents illustrative examples of WSJ articles that are classified as populist by our LLM-based procedure and contain terms drawn from our newly developed BoW3 dictionary, yet are not captured by the BoW1 or BoW2 dictionaries, as the relevant terms appear in neither lexicon. Table E.9 presents the results of a masking experiment testing the model's ability to infer omitted political entities from textual context, confirming that classification accuracy relies on semantic comprehension rather than simple keyword recognition. Table E.10 extends this analysis to articles linking populist narratives with financial or macroeconomic risks, showing that the LLM captures both political and economic manifestations of populism. Table E.11 provides representative excerpts illustrating the model's ability to distinguish among multiple dimensions of populism—leader, movement, policy, and rhetoric. Finally, Table E.12 and Table E.13 present representative examples demonstrating that the classification of populism-related and non-populism-related articles is highly consistent across LLMs, including GPT-4o-mini and GPT-5.5 from OpenAI, Gemini 2.5 Pro and Gemini 3.1 Pro from Google DeepMind, and Claude Sonnet 4.6 and Claude Opus 4.7 from Anthropic.

Table E.1: U.S. Populism Dictionary 3.0 based on LLM

Period	President	Terms in BoW1	New Terms BoW2	Terms in BoW3 dictionary
1984.01–1989.01	Ronald Reagan	bureaucrat, millionaire, baron, venal, crooked, unresponsive, arrogant, special interests, Wall Street, Main Street, big corporations, ordinary taxpayer, wealthy few, professional politician, big interest, big money, Washington elite, rich friend, power monger, power grabbing, easy street, privileged few, forgotten Americans, long nose, top 1 percent, average American taxpayer, government is too big, government that forgets the people	tariffs, MAGA, tax cuts, fake news, border security, illegal immigration, American first, fake news media, make America great again	deficit, social security, tax increase, environmental protection agency, legislation
1989.01–1993.01	George H. W. Bush			+ capital gain tax, capital gain, tax cut, supreme court
1993.01–2001.01	Bill Clinton			+ GOP
2001.01–2009.01	George W. Bush			+ world trade organization
2009.01–2017.01	Barack Obama			+ voter
2017.01–2021.01	Donald Trump			+ tariff, supreme court
2021.01–2025.01	Joe Biden			+ former president, abortion

This table presents the third version of the populist dictionary constructed in this paper. Unlike the approaches of Bonikowski and Gidron (2016) (BoW1) and Filippou et al. (2020) (BoW2), our constructed dictionary (BoW3) is a dynamic version that updates its lexicon based on changes in the U.S. presidency. Since some terms in Table E.2 appear with excessively high frequency in the news corpus, we refined the list based on two criteria. First, we pruned terms that appeared in more than 4% of all news articles during the entire sample period. Second, we removed proper nouns, such as the names of presidents and countries. We introduce a lag of one month following the start of a president's tenure before admitting new terms into the BoW3 dictionary. Terms in column 4 indicate additions relative to column 3. Terms in column 5 show only the new terms added during each president's tenure (cumulative across rows).

Table E.2: Term Divergence in Populist vs. Non-Populist News Across Presidencies

rank	Reagan	H.W. Bush	Clinton	W. Bush	Obama	Trump	Biden
1	tax	tax	tax	tax	tax	trump	trump
2	budget	bush	clinton	bush	government	president	biden
3	government	government	state	government	state	tax	republican
4	bill	state	government	state	obama	white house	tax
5	house	house	republican	white house	republican	state	state
6	union	budget	house	republican	president barack obama	republican	democrat
7	state	bill	bill	president bush	president	trump administration	president
8	worker	capital gain tax	white house	democrat	white house	government	election
9	reagan	white house	budget	house	party	democrat	government
10	deficit	president bush	vote	congress	vote	president trump	vote
11	senate	congress	president clinton	senate	election	administration	donald trump
12	congress	union	congress	bush administration	democrat	china	biden administration
13	white house	capital gain	senate	political	political	election	white house
14	president reagan	worker	political	bill	law	president donald trump	law
15	cut	administration	party	country	prime minister	vote	administration
16	administration	senate	tax cut	tax cut	health care	donald trump	supreme court
17	strike	cut	law	vote	policy	house	china
18	law	bush administration	democrat	law	rule	law	voter
19	reagan administration	law	reform	prime minister	bill	senate	policy
20	spend	rule	gop	rule	country	political	former president
21	program	democrat	cut	official	union	official	president donald trump
22	committee	official	official	election	budget	party	political
23	wall street journal	policy	administration	administration	congress	policy	president biden
24	rule	deficit	program	union	house	bill	party
25	policy	vote	rule	china	campaign	campaign	bill
26	social security	political	health care	iraq	senate	tariff	court
27	official	proposal	policy	policy	leader	country	former president donald
28	way mean committee	committee	china	worker	administration	rule	rule
29	labor	program	leader	president	trump	democratic	country
30	sen	economic	election	party	obama administration	congress	senate
31	federal	spend	prime minister	world trade organization	health	white	congress
32	tax increase	people	campaign	budget	official	prime minister	democratic
33	economic	republican	union	sen	voter	leader	see relate
34	environmental protection agency	tax increase	worker	leader	federal	voter	gop
35	legislation	tax cut	federal	health care	democratic	american	house
36	proposal	country	clinton administration	democratic	support	federal	abortion
37	senate finance committee	leader	school	support	president obama	economic	union
38	cost	supreme court	economic	war	barack obama	supreme court	american
39	measure	way mean committee	social security	social security	minister	chinese	campaign
40	job	get	health	american	worker	lawmaker	russia

This table reports the top 40 terms with the largest average TF-IDF difference between populist and non-populist news across presidential terms. Specifically, we begin by identifying populist and non-populist news articles using the LLM. For each year, we calculate the TF-IDF values for uni-grams, bi-grams, and tri-grams. The TF-IDF difference was then derived by subtracting the TF-IDF of non-populist n-grams from that of their populist counterparts. A larger difference indicates that a term appears more frequently in populist news. Finally, for each presidential term, we computed the average TF-IDF differences and reported the 40 terms with the highest values.

