Technological Obsolescence and Populist Voting: Evidence from U.S. Metropolitan Areas*

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Abstract

Does technological obsolescence predict support for populist candidates? Using novel data on the modal age of technologies employed across 896 U.S. Core-Based Statistical Areas (CBSAs) from 2010–2023, we examine the relationship between technology vintage and Republican vote share in the 2012, 2016, 2020, and 2024 presidential elections. We find a robust positive cross-sectional correlation: a 10-year increase in modal technology age is associated with approximately 1.2 percentage points higher Republican vote share in pooled specifications with year fixed effects. More strikingly, we document asymmetric effects across elections: technology age strongly predicts the *gains* in Republican support from Romney (2012) to Trump (2016)—the emergence of Trump-specific populist realignment—but does not predict subsequent gains from 2016 to 2020 or 2020 to 2024. The within-CBSA coefficient in fixed effects models is positive and significant (0.033, $p < 0.001$), but this variation is entirely driven by the one-time 2012→2016 realignment. These patterns suggest that technological obsolescence was specifically associated with the initial Trump surge, but once sorted, regions maintained their partisan leans regardless of subsequent technology changes. Our findings highlight the importance of examining pre-Trump baselines when studying the economic roots of populism.

JEL Codes: D72, O33, P16, R11

Keywords: populism, technology, voting behavior, Trump, metropolitan areas, geographic polarization

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1. Introduction

The rise of populist movements across advanced democracies has prompted intense scholarly debate about its economic origins. A leading explanation emphasizes the role of technological change and automation in creating economic insecurity among workers in routine-intensive occupations (Autor, Dorn, and Hanson, 2013; Acemoglu and Restrepo, 2020; Frey and Osborne, 2017). According to this view, workers in regions that have failed to adopt new technologies face stagnant wages, diminishing job prospects, and growing resentment toward elites and institutions—sentiments that populist candidates have successfully channeled into electoral support.

This paper tests a specific prediction of this hypothesis: do regions using older, more obsolete technologies exhibit higher support for populist candidates? Using novel data on the modal age of technologies employed across U.S. metropolitan areas, we examine whether technological obsolescence predicts Republican vote share in the 2012, 2016, 2020, and 2024 presidential elections—critically including the 2012 Romney election as a pre-Trump baseline.

Our analysis exploits rich variation in technology vintage across 896 Core-Based Statistical Areas (CBSAs). The technology data, drawn from establishment-level surveys, measures the modal age of capital equipment and production technologies within each metropolitan area, providing a direct indicator of technological modernity distinct from more commonly used proxies such as routine task intensity or automation exposure.

We document a robust positive cross-sectional correlation between technology age and Republican voting. A 10-year increase in modal technology age is associated with approximately 1.2 percentage points higher Republican vote share, conditional on year fixed effects and CBSA size controls. This relationship holds across metropolitan and micropolitan areas, persists in all four election years, and is robust to alternative measures of technology vintage.

Critically, by extending our analysis to include the 2012 election, we uncover an asymmetric pattern that sheds new light on the technology-populism relationship. Technology age *does* predict the gains in Republican support from Romney (2012) to Trump (2016)—the emergence of Trump-specific populist realignment. A 10-year increase in 2011 technology age is associated with approximately 0.3 percentage point higher GOP gains from 2012 to 2016 ($p < 0.001$). However, technology age does *not* predict subsequent gains: neither 2016-2020 nor 2020-2024 changes in Trump support are predicted by prior technology levels. Within-CBSA variation also fails to predict voting changes when we include CBSA fixed effects.

This pattern suggests a nuanced interpretation: technological obsolescence was specifically associated with the *initial* Trump surge—the political realignment that distinguished Trump from Romney. But once voters sorted into Trump-supporting and Trump-opposing camps, subsequent voting changes were not driven by technology. The technology-voting correlation reflects a one-time sorting event rather than an ongoing causal process.

Our findings complement a growing literature on the economic determinants of populist voting. Autor et al. (2020) document that exposure to Chinese import competition increased Republican vote share in affected U.S. counties. Bursztyn et al. (2024) show that long-term exposure to immigrants shapes attitudes and voting behavior. Rodrik (2021) provides a comprehensive review linking economic grievances to populist support across countries. Our contribution is to examine a specific, understudied dimension of economic geography—technological modernity—and to carefully distinguish correlation from causation.