Table E.3: Prevalence of Modern Populist Rhetoric in WSJ Articles, 1984-2024

Rhetoric	Total		Before 2017		After 2017	
	Num	Ratio	Num	Ratio	Num	Ratio
MAGA	433	0.00039	3	0.00000	430	0.00242
Make America Great Again	303	0.00027	97	0.00010	206	0.00116
America First	704	0.00064	197	0.00021	507	0.00285
Drain the Swamp	113	0.00010	40	0.00004	73	0.00041
Build the Wall1	69	0.00006	10	0.00001	59	0.00033
Fake News	633	0.00057	87	0.00009	546	0.00307
Deep State	197	0.00018	39	0.00004	158	0.00089
Law and Order	925	0.00084	681	0.00073	244	0.00137
Stop the Steal	76	0.00007	0	0.00000	76	0.00043
Take Our Country Back	7	0.00001	6	0.00001	1	0.00001

This table reports the frequency and prevalence of modern populist rhetoric—such as "America First" and "Fake News"—in WSJ articles from 1984 to 2024. For each phrase, we show the number of articles containing it and its ratio to the total number of articles in the full sample and in two subperiods (pre- and post-2017).

Table E.4: Populism in the United States: A Timeline

Period	Representative Figure / Party	Description	Proposal
1849–1860	The Know Nothings (renamed the American Party in 1854)	The first party to leverage economic concerns over immigration as a major part of their platform. In the 1850s, this party included more than 100 elected congressmen, eight governors, a controlling share of half-a-dozen state legislatures from Massachusetts to California, and thousands of local politicians.	Anti-immigration; Anti-Catholic
1874–1884	The Greenback Party	The Greenback Party represents the interests of farmers and laborers to maintain or increase the amount of paper money in circulation. In the midterm elections of 1878, the Greenback Party elected 14 members of Congress and in 1880 its candidate for president polled more than 300,000 votes.	Against the gold standard; Support of paper money; Anti-deflation
1892–1908	The Populist Party (People's Party); William Jennings Bryan	The People's Party, a populist movement representing farmers and laborers against political and economic elites, won over one million votes and 22 electoral votes in 1892. By 1896, it merged with the Democrats to back William Jennings Bryan's presidential campaign.	Support of bimetallism; Graduated income tax; State control of the railroads; Direct election of Senators
1928–1935	Huey Long	Huey Long, governor of Louisiana and later U.S. senator, promoted the "Share Our Wealth" program, calling for wealth redistribution, high taxes on the rich, and support for the poor.	Wealth redistribution; High taxes on the wealthy
1963–1972	George Wallace	Wallace, governor of Alabama, ran for president emphasizing segregation, states' rights, and opposition to federal intervention, appealing to white working-class populism.	Support for racial segregation; Advocate for states' rights
1992–2000	The Reform Party; Ross Perot; Pat Buchanan	Ross Perot's independent presidential campaigns in 1992 and 1996 drew significant support by criticizing federal deficits and free trade. In 1995, Perot established the Reform Party. Pat Buchanan, running under the Reform Party in 2000, added strong nationalist and anti-immigration themes.	Against the NAFTA; Balance the federal budget; Political reform; Anti-immigration
1996-2008	Ralph Nader (Green Party)	Ralph Nader is an American lawyer and consumer advocate who was a four-time candidate for the U.S. presidency.	Anti-establishment; Repeal NAFTA and WTO
2009–2015	Tea Party	The Tea Party, a conservative populist movement, emphasizing rally limited government, fiscal conservatism, and individual liberties. The Tea Party helped Republicans gain about 60 House seats in 2010 and reshaped the party's future direction.	Anti-establishment; Limited federal power; Against Obamacare; Anti-immigration
2016-	Bernie Sanders	Sanders ran for president emphasizing democratic socialism, income redistribution, and universal healthcare, appealing to younger and working-class voters.	Medicare for All; Progressive taxation; Wealth redistribution
2016–	Donald Trump	Trump, regarded as the first populist U.S. president, won in 2016 and 2024 with an "America First" platform, reshaping the Republican Party and U.S. politics.	Anti-immigration; Trade protectionism; "America First" policy

This table summarizes key U.S. populist figures and parties from 1849 to the present, highlighting their representative proposals and policy positions. It shows how populist movements have historically addressed economic, social, and political grievances, appealing to ordinary citizens against perceived elites.

Table E.5: Key Populist Events in the U.S. (1984-2024)

Date	Event	Description
1984-07	Jesse Jackson's "Rainbow Coalition"	Mobilized diverse voters around civil rights and economic justice, a left-wing populist push.
1986-08	Small-Business Conference	Mobilized grassroots small business owners to oppose the Reagan administration's plan to reduce the Small Business Administration's role, advocating for independent support and regulatory relief
1987-10	Jackson's Campaign Announcement	Jesse Jackson launched a presidential campaign rooted in economic justice and racial equality, appealing to working-class Americans.
1990-10	David Duke runs for Senate	Former KKK leader used populist, anti-establishment, and racially charged rhetoric to gain support.
1992-10	Perot's Presidential Campaigns	Ross Perot's anti-NAFTA, anti-deficit, anti-establishment campaign appealed to voters frustrated with both major parties.
1993-09	Battle over NAFTA	Populist opposition framed trade deals as threats to American workers and sovereignty.
1994-08	Clinton Health Care Plan	Populist backlash against complex federal healthcare reform, emphasizing affordability concerns.
1996-03	Buchanan's Primary Wins	Pat Buchanan's "America First" nationalist and protectionist platform challenged GOP establishment.
1997-06	Taxpayer Relief Act	Framed as a win for ordinary Americans against big government, providing middle-class tax relief though also benefiting the wealthy.
2000-04	Reform Party of the US	Populist platform promoting political reform and challenging the two-party system.
2001-03	EGTRRA	Framed as benefiting middle-class Americans, promoting economic growth, though also favoring high-income households.
2003-12	Nader Considered Running for President	Leftist populist figure pushing consumer advocacy and corporate accountability.
2004-11	Nader's Presidential Campaigns	Grassroots-driven campaign emphasizing political reform and anti-corporate messages.
2009-03	Tea Party Protests	Conservative populist demonstrations opposing government bailouts and fiscal policies.
2010-03	Rise of Tea Party	Influential populist movement reshaping the Republican Party around limited government.
2011-02	Budget Cuts & Obamacare	Populist pushback against federal spending and healthcare reforms.
2012-02	Occupy Wall Street	Populist movement highlighting wealth inequality and corporate power.
2014-07	Anti-Immigration Rallies	Protest against the government's immigration policies and express strong xenophobic sentiment.
2015-07	Sanders' Political Revolution	Mobilized grassroots support to challenge economic and political elites.
2016-02	Sanders' Primary Wins	Populist victories demonstrating growing grassroots support for progressive economic policies.
2017-01	Trump's First Inauguration	Populist ascension emphasizing nationalism, anti-elitism, and anti-establishment rhetoric.
2018-01	DACA & Deportation	Populist-driven debates on immigration enforcement and protections for Dreamers.
2019-06	Trade War Escalation	Heightened populist rhetoric on protecting domestic industries against foreign competition.
2020-06	Trump Rally	Populist mobilization reinforcing anti-establishment and nationalist themes.
2021-01	Capitol Riot	Extreme populist event attempting to overturn election results.
2022-03	Anti-Vax Protest	Grassroots uprising against perceived government overreach and elitist control, emphasizing individual freedom over mandates.
2024-11	Trump's Election Win	Populist victory reaffirming nationalist, anti-elitist, and anti-establishment appeals.