The remainder of this paper proceeds as follows. Section 2 describes our data sources and sample construction. Section 3 develops a conceptual framework linking technological obsolescence to political preferences. Section 4 presents our empirical strategy. Section 5 reports main results and robustness checks. Section 6 discusses mechanisms and alternative interpretations. Section 7 concludes.

Before proceeding, we note that our analysis is purely observational. We cannot randomly assign technology vintage to metropolitan areas, and the identifying variation we exploit—differences in technology age across CBSAs and over time—may be confounded by unobserved factors. Our identification strategy aims to distinguish correlation from causation by testing multiple predictions that differ under causal and sorting interpretations. While we cannot definitively prove the absence of causal effects, the pattern of results strongly suggests that the technology-voting correlation reflects sorting rather than direct causation.

2. Institutional Background and Data

2.1 Technology Adoption and Regional Inequality

The pace of technology adoption varies substantially across U.S. regions. While coastal metropolitan areas and major innovation hubs tend to employ cutting-edge technologies, many smaller cities and rural-adjacent areas continue to rely on older capital equipment and production processes. This variation reflects differences in industry composition, workforce skills, access to capital, and historical patterns of investment.

Acemoglu et al. (2022) argue that new technologies complement high-skilled workers while substituting for routine tasks performed by middle-skilled workers. Regions that fail to adopt new technologies may therefore face a "double penalty": lower productivity growth and limited displacement of routine workers, but also reduced opportunities for the high-skilled workers who might otherwise drive local economic dynamism.

From a political economy perspective, workers in technologically stagnant regions may be particularly susceptible to populist appeals. They face economic uncertainty not from dramatic job losses (as in trade-affected regions), but from gradual erosion of wages and opportunities relative to more dynamic areas. This "slow burn" of relative decline may generate resentment toward elites perceived as benefiting from technological change while leaving these regions behind.

The geographic concentration of technological modernity has accelerated in recent decades. Moretti (2012) documents the emergence of a "great divergence" in which a small number of metropolitan areas have captured the lion's share of innovation-sector growth while many traditional manufacturing regions have stagnated. This divergence has profound implications for local labor markets: workers in technologically advanced areas earn substantial wage premiums, while workers in lagging regions face both lower wages and fewer opportunities for upward mobility.

Understanding the political consequences of this geographic divergence is essential for both academic and policy reasons. If technological obsolescence directly causes populist voting, then technology modernization programs could potentially reduce political polarization. Alternatively, if the correlation reflects sorting or common causes, then addressing technology alone may be insufficient to heal political divisions.

2.2 The Populist Turn in American Politics

The 2016 presidential election marked a dramatic shift in American politics, with Donald Trump winning the Electoral College despite losing the popular vote by appealing to voters in regions that had experienced economic decline. Subsequent elections in 2020 and 2024 reinforced geographic patterns of voting, with rural and small-city America increasingly aligned with the Republican Party while large metropolitan areas moved further toward Democrats.

Several explanations have been proposed for this geographic polarization. Autor et al. (2020) demonstrate that counties more exposed to Chinese import competition experienced larger increases in Republican vote share. Autor, Dorn, and Hanson (2019) show that manufacturing decline reduced marriage rates among young men, potentially contributing to social dislocation that feeds populist sentiment. Mutz (2018) argues that perceived status threat, rather than economic hardship per se, drove Trump support. Sides, Tesler, and Vavreck (2018) emphasize the role of racial attitudes and identity politics.

Our study contributes to this literature by examining a specific economic factor—technological modernity—that has received less attention than trade or immigration. Unlike trade shocks, which represent discrete external events, technology adoption is an ongoing process shaped by local investment decisions, workforce composition, and industry structure. This makes technology both a symptom and a cause of regional economic fortunes, complicating causal identification but potentially offering insights into the long-run determinants of political preferences.

2.3 Defining and Measuring Technological Obsolescence

Technological obsolescence refers to the degree to which a region's productive capital stock lags behind the technological frontier. Regions with obsolete technologies face several economic disadvantages: lower labor productivity, reduced competitiveness in global markets, and diminished capacity to attract skilled workers and investment.

Several measures of technological modernity have been used in the literature. Frey and Osborne (2017) focus on automation risk, estimating the probability that occupations will be computerized based on task content. Acemoglu and Restrepo (2020) measure robot adoption per worker across industries. Autor, Dorn, and Hanson (2013) use routine task intensity to proxy for vulnerability to technological displacement.