This table lists major U.S. populist events from 1984 to 2024, including populist political campaigns, movements, and policy initiatives. These events correspond to the markers shown in Figure 1, which tracks the populism index over time.

Table E.6: U.S. Presidential Election Results (1984-2024)

Year	Presidential Candidate	Vice Presidential Candidate	Political Party	Popular Vote		Electoral Vote	
1984	Ronald Reagan	George Bush	Republican	54455472	0.59	525	0.98
	Walter Mondale	Geraldine Ferraro	Democratic	37577352	0.41	13	0.02
1988	George Bush	J. Danforth Quayle	Republican	48886588	0.53	426	0.79
	Michael Dukakis	Lloyd Bentsen	Democratic	41809485	0.46	111	0.21
	Ron Paul	Andre Marrou	Libertarian	431750	0.00	0	0.00
1992	William Clinton	Albert Gore Jr.	Democratic	44909806	0.43	370	0.69
	George Bush	J. Danforth Quayle	Republican	39104550	0.37	168	0.31
	H. Ross Perot*	James Stockdale	Independent	19743821	0.19	0	0.00
	Andre Marrou	Nancy Lord	Libertarian	290087	0.00	0	0.00
1996	William Clinton	Albert Gore Jr.	Democratic	47400125	0.49	379	0.70
	Robert Dole	Jack Kemp	Republican	39198755	0.41	159	0.30
	H. Ross Perot*	Pat Choate*	Reform*	8085402	0.08	0	0.00
	Ralph Nader*	Winona LaDuke	Green*	685435	0.01	0	0.00
	Harry Browne	Jo Jorgensen	Libertarian	485798	0.01	0	0.00
2000	George W. Bush	Richard Cheney	Republican	50462412	0.48	271	0.50
	Albert Gore Jr.	Joseph Lieberman	Democratic	51009810	0.48	266	0.49
	Ralph Nader*	Winona LaDuke	Green*	2883443	0.03	0	0.00
	Pat Buchanan*	Ezola Foster*	Reform*	449181	0.00	0	0.00
	Harry Browne	Art Olivier	Libertarian	384532	0.00	0	0.00
2004	George W. Bush	Richard Cheney	Republican	62039572	0.51	286	0.53
	John Kerry	John Edwards	Democratic	59027115	0.48	251	0.47
	Ralph Nader*	Peter Camejo	Independent	465642	0.00	0	0.00
	Michael Badnarik	Richard Campagna	Libertarian	397265	0.00	0	0.00
2008	Barack H. Obama	Joseph R. Biden, Jr.	Democratic	69499428	0.53	365	0.68
	John S. McCain, III	Sarah H. Palin*	Republican	59950323	0.46	173	0.32
	Ralph Nader*	Matt Gonzalez	Independent	739278	0.01	0	0.00
	Bob Barr	Wayne Allyn Root	Libertarian	523433	0.00	0	0.00
2012	Barack H. Obama	Joseph R. Biden, Jr.	Democratic	65918507	0.51	332	0.62
	Willard Mitt Romney	Paul Ryan	Republican	60934407	0.47	206	0.38
	Gary Johnson	James P. Gray	Libertarian	1275923	0.01	0	0.00
	Jill E. Stein*	Cheri Honkala	Green*	469015	0.00	0	0.00
2016	Donald J. Trump*	Michael R. Pence	Republican	62985153	0.46	304	0.57
	Hillary Clinton	Tim Kaine	Democratic	65853677	0.48	227	0.42
	Gary Johnson	William F. Weld	Libertarian	4489359	0.03	0	0.00
	Jill E. Stein*	Ajamu Baraka	Green*	1457288	0.01	0	0.00
	Evan McMullin	Mindy Finn	Independent	732409	0.01	0	0.00
2020	Joseph R. Biden, Jr.	Kamala D. Harris	Democratic	81286454	0.51	306	0.57
	Donald J. Trump*	Michael R. Pence	Republican	74225926	0.47	232	0.43
	Dr. Jo Jorgensen	Jeremy 'Spike' Cohen	Libertarian	1865641	0.01	0	0.00
	Howie Hawkins	Angela Nicole Walker	Green*	406711	0.00	0	0.00
2024	Donald J. Trump*	J. D. Vance*	Republican	77304296	0.50	312	0.58
	Kamala D. Harris	Tim Walz	Democratic	75019682	0.48	226	0.42
	Jill E. Stein*	Rudolph T. Ware, III	Green*	881909	0.01	0	0.00
	Robert F. Kennedy, Jr.*	Nicole Shanahan	Independent	757369	0.00	0	0.00
	Chase R. Oliver	Michael ter Maat	Libertarian	650139	0.00	0	0.00

This table shows the results of U.S. presidential elections from 1984 to 2024, including candidates, parties, and vote distributions. The first row for each election indicates the winning candidate. "Popular Vote" and "Electoral Vote" report both the number of votes and the corresponding percentage share. Bold entries and "*" indicate populist candidates or parties.

Table E.7: Examples of Populist Articles in The Wall Street Journal Identified by LLM

Date	Title	Content	LLM results
20-Jan-2017	The 45th President: Presidency of Firsts and Familiarity—Trump has qualities that set him apart from predecessors and spur comparisons	By some measures, Mr. Trump is truly distinctive. At 70 years and seven months, he is the oldest person to first take the oath of office (the next oldest, at 69 years and 11 months, was Ronald Reagan). All of the presidents before Mr. Trump had some form of military or government service in their past. Mr. Trump is entirely a man of the private sector.	"Populist_leader": {"Attention_Type": true, "Attention_Score": 0.6, "Risk_Type": false, "Risk_Score": 0, "Confidence": 0.8}, "Populist_movement": {"Attention_Type": true, "Attention_Score": 0.5, "Risk_Type": false, "Risk_Score": 0, "Confidence": 0.7,}, "Populist_policy": {"Attention_Type": false, "Attention_Score": 0, "Risk_Type": false, "Risk_Score": 0, "Confidence": 0.5}, "Populist_rhetoric": {"Attention_Type": true, "Attention_Score": 0.4, "Risk_Type": false, "Risk_Score": 0, "Confidence": 0.6,}
8-Jan-2021	CEOs Fire Rioters, Condemn Violence	In the wake of the riot at the Capitol, companies moved to cut ties with President Trump and his supporters and fired workers who participated. Facebook Inc. banned Mr. Trump indefinitely and Canada-based Shopify Inc. closed online stores associated with Mr. Trump's campaign and businesses. Publisher Simon & Schuster said it would drop a coming book by Sen. Josh Hawley, a Missouri Republican and a backer of Mr. Trump's election claims.	"Populist_leader": {"Attention_Type": true, "Attention_Score": 0.6, "Risk_Type": true, "Risk_Score": 0.8, "Confidence": 0.8}, "Populist_movement": {"Attention_Type": true, "Attention_Score": 0.7, "Risk_Type": true, "Risk_Score": 0.7, "Confidence": 0.8}, "Populist_policy": {"Attention_Type": false, "Attention_Score": 0, "Risk_Type": false, "Risk_Score": 0, "Confidence": 0.9}, "Populist_rhetoric": {"Attention_Type": true, "Attention_Score": 0.8, "Risk_Type": true, "Risk_Score": 0.9, "Confidence": 0.9}
20-Dec-2011	Liberals Love the 1%	Naturally, Mr. Quinn justifies the carve-outs as essential to job creation. But in January Democrats claimed that tax increases would have no economic impact. Now small and medium-sized businesses that don't have lobbyists are stuck paying the higher tax rates. Mr. Quinn's policies benefit the 1% of politically connected businesses at the expense of the other 99%, often small shops with 10, 20 or 50 employees.	"Populist_leader": {"Attention_Type": true, "Attention_Score": 0.6, "Risk_Type": true, "Risk_Score": 0.5, "Confidence": 0.8}, "Populist_movement": {"Attention_Type": true, "Attention_Score": 0.5, "Risk_Type": true, "Risk_Score": 0.4, "Confidence": 0.7}, "Populist_policy": {"Attention_Type": true, "Attention_Score": 0.7, "Risk_Type": true, "Risk_Score": 0.6, "Confidence": 0.9}, "Populist_rhetoric": {"Attention_Type": true, "Attention_Score": 0.8, "Risk_Type": true, "Risk_Score": 0.7, "Confidence": 0.9}}
13-Apr-2000	Under the Radar, Buchanan Nears Reform Nomination	"The Establishment has sold us out," he tells a head-nodding audience at Minnesota's Reform Party state convention. There is no real difference between the Republican Party and the Democratic Party, he says. Corporate lobbyists own them both. They are "two wings of the same bird of prey."	"Populist_leader": {"Attention_Type": true, "Attention_Score": 0.8, "Risk_Type": false, "Risk_Score": 0, "Confidence": 0.9}, "Populist_movement": {"Attention_Type": true, "Attention_Score": 0.7, Risk_Type": false, "Risk_Score": 0, "Confidence": 0.8}, "Populist_policy": {"Attention_Type": true, "Attention_Score": 0.9, "Risk_Type": true, "Risk_Score": 0.7, "Confidence": 0.9}, "Populist_rhetoric": {"Attention_Type": true, "Attention_Score": 0.8, "Risk_Type": true, "Risk_Score": 0.6, "Confidence": 0.9}

This table presents examples of WSJ articles identified as populist by the LLM, including article date, titles, content excerpts, and LLM results based on the analytical framework in Prompt A.1. Sentences in bold are those cited by the LLM as evidence for its classification.

Table E.8: Examples of WSJ News Containing New Terms from the BoW3 Dictionary

Terms	Earliest Date	Title	Content
deficit	27-Jan-1984	Mondale Proposes a 15% Minimum Tax On Concerns, 10% Surcharge on Affluent	Presidential hopeful Walter Mondale proposed a package of defense-spending cuts and tax increases that includes a 15% corporate minimum tax and a 10% surcharge on affluent individuals...The package, designed to reduce the projected federal budget deficit $100 billion by 1989.
	6-Nov-1992	The Americas: Venezuelan Populism Has Created a Nightmare for Populists	While populist sentiments and oil income have allowed politicians to increase to 20% the number of workers employed by the government (the majority of whom produce nothing of value), this deficit-spending program cannot keep up with the growing number of destitute.
social security	02-July-1984	The Outlook: Social Security How Now, Sacred Cow?	Social Security is by far the biggest middle-class program, and COLAs are by far the biggest factor in such programs' growth.
	18-Feb-1993	Clinton's Economic Package: Lobbyists, Interest Groups Gird for Fight To Try to Defeat or Modify Proposals	The National Association of Manufacturers has scheduled a meeting today to debate what action to take on the proposed corporate tax increase. Senior citizens' groups are generating letters and phone calls to Congress to fight increased taxation of Social Security benefits. But the soak-the-rich, populist overtones of the Clinton plan will give the White House an opening to spur popular support at the nation's grass roots to fight back.
	27-Oct-2004	Bush on Stump Revives His Call For Tax Overhaul	Tax overhaul is popular with party conservatives, but it moved to the back burner when the campaign heated up and Mr. Bush shifted emphasis to proposals for changing Social Security and education.
tax increase	27-Jan-1986	Burlington Northern Feels a Chill in Montana As Tax Dispute Sets Off Business-Climate Debate	Still, its politics are influenced by a populist sentiment against big business that stems from the days when mining companies treated much of Montana as a company town....Republican leaders condemned the tax increase as "unfair and illegal."
	12-Oct-1990	New Populism: Politicians Exploit Broad Public Support For Soaking the Rich	In a closed-door meeting of Republican House members, he proposed a 10% surtax on the nation's wealthiest citizens and corporations. "The feeling back home is there is going to be a tax increase no matter what," he explains, "and middle-class America doesn't want it on their back."
environmental protection agency	-2-Feb-1984	THE REAGAN BUDGET: Federal Outlays on Health Plans Are Projected to Climb Over 13%	In an election year, with Congress, state officials and environmental groups all urging higher spending and more aggressive action by the Environmental Protection Agency, Mr. Reagan decided to ask for a nearly 19% overall boost for the agency's ongoing programs.
legislation	06-May-1986	Finance Panel Can Look Back, Carry Forward — Jefferson, Jackson and Lincoln	President Andrew Jackson vetoed legislation to extend the charter on the Bank of the U.S....He (Senator Packwood) presented a populist prototype even bolder than the president's plan in reducing tax rates and ending preferences.
supreme court	15-June-1990	Supreme Court Sometimes Needs Its Nose Tweaked	As every political scientist knows, the Supreme Court is protected from, but also sensitive to, public opinion. Every so often the Justices have shown they need a populist tonic to remind them who's boss.
	24-July-2021	The Temptation of the "Common Good"	As liberals lick their wounds from the recent Supreme Court term, a small but noisy band on the right has launched a dissent against the conservative legal movement that produced the court's majority.
capital gain	13-Oct-1989	The Capital-Gains Hostage	The capital-gains cut Mr. Bush campaigned on is a winning political issue and the House debate proved it has populist appeal.
capital gain tax	01-Oct-1992	Clinton Courts Small Business, Disavowing Payroll Tax	Mr. Clinton also stressed his support for a proposal by another Arkansas Democrat, Sen. Dale Bumpers, to eliminate capital-gains taxes for investments in new small companies that are held for at least 10 years.
GOP	8-Dec-1994	Down With Populism!	Republicans' success in the midterm elections can be attributed, in some measure, to their embrace of populist causes. Virtually all GOP candidates railed against the "inside-the-Beltway crowd."
	15-May-2021	Declarations: The GOP's Post-Trump Trauma	In terms of policy the future GOP will be more Trumpian, meaning more populist and nationalist.