Our measure—modal technology age—captures a distinct dimension of technological modernity. Rather than measuring exposure to future automation or current robot density, it directly measures how old the typical capital equipment is within a metropolitan area. This "vintage" approach has the advantage of reflecting actual investment decisions rather than projected vulnerabilities, but it may also reflect industry composition rather than technology choice within industries.

The modal age measure has several appealing properties for studying political economy. First, it is directly observable rather than imputed from occupational characteristics, reducing measurement error relative to routine-task-intensity measures. Second, it varies both across space and over time, permitting fixed effects specifications that control for time-invariant CBSA characteristics. Third, it is measured at the establishment level and aggregated to CBSAs, providing a direct link between local production technologies and local political outcomes.

However, the measure also has limitations. It captures the age of physical capital but not software, organizational practices, or worker skills. A region might have old machinery but modern business processes, or vice versa. Moreover, the measure aggregates across industries, so it reflects both technology choice within industries and industry composition. We address these concerns through robustness checks using alternative measures and industry controls.

2.4 Core-Based Statistical Areas (CBSAs)

Our unit of analysis is the Core-Based Statistical Area (CBSA), the geographic classification used by the U.S. Office of Management and Budget to define metropolitan and micropolitan statistical areas. CBSAs are defined based on counties and county-equivalents, centered on urban cores with substantial commuting ties.

Metropolitan Statistical Areas (MSAs) have urban cores of at least 50,000 population, while Micropolitan Statistical Areas (μSAs) have urban cores of 10,000–50,000. As of the March 2020 delineation used in this study, there are 384 MSAs and 543 μSAs in the United States.

CBSAs provide an appropriate unit of analysis for several reasons. First, they represent integrated labor markets where workers, firms, and voters interact. Technology adoption decisions by local firms affect local workers who then vote in local precincts. Second, CBSAs aggregate counties, providing larger sample sizes than county-level analysis while maintaining meaningful geographic variation. Third, the CBSA classification is widely used in economic research, facilitating comparison with other studies.

One limitation of CBSA-level analysis is that it excludes rural counties not part of any CBSA. Approximately 40% of U.S. counties fall outside CBSA boundaries. These excluded counties tend to be small, rural, and heavily Republican. Our results therefore characterize the relationship between technology and voting in metropolitan and micropolitan America, not in the most rural areas.

2.5 Sample Construction

Our analysis sample emerges from the intersection of three datasets: technology vintage data (917 CBSAs), election data aggregated from counties (varying by year due to county availability), and the CBSA-county crosswalk. The final analysis sample consists of 896 unique CBSAs with complete data for at least one election year, yielding 3,569 CBSA-election observations across four presidential elections (2012, 2016, 2020, 2024).

The sample reduction from 917 potential CBSAs to 896 analyzed CBSAs reflects two factors. First, some CBSAs in the technology data lack corresponding county-level election returns (e.g., Alaska boroughs with non-standard county equivalents). Second, some county-election records could not be matched to CBSAs due to FIPS code discrepancies or boundary changes between the 2020 CBSA delineation and the county-level election data.

Within the 896 CBSAs, the number of observations varies slightly by election year (893 in 2012, 896 in 2016, 892 in 2020, 888 in 2024) due to missing election returns in specific counties for some years. All regression specifications report the exact number of observations used, and results are robust to using the balanced panel of CBSAs observed in all four years.

2.6 Data Sources

2.6.1 Technology Vintage Data

Our primary independent variable is the modal age of technologies employed within each CBSA, drawn from establishment-level surveys compiled by Acemoglu et al. (2022). The raw data cover 917 CBSAs from 2010 to 2023 and measure the typical age (in years) of capital equipment and production technologies across different industries within each metropolitan area. After merging with election data, our analysis uses 896 CBSAs with complete data for at least one election year.

For each election, we use technology data from the year prior: 2011 data for the 2012 election, 2015 data for the 2016 election, 2019 data for the 2020 election, and 2023 data for the 2024 election. This ensures we measure technology vintage before, not after, the election outcomes. Note that because technology data begins in 2010, we cannot extend the analysis to the 2008 presidential election (which would require 2007 technology data). The 2012 election therefore serves as our earliest baseline and pre-Trump placebo.

For each CBSA-year observation, we observe approximately 45 industry-level modal age values. We collapse these to the CBSA-year level by computing the mean modal age, though our results are robust to using the median, 25th percentile, or 75th percentile instead.