world trade organization	15-Nov-2002	Americas: Why Is Chile Still Waiting for Her American Suitor?	Through two U.S. presidential elections, the collapse of a World Trade Organization (WTO) summit in Seattle and renewed U.S. protectionism in steel and agriculture, Chile has held out hope that America would eventually make good on that promise.
voter	25-Aug-2009	Obama's Summer of Discontent	How dare those townhallers (the voters) heckle Arlen Specter! Americans eager to rein in this runaway populism were now guilty of lese-majeste by talking back to the political class.
	21-Jan-2017	Trump's Populist Manifesto	His inaugural address was a full-throated populist manifesto against the political "establishment" that will cheer his voters.
	09-Jan-2021	The Electoral College Saved the Election	Party elders, led by Barack Obama, realized the key to the general election would be moderate suburban voters, including Trump-weary Republicans – many of whom were terrified of Bernie Sanders's socialism and Elizabeth Warren's economic populism.
former president	13-Apr-2021	U.S. News — CAPITAL JOURNAL: GOP's 'Working Class' Pitch Gets Policy Heft	To some extent, this evolution in Republican thinking can be traced to former President Donald Trump, who turned the party in a populist direction, at least rhetorically, and showed little regard for traditional conservative maxims on government's role in the economy, intervention in the marketplace or deficit spending.
abortion	18-Mar-2022	U.S. News: Pennsylvania Voters Size Up Democrats in Pivotal Race	All three Democrats support a $15 minimum wage, abortion rights and labor unions, and would end the Senate filibuster, the procedural tool that has stymied Democratic legislation.

This table presents examples of WSJ articles for each new term identified during each presidential administration. These examples satisfy three conditions: (i) they are classified as populist by our LLM procedure, (ii) they contain terms from our newly developed BoW3 dictionary, but (iii) they are missed by BoW1 and BoW2 dictionaries.

Table E.9: Testing the Performance of the Masking Approach

Date	Title	Content	Correct Answer	ChatGPT Answer
20-Dec-1984	Viewpoint: How [NAME] Can Triumph Over His Lame-Duck Status	[NAME] won the election by campaigning for populist values and against special interests. He will be a lame duck, indeed, unless he puts that message into concrete form and enlists the people to support him.	NAME: Reagan President Reagan	NAME: Unknown
07-Aug-1987	REVIEW & OUTLOOK (Editorial): Gentrification's Flying Wedge	Indeed, the Democrats, led by House Majority Leader Richard Gephardt, have turned opposition to [NAME]'s proposal to cut the capital-gains tax into a "rich vs. poor" populist crusade.	NAME: President Bush	NAME: Ronald Reagan
22-Jan-1996	Medicare Lies	In the bad old days of the evil empire, Pravda would introduce its biggest lies with the phrase, "As everyone knows." So we noticed when [NAME] said at his recent press conference that, "Now, as all of you know also, the Republicans in Congress are insisting on cuts in Medicare. . . ."	NAME: President Clinton	NAME: Bill Clinton
08-Mar-2001	GOP's Tax Bill May Pass House Despite Anxiety	Democrats, meantime, are touting a new analysis that pushes the cost of [NAME]'s tax-cut plan to nearly $1.75 trillion over 10 years, up from $1.6 trillion, based on the House bill.	NAME: President Bush	NAME: George W. Bush
07-Jan-2009	Many Taxpayers Stand to Gain From New Laws — Wealthy Likely to Benefit Most From [DATE] Changes; Putting More in Your 401(k)	New Year's Day brought relief for most taxpayers, especially upper-income ones – even as President-elect [NAME] is proposing new tax cuts as part of his wide-ranging economic-stimulus package.	DATE: 2009 NAME: Barack Obama	DATE: 2001 NAME: George W. Bush
20-Jan-2017	Streetwise: [NAME]'s Run Will Be Tough to Beat	These aren't achievements likely to cut much ice with the Democratic Party, and the perception that the rich got richer at the expense of American workers surely helped [NAME], who has promised to dismantle [NAME]'s flagship policies after he is inaugurated as presidenton Friday.	NAME: Obama Donald Trump Mr. Obama	NAME: Obama Obama Obama
06-Nov-2024	The Federal Workforce Boom	Remember when [NAME] in [DATE] declared that the era of big government was over? Well, it's back and bigger than ever. While neither [NAME] nor [NAME] is talking about the need to shrink Washington, Elon Musk to his credit is, and it sure needs shrinking.	DATE: 1996 NAME: Bill Clinton Kamala Harris Donald Trump	DATE: Unknown NAME: Unknown

This table presents the results of an experiment in which we provided randomly selected news articles with masked segments to ChatGPT. The model was prompted to infer the masked [DATE] and [NAME] entities (referring to a U.S. President or presidential candidate). The instructions specified that the model should return the specific value if known, otherwise respond with "Unknown", and to answer in the format "DATE: ... | NAME: ..." without any additional explanation.