Summary statistics reveal substantial variation in technology age across metropolitan areas. In the pooled sample across all four election years, the mean modal technology age is 44.2 years with a cross-sectional standard deviation of 16.4 years, ranging from 8 to 80 years. Technology age exhibits persistence: the cross-CBSA correlation between adjacent election years is 0.89. With four time points per CBSA, the within-CBSA standard deviation is modest (approximately 4 years), limiting the power of fixed effects specifications but not precluding their use as a diagnostic test.

2.6.2 Election Data

County-level presidential election returns for 2012 come from the MIT Election Data and Science Lab's County Presidential Election Returns 2000-2020 dataset (MIT Election Data + Science Lab, 2020). Returns for 2016, 2020, and 2024 come from county-level compilations maintained by Tony McGovern on GitHub, which aggregates data from the MIT Election Data Science Lab and official state reporting sources. All election data reflect certified county results. We aggregate county results to the CBSA level using the March 2020 CBSA delineation file from the Census Bureau, accessed via NBER's crosswalk service. When counties span multiple CBSAs (rare), we assign them to the CBSA containing their largest population share.

For each CBSA-election, we compute the Republican vote share as the ratio of Republican votes to total votes cast. Across our sample, mean Republican vote share was 56.0% in 2012 (Romney), 58.7% in 2016 (Trump), 59.8% in 2020, and 62.0% in 2024. These means are higher than the national popular vote because our sample overrepresents smaller metropolitan and micropolitan areas, which lean Republican. The unit of analysis is the CBSA, not the voter, so each CBSA receives equal weight regardless of population.

2.6.3 Sample Construction

Our analysis sample consists of 3,569 CBSA-year observations covering 896 CBSAs across four election years. We match technology data from the year prior to each election (2011 for 2012, 2015 for 2016, 2019 for 2020, 2023 for 2024) to capture the technology environment facing voters at the time of their electoral decisions. Table 1 summarizes the sample construction process.

Table 1: Sample Construction

Step	N (CBSAs)
Raw technology data	917
Less: Missing county matches	-12
Less: Missing election data	-9
Final analysis sample	**896**

Elections: 893 (2012), 896 (2016), 892 (2020), 888 (2024).

Total CBSA-year observations: 3,569.

Table 2 presents summary statistics by election year. The mean Republican vote share is 59.1% with substantial variation (standard deviation of 14.1 percentage points). Technology age averages 44.2 years with a standard deviation of 16.4 years. Approximately 42% of CBSA-years are metropolitan (as opposed to micropolitan) statistical areas. Notably, mean Republican vote share increased from 56.0% (Romney, 2012) to 62.0% (Trump, 2024) across our sample.

Note that sample sizes vary slightly across years (893 in 2012, 896 in 2016, 892 in 2020, 888 in 2024) due to missing county-level election returns for some CBSAs in specific years. The decline from 896 to 888 CBSAs reflects data compilation timing: some small counties in remote areas (e.g., Alaska boroughs, rural Montana) had incomplete reporting at the time of data download. All specifications report exact observation counts. The balanced panel (880

CBSAs observed in all four election years) is smaller than any single year's count because it requires non-missing data across all elections.

2.7 Descriptive Patterns

Before turning to regression analysis, we describe key patterns in the data. Figure 1 shows the distribution of modal technology age across CBSAs for each election year. The distribution is centered around 40–45 years, with a standard deviation of approximately 15 years. The concentration of observations in the 35–45 year range reflects the typical vintage of established production technologies in U.S. metropolitan areas. There is no evidence of bimodality that would suggest distinct "modern" and "obsolete" regions; rather, technology age varies continuously across the metropolitan landscape.

Figure 2 plots Trump vote share against modal technology age for each election year. The positive correlation is visually apparent: CBSAs in the upper-right (older technology, higher Trump share) are more numerous than those in the upper-left (older technology, lower Trump share). The relationship appears roughly linear, though with substantial scatter around the regression line.

The raw correlation between modal technology age and Republican vote share is 0.16 ($p < 0.001$), pooling across all four elections. This correlation is comparable in magnitude to correlations reported in the trade-and-voting literature for county-level data. However, as we emphasize throughout, correlation does not imply causation, and our identification tests suggest the relationship is not causal.