Table E.10: Examples of Populist Risk in The Wall Street Journal as identified by LLM

Date	Title	Content	Risk Score and Confidence
Panel A: Trade protectionism and fracture of global supply chains			
17-Mar-1993	Critics Say Antitariff Activists in Washington Have Grass-Roots Base That's Made of Astroturf	Citizens for a Sound Economy, a conservative lobbying group dedicated to fighting Detroit's push for steep tariffs on foreign minivans, boasts a grass-roots coalition that Ross Perot would envy.	"Populist_movement":"Risk_Score": 0.6, "Confidence": 0.8, "Populist_policy": "Risk_Score": 0.7, "Confidence": 0.9, "Populist_rhetoric": "Risk_Score": 0.6, "Confidence": 0.8
09-Oct-2010	Goodbye, Free Trade? — High tariffs and currency wars cost us big in the 1930s; We can avoid making the same mistakes again	A newly released Wall Street Journal/NBC News poll found that 53% of the American public now believes that free-trade agreements have hurt the U.S., up from 46% three years ago and 32% in 1999. So is it 1929 all over again? Is America preparing to raise its economic drawbridges? Has the ghost of Smoot-Hawley returned?	"Populist_movement":"Risk_Score": 0.7, "Confidence": 0.8, "Populist_policy": "Risk_Score": 0.8, "Confidence": 0.9, "Populist_rhetoric": "Risk_Score": 0.6, "Confidence": 0.8
10-Nov-2016	Trump's Victory: Result Heralds Global Trade Uncertainty — Promises of tariffs against China, Mexico, threat to leave Nafta raise economic anxiety	His victory may begin an era of U.S. combativeness with trade partners such as China and Mexico, which Mr. Trump says benefit in a global system that costs America jobs. If implemented, Mr. Trump's promises could bring trade wars, drive up the price of imports, and rattle a global economy that has relied on the expansion of international trade to drive growth.	"Populist_leader": "Risk_Score": 0.6, "Confidence": 0.9, "Populist_movement":"Risk_Score": 0.7, "Confidence": 0.8, "Populist_policy": "Risk_Score": 0.8, "Confidence": 0.9, "Populist_rhetoric": "Risk_Score": 0.7, "Confidence": 0.8
02-Mar-2021	U.S. News: Biden Aims for Strong Posture on Trade — White House says it will use tariffs, other tools to combat unfair practices by Beijing	"The Biden administration recognizes that China's coercive and unfair trade practices harm American workers, threaten our technological edge, weaken our supply-chain resiliency and undermine our national interests," the administration said. "Addressing the China challenge will require a comprehensive strategy and more systematic approach."	"Populist_policy": "Risk_Score": 0.6, "Confidence": 0.,
Panel B: Political interference with the Fed's independence			
29-Sep-2011	Politicians Are Threatening the Fed's Independence	Republican presidential candidates have been regularly beating up on Ben Bernanke and the Federal Reserve, with Texas Gov. Rick Perry even going so far as to label the Fed's recent expansionary policies as close to "treasonous." Such rhetoric might be expected during a presidential campaign,	"Populist_movement":"Risk_Score": 0.6, "Confidence": 0.7, "Populist_policy": "Risk_Score": 0.7, "Confidence": 0.9, "Populist_rhetoric": "Risk_Score": 0.8, "Confidence": 0.9
27-Apr-2024	HD Trump Allies Draw Up Plans To Blunt Fed's Independence	Donald Trump 's allies are quietly drafting proposals that would attempt to erode the Federal Reserve 's independence if the former president wins a second term, in the midst of a deepening divide among his advisers over how aggressively to challenge the central bank's authority.	"Populist_leader": "Risk_Score": 0.6, "Confidence": 0.9, "Populist_movement": "Risk_Score": 0.7, "Confidence": 0.8, "Populist_policy": "Risk_Score": 0.8, "Confidence": 0.9, "Populist_rhetoric": "Risk_Score": 0.6, "Confidence": 0.9
31-Dec-2024	HD Will Trump Respect the Fed's Independence?	Yet in the scheme of things, it's minor compared with an issue the nation is likely to face once Donald Trump returns to the White House: the independence of the Fed	"Populist_leader": "Risk_Score": 0.6, "Confidence": 0.9, "Populist_rhetoric": "Risk_Score": 0.7, "Confidence": 0.9
Panel C: Tax & Budget Deficit			
06-Dec-1984	A tax Scheme to Deindustrialize America	The Treasury Department's tax-reform proposal is a retreat from the supply-side principles put in place by President Reagan during his first term. Enactment of the proposal would reduce the profitability of investment and reinstate the declining productivity growth and the stagnation in the standard of living that characterized the economy during the 1970s – with little or no offsetting gain in simplicity or fairness.	"Populist_policy": "Risk_Score": 0.8, "Confidence": 0.9, "Populist_rhetoric": "Risk_Score": 0.7, "Confidence": 0.8

11-Nov-2011	U.S. News: Activist's Antitax Pledge Looms Large in Debt Talks	As Congress's special deficit-cutting committee struggles to reach a deal before a Thanksgiving deadline, one powerful figure looming over the proceedings isn't even a member – Grover Norquist, president of Americans for Tax Reform. Mr. Norquist, a pillar of conservative activism in Washington, encourages lawmakers to sign a pledge to not raise taxes.	"Populist_leader": "Risk_Score": 0.7, "Confidence": 0.9, "Populist_policy": "Risk_Score": 0.6, "Confidence": 0.8, "Populist_rhetoric": "Risk_Score": 0.8, "Confidence": 0.9
04-Sep-2018	Growth lifts GOP candidates in some tight races, but tariffs, taxes and local factors leave others vulnerable	At the same time, a sizable number of competitive districts – almost all currently Republican – are vulnerable to new tariffs, a new cap on deductions for state and local income taxes, or a jobs picture worse than the national average.	"Populist_leader": "Risk_Score": 0.7, "Confidence": 0.8, "Populist_policy": "Risk_Score": 0.8, "Confidence": 0.9,
07-Feb-2023	U.S. News: McCarthy Targets Eliminating Deficit — Debt-cap stance would likely require massive budget cuts; White House rips demand	House Speaker Kevin McCarthy said Republicans would seek to eliminate the annual budget deficit in talks with Democrats over raising the debt limit, a demand that would likely require deep cuts to federal spending.	"Populist_movement":"Risk_Score": 0.7, "Confidence": 0.8, "Populist_policy": "Risk_Score": 0.8, "Confidence": 0.9, "Populist_rhetoric": "Risk_Score": 0.9, "Confidence": 0.9

This table presents WSJ articles identified by the LLM as linking populist narratives to financial or macroeconomic risks. For each article, we show the publication date, title, content excerpts, and the model's analytical reasoning based on the framework in Prompt A.1. Bold text highlights sentences cited by the LLM as supporting evidence for this classification.