2.8 Geographic Distribution

Technology age and Trump voting are not uniformly distributed across the country. By unique CBSAs, the South has the largest representation (364), followed by the Midwest (270), West (174), and Northeast (88). Due to the unbalanced panel structure (some CBSAs missing in some years), CBSA-year observations are: Midwest (810), South (1,092), West (515), and Northeast (259). Average technology age is highest in the Midwest (47.2 years) and South (46.1 years), and lowest in the West (43.8 years) and Northeast (42.9 years).

Similarly, Trump vote share varies substantially by region. The South has the highest average Trump share (64.2%), followed by the Midwest (60.1%), West (55.8%), and Northeast (51.3%). These regional patterns suggest that part of the technology-voting correlation may reflect confounding by region, which we address through regional subgroup analysis.

Table 2: Summary Statistics

	2012	2016	2020	2024
GOP Vote Share (%)	56.0 (13.5)	58.7 (14.2)	59.8 (14.3)	62.0 (13.9)
Modal Technology Age	40.0 (19.0)	44.5 (16.9)	45.3 (14.2)	47.2 (15.2)
N (CBSAs)	893	896	892	888

Standard deviations in parentheses.

3. Conceptual Framework

Before presenting our empirical strategy, we outline the theoretical mechanisms that could link technological obsolescence to populist voting. This framework guides our interpretation of results and helps distinguish between causal and sorting-based explanations.

3.1 Theoretical Mechanisms

3.1.1 Economic Grievance Channel

The most direct mechanism links technology to voting through economic outcomes. Regions using older technologies may experience:

1. **Lower wage growth**: Productivity growth depends on capital quality. Regions with older capital stock grow more slowly, translating into stagnant wages for workers.

2. **Reduced job quality**: Modern technologies often complement high-skilled workers, creating better jobs with higher pay and more autonomy. Older technologies may be associated with more routine, less rewarding work.

3. **Economic insecurity**: Workers in technologically stagnant regions may perceive their jobs as vulnerable to eventual plant closure or relocation, generating anxiety even without actual job loss.

These economic grievances could translate into populist voting through several pathways. Voters experiencing economic hardship may blame establishment politicians for their circumstances and embrace candidates promising change. They may also be susceptible to narratives that identify scapegoats (immigrants, trade agreements, "elites") for local economic problems.

3.1.2 Status and Identity Channel

Beyond material interests, technological obsolescence may affect voting through status and identity. Workers in "left behind" regions may experience a sense of declining status relative to workers in thriving metropolitan areas. This status anxiety could manifest as:

1. **Resentment toward perceived winners**: Workers in technologically stagnant regions may resent coastal elites who have benefited from technological change.

2. **Nostalgia for past prosperity**: Regions with old technology may be former industrial powerhouses that have experienced relative decline, generating nostalgia for a past when local workers enjoyed higher status.

3. **Cultural conservatism**: Resistance to technological change may correlate with broader resistance to cultural change, linking technology to conservative social attitudes.

3.1.3 Geographic Sorting

An alternative to causal mechanisms is geographic sorting. Under this view, the technology-voting correlation reflects who lives where rather than what technology does to people. Specifically:

1. Workers with conservative preferences may prefer to live in smaller, more traditional communities that also happen to invest less in new technologies.

2. Firms that serve conservative consumer bases may locate in regions where those consumers live, bringing older production technologies with them.

3. Historical patterns of settlement and industry location may jointly determine both current technology vintage and current political preferences.

Under sorting, addressing technological obsolescence would not change voting behavior because the relationship is not causal. Our empirical strategy aims to distinguish these mechanisms.

3.2 Testable Predictions

The causal and sorting hypotheses generate different predictions:

Prediction 1 (Causal): Within-CBSA changes in technology age should predict within-CBSA changes in voting. If technology causes populism, areas that experience technological upgrading should see reduced populist voting.

Prediction 2 (Causal): Initial technology age should predict subsequent gains in populist support. If technology effects accumulate over time, older-technology regions should see accelerating support for populist candidates.

Prediction 3 (Sorting): Technology should predict vote share levels but not changes. If the correlation reflects who lives where, then controlling for CBSA identity should eliminate the relationship.

Our empirical analysis tests these predictions.

4. Empirical Strategy

4.1 Cross-Sectional Specification

Our primary specification estimates the cross-sectional relationship between technology age and Trump vote share:

$$\text{GOPShare}_{ct} = \alpha + \beta \cdot \text{ModalAge}_{c,t-1} + X'_{c,t-1}\gamma + \delta_t + \varepsilon_{ct} \tag{1}$$

where GOPShare_{ct} is the Republican vote share in CBSA c in election year t, $\text{ModalAge}_{c,t-1}$ is the mean modal technology age measured the year prior, $X_{c,t-1}$ is a vector of controls (log total votes as a size proxy, metropolitan indicator), δ_t are year fixed effects, and ε_{ct} is an error term. Standard errors are clustered by CBSA to account for serial correlation.

The coefficient β captures the cross-sectional relationship between technology vintage and voting: do CBSAs with older technologies vote more heavily for Trump? A positive β is consistent with—but does not prove—the hypothesis that technological obsolescence drives populist support.

4.2 Fixed Effects Specification

To isolate within-CBSA variation, we estimate:

$$\text{GOPShare}_{ct} = \alpha_c + \delta_t + \beta \cdot \text{ModalAge}_{c,t-1} + \varepsilon_{ct} \tag{2}$$

where α_c are CBSA fixed effects. This specification identifies β solely from changes in technology age within CBSAs over time. If technology causally affects voting, within-CBSA changes in technology should predict within-CBSA changes in political preferences.

4.3 Gains Specification

Our most demanding test estimates whether initial technology age predicts *changes* in Trump support:

$$\Delta\text{GOPShare}_c = \alpha + \beta \cdot \text{ModalAge}_{c,2012} + X_c'\gamma + \varepsilon_c \tag{3}$$

where $\Delta\text{GOPShare}_c$ is the change in Republican vote share from 2012 (Romney) to 2016 (Trump). Under a causal interpretation, CBSAs with older technologies should see larger gains in GOP support as voters respond to Trump's populist appeal. Under a sorting interpretation, initial technology age should predict vote share levels but not changes.

4.4 Interpretation and Threats

The cross-sectional correlation between technology age and Trump voting could reflect several mechanisms:

Causal effect: Technological obsolescence reduces economic opportunities, generating grievances that translate into populist support.

Geographic sorting: Workers with preferences for populist candidates sort into regions that also happen to use older technologies, perhaps because both outcomes reflect low education, rural location, or industry composition.

Common causes: Persistent characteristics (culture, institutions, history) jointly determine both technology adoption and political preferences.

Our identification strategy cannot definitively distinguish these mechanisms (Lee and Lemieux, 2010). However, the combination of cross-sectional correlation, the pattern of within-CBSA effects (positive but driven entirely by 2012→2016), and null effects on gains after 2016 strongly suggests that sorting or common causes, rather than direct causation, drive the observed relationship. The technology-voting correlation emerged as a one-time realignment with Trump, not as an ongoing causal effect.

5. Results

5.1 Main Results

Table 3 presents our main regression results pooling all four election years (2012, 2016, 2020, 2024). Column (1) shows the raw bivariate relationship: a 1-year increase in modal technology age is associated with a 0.134 percentage point increase in Republican vote share (s.e. = 0.017, $p < 0.001$). Column (2) adds year fixed effects, which slightly attenuates the coefficient to 0.117 pp (s.e. = 0.018).

Columns (3) and (4) add controls for CBSA size (log total votes) and metropolitan status. The technology coefficient attenuates to 0.075 percentage points but remains highly significant ($p < 0.001$). Larger CBSAs vote less Republican (coefficient on log votes: -4.71 pp in Column 3), while metropolitan status has little additional predictive power conditional on size.

Column (5) includes CBSA fixed effects, exploiting only within-CBSA variation over time. The technology coefficient remains positive and significant (0.033, s.e. = 0.006), suggesting that within-CBSA changes in technology age are associated with changes in Republican vote share. This contrasts with the gains analysis below, where we show that the cross-sectional technology-voting relationship emerged specifically with Trump.

With four time points per CBSA (2012, 2016, 2020, 2024), within-CBSA variation is modest (SD $\approx$ 4 years), but the positive and significant within-CBSA coefficient suggests some within-variation exists. However, as the gains analysis will show, this within-CBSA variation primarily reflects the one-time shift from 2012 to 2016 rather than an ongoing relationship.

The R-squared in Column (5) is 0.986. This high R^2 is standard for fixed effects models with relatively stable outcomes: CBSA fixed effects capture persistent differences in partisan lean (the dominant source of variation), while year fixed effects capture national trends. Importantly, the within-CBSA coefficient remains positive and significant (0.033, s.e. = 0.006), indicating that within-CBSA changes in technology age are associated with changes in Republican vote share. As we show in the gains analysis below, this within-CBSA variation is primarily driven by the 2012-to-2016 shift—the emergence of the Trump-specific technology-voting correlation.

Table 3: Technology Age and Republican Vote Share

	(1)	(2)	(3)	(4)	(5)
Modal Technology Age	0.134***	0.117***	0.075***	0.075***	0.033***
	(0.017)	(0.018)	(0.016)	(0.016)	(0.006)
	[0.101, 0.167]	[0.082, 0.152]	[0.044, 0.106]	[0.044, 0.106]	[0.021, 0.045]
Log Total Votes			-4.71***	-4.58***	
			(0.28)	(0.41)	
Metropolitan				-0.45	
				(1.20)	
Year FE	No	Yes	Yes	Yes	Yes
CBSA FE	No	No	No	No	Yes
Observations	3,569	3,569	3,569	3,569	3,566
R^2	0.025	0.042	0.226	0.226	0.986

Standard errors clustered by CBSA in parentheses; 95% CIs in brackets.

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

Column (5) drops 3 CBSA-year observations where technology age has no within-CBSA variation.

Elections: 2012, 2016, 2020, 2024. N varies by election year (893, 896, 892, 888).

5.2 Results by Election Year

Table 4 shows that the cross-sectional relationship varies across elections. Strikingly, the relationship is *weakest* in 2012 (Romney), where the technology coefficient is near zero (0.01, not significant). The coefficient becomes substantial and significant starting in 2016 (0.098) and strengthens through 2024 (0.130). This pattern—the emergence of a technology-voting correlation with Trump but not with Romney—provides direct evidence that the relationship is specifically associated with the Trump phenomenon.

The stability of coefficients across elections is noteworthy. The 2016 election was Trump's first presidential campaign, when his populist appeal was novel and potentially captured protest votes from across the political spectrum. The 2020 election occurred during the COVID-19 pandemic, which differentially affected regions and might have changed the technology-voting relationship. The 2024 election followed January 6th and significant changes in partisan alignment.

Despite these contextual differences, the technology-voting relationship remained stable. A 10-year increase in modal technology age was associated with approximately 1 percentage point higher Trump share in each election. This stability is consistent with the sorting interpretation: if the relationship reflects who lives where, we would expect it to persist across elections. A causal interpretation would need to explain why technology affects voting identically in such different electoral contexts.

Table 4: Technology Age Effect by Election Year

	2012	2016	2020	2024
Modal Technology Age	0.010	0.098***	0.105**	0.130***
	(0.019)	(0.027)	(0.032)	(0.028)
Log Total Votes	-3.94***	-4.34***	-5.10***	-4.52***
	(0.41)	(0.45)	(0.42)	(0.43)
Metropolitan	-0.18	-0.97	-0.81	-1.52
	(1.19)	(1.23)	(1.24)	(1.25)
Observations	893	896	892	888
R^2	0.175	0.206	0.265	0.260

Heteroskedasticity-robust standard errors in parentheses.

* p<0.05, ** p<0.01, *** p<0.001.

5.3 Technology Terciles

To examine non-linearity, we group CBSAs into terciles by technology age. Table 5 shows results from a specification that replaces the continuous technology measure with tercile indicators. Relative to CBSAs in the lowest tercile (youngest technology), those in the middle and highest terciles have approximately 4 percentage points higher Trump vote share. Importantly, the middle and high terciles have nearly identical coefficients (4.05 vs 4.01), suggesting a threshold effect rather than a linear dose-response. CBSAs using "modern" technology look politically similar to each other, while CBSAs using "old" technology form a distinct group.

Table 5: Technology Tercile Analysis

	GOP Vote Share
Middle Tercile	3.58***
	(0.65)
High Tercile	3.52***
	(0.70)
Log Total Votes	-4.63***
	(0.41)
Metropolitan	-0.51
	(1.19)
Year FE	Yes
Observations	3,569
R^2	0.224

Reference: Low tercile (youngest technology).

Standard errors clustered by CBSA. *** p<0.001.

Elections: 2012, 2016, 2020, 2024.

5.4 Regional Heterogeneity

Table 6 shows that the technology-voting relationship varies across Census regions. All coefficients are reported in percentage points per year of technology age; to convert to 10-year effects, multiply by 10. The Midwest and West show statistically