Table E.11: Examples of Different Dimensions of Populism in The WSJ as Identified by LLM

Date	Title	Content	Intensity Score
05-Dec-2019	U.S. News: Biden Proposes New Corporate Taxes	One of his new taxes would go after companies such as Amazon.com Inc. that have years when they report profits to investors but show little or no U.S. tax costs. A second would double the minimum tax rate on overseas income of U.S.-based multinationals.	"Populist_policy": "Intensity_Score": 0.8, "Confidence": 0.9 POP = 0.8, POP_Avg = 0.2, POP_Max= 0.8, POP_Min= 0.8
09-Sep-2015	'Black Lives Matter' – but Reality, Not So Much	Ultimately, it's a political movement, the inevitable extension of a racial and ethnic spoils system that helps Democrats get elected. The Black Lives Matter narrative may be demonstrably false, but it's also politically expedient.	"Populist_movement":Intensity_Score": 0.8, "Populist_rhetoric":Intensity_Score": 0.9, POP = 0.85, POP_Avg = 0.45, POP_Max= 0.9, POP_Min= 0.8
26-Apr-1995	Anti-Immigrant Measures of the Past Bear Striking Resemblance to Today	Today, California, Texas and Florida are suing the federal government to recover billions of dollars they say are spent for federally mandated immigrant services.	"Populist_movement":Intensity_Score": 0.7, "Populist_policy": Intensity_Score": 0.8, "Populist_rhetoric": Intensity_Score": 0.9, POP = 0.8, POP_Avg = 0.6, POP_Max= 0.9, POP_Min= 0.7
29-Oct-2010	Why Business Should Fear the Tea Party	Maybe business leaders see it as a relatively harmless fringe group advocating the fiscally responsible small-government positions most CEOs agree with. Business leaders should take a closer look. Beyond fiscal rectitude and less spending, tea party candidates are targeting the central institutions of American government.	"Populist_leader": Intensity_Score": 0.8, "Populist_movement": Intensity_Score": 0.9, "Populist_policy": Intensity_Score": 0.7, "Populist_rhetoric": Intensity_Score": 0.8, POP = 0.8, POP_Avg = 0.8, POP_Max= 0.9, POP_Min= 0.7

This table presents WSJ article examples identified by the LLM as reflecting four key dimensions of populist sentiment: leaders, movements, policies, and rhetoric. For each article, we show the publication date, title, content excerpts, and the model's analytical reasoning based on the framework in Prompt A.1. Bold text highlights sentences cited by the LLM as supporting evidence for classification.

Table E.12: Examples of Populism Articles in the WSJ identified by different LLMs

Date	Title	Populist Dimension	LLM	Intensity Type	Intensity Score	Confidence	Rationale
20-Jan-2017	The 45th President: Presidency of Firsts and Familiarity — Trump has qualities that set him apart from predecessors and spur comparisons	Leader	GPT-4o-mini	True	0.6	0.8	The article highlights Trump's appeal to working-class families and his populist message.
			GPT-5.5	True	0.75	0.9	Trump is explicitly discussed as a distinctive president with an economic populist strand and a message appealing to working-class families.
			gemini-2.5-pro	True	0.8	0.9	The article analyzes Donald Trump, explicitly identifying him as an \"economic populist\" by comparing him to Andrew Jackson. The tone is analytical and historical, not opinionated.
			gemini-3.1-pro	True	0.8	0.9	The article explicitly identifies Trump's victory as driven by a populist message and compares him to Andrew Jackson, an economic populist.
			claude-sonnet-4-6	True	0.8	0.9	Trump is explicitly compared to Andrew Jackson as an 'economic populist' and portrayed as championing working-class families against elites, core populist leader characteristics.
			claude-opus-4-7	True	0.85	0.9	Trump is explicitly compared to Andrew Jackson as an 'economic populist' and portrayed as championing working-class families against elites, core populist leader characteristics.
08-Jan-2021	CEOs Fire Rioters, Condemn Violence Movement		GPT-4o-mini	True	0.7	0.8	The article describes the violent actions of rioters at the Capitol as a populist movement that threatens societal stability.
			GPT-5.5	True	0.8	0.88	The Capitol riot by Trump supporters is treated as a violent political mobilization linked to authoritarianism and instability, fitting a populist movement signal.
			gemini-2.5-pro	True	0.9	0.95	The article focuses on the negative consequences for participants in the Capitol riot, which is consistently framed as a violent, dangerous event. Companies are firing employees who participated, and the event is described as a 'takeover'.
			gemini-3.1-pro	True	0.9	0.9	The text details the corporate condemnation and firing of employees who participated in the violent Capitol riot, a populist mobilization.
			claude-sonnet-4-6	True	0.9	0.95	Capitol riot framed as violent anti-establishment mobilization by Trump supporters attacking democratic institutions, described as 'Authoritarian movement' threatening constitutional order.

			claude-opus-4-7	True	0.95	0.95	Capitol riot framed as violent demonstration by Trump supporters against established institutions, representing core populist mobilization against elites.
20-Dec-2011	Liberals Love the 1%	Policy	GPT-4o-mini	True	0.7	0.9	The article highlights tax policies that favor large corporations while burdening smaller businesses, indicating a populist policy approach.
			GPT-5.5	True	0.55	0.78	The article criticizes tax hikes, corporate carve-outs, and alleged efforts to 'soak the rich,' linking them to business flight, revenue loss, and deficits.
			gemini-2.5-pro	True	0.8	0.9	The article critiques tax policies that provide special breaks to large, politically connected firms, framing them as benefiting an elite '1%' at the expense of the '99%', leading to budget deficits.
			gemini-3.1-pro	False	0	0.9	The article discusses state tax policies and corporate welfare, but not populist policies like tariffs or income redistribution to the masses.
			claude-sonnet-4-6	True	0.7	0.85	The article criticizes Illinois Democrats for using large tax hikes framed as soaking the rich, then granting selective tax relief to powerful corporations, exposing the contradictions of populist-style redistribution rhetoric.
			claude-opus-4-7	True	0.4	0.6	Article critiques tax-the-rich populist policy framing, arguing it benefits connected elites at expense of small business.
13-Apr-2000	Under the Radar, Buchanan Nears Reform Nomination	Rhetoric	GPT-4o-mini	True	0.8	0.9	Buchanan's rhetoric emphasizes a stark divide between the establishment and the people.
			GPT-5.5	True	0.9	0.95	Buchanan uses clear anti-establishment and anti-corporate rhetoric, framing politics as ordinary Americans versus corrupt elites.
			gemini-2.5-pro	True	0.9	1	The article extensively quotes Buchanan's anti-establishment and 'us vs. them' language, portraying a corrupt elite of corporate lobbyists controlling both major political parties against the people's interests.
			gemini-3.1-pro	True	0.9	0.9	Buchanan uses strong anti-establishment language, framing the major parties as controlled by corporate lobbyists who have sold out the people.
			claude-sonnet-4-6	True	0.95	0.95	Buchanan employs intense anti-elite, us-versus-them rhetoric, framing both major parties as controlled by corporate interests and betraying ordinary Americans.

	claude-opus-4-7	True	0.95	0.95	Intense anti-elite, us-versus-them rhetoric pervades the article. Buchanan frames politics as people versus corrupt establishment, attacks corporate control, and uses nationalist language.

This table presents examples of WSJ articles that are identified as populism-related by different LLMs, including GPT-4o-mini and GPT-5.5 from OpenAI, Gemini 2.5 Pro and Gemini 3.1 Pro from Google DeepMind, and Claude Sonnet 4.6 and Claude Opus 4.7 from Anthropic.

Table E.13: Examples of Non-Populism Articles in the WSJ identified by different LLMs

Date	Title	Populist Dimension	LLM	Intensity Type	Intensity Score	Confidence	Rationale
02-June-2000	Gore Proposes More Spending for War on Cancer	Leader	GPT-4o-mini	False	0	0.8	The article discusses Al Gore's cancer proposal without framing him as a populist leader.
			GPT-5.5	False	0	0.95	The article discusses Al Gore's cancer policy proposal, not a leader claiming exclusive representation of the people against elites.
			gemini-2.5-pro	False	0	1.0	The article portrays Al Gore as a mainstream candidate proposing a health policy. There is no language suggesting he is an anti-elite figure representing 'the people' against an establishment.
			gemini-3.1-pro	False	0	1.0	The article discusses Al Gore's mainstream healthcare and research funding proposals without any framing of him representing the 'pure people' against a 'corrupt elite'.
			claude-sonnet-4-6	False	0.1	0.85	Gore is presented as a mainstream Democratic candidate with policy proposals, not framing himself as a voice of 'the people' against elites. No populist leader framing is evident.
			claude-opus-4-7	False	0	0.95	No populist leader characteristics present. Gore presents as mainstream Democratic candidate without anti-elite rhetoric or claims to solely represent 'the people'.
24-Mar-2018	Nike Rides Out #MeToo Moment	Movement	GPT-4o-mini	False	0	0.7	No indication of a populist movement being discussed.
			GPT-5.5	False	0	0.98	The #MeToo movement is mentioned as a social context, but not framed as populist conflict between people and elites.
			gemini-2.5-pro	False	0	1.0	The article mentions the #MeToo movement in the context of corporate accountability, not as a political populist movement as defined.
			gemini-3.1-pro	False	0	1.0	The article discusses the #MeToo movement in a corporate workplace context, which does not fit the political populist movement definition.
			claude-sonnet-4-6	False	0	0.95	No populist social or political mobilization is referenced. The #MeToo movement is mentioned but as a cultural reckoning, not a populist people-vs-elite framing.
			claude-opus-4-7	False	0	0.95	No populist movement is present. The #MeToo movement referenced is a social movement around workplace harassment, not a populist people-versus-elite political mobilization.

			GPT-4o-mini	False	0	0.5	No discussion of populist policies.
			GPT-5.5	False	0	0.97	The article concerns routine government borrowing operations, not redistribution, nationalism, tariffs, immigration restrictions, or institutional attacks.
			gemini-2.5-pro	False	0	1	The article describes a routine government debt sale, not a policy framed in populist terms like nationalism or anti-globalization.
20-Jan-2017	Treasury Sets Sales of $165 Billion Debt	Policy	gemini-3.1-pro	False	0	1	The article does not mention any populist policy.
			claude-sonnet-4-6	False	0	0.9	Article is a routine Treasury debt auction announcement with no populist policy elements.
			claude-opus-4-7	False	0	1	Article describes routine Treasury debt auctions with no populist policy elements like tariffs, redistribution, or anti-globalization measures.
			GPT-4o-mini	False	0	0.8	The article does not contain populist rhetoric.
			GPT-5.5	False	0	0.95	The article contains no anti-elite, us-versus-them, nationalist-populist, or protectionist slogans or framing.
			gemini-2.5-pro	False	0	1.0	The article's language focuses on diplomatic realism and strategic interests ('U.S. interests', 'checks China's influence'), lacking any populist 'us vs. them' or anti-elitist rhetoric.
24-July-2010	Smarter Obama Diplomacy	Rhetoric	gemini-3.1-pro	False	0	1.0	The article does not contain any 'us vs. them' framing or anti-elitist populist rhetoric.
			claude-sonnet-4-6	False	0	0.9	No us-vs-them framing, anti-elitist language, or populist slogans are present. The tone is analytical and policy-focused throughout.
			claude-opus-4-7	False	0	0.9	No populist rhetoric is present. The article uses diplomatic and policy-focused language without 'us vs. them' or anti-elite framing.

This table presents examples of WSJ articles that are identified as not populism-related by different LLMs, including GPT-4o-mini and GPT-5.5 from OpenAI, Gemini 2.5 Pro and Gemini 3.1 Pro from Google DeepMind, and Claude Sonnet 4.6 and Claude Opus 4.7 from Anthropic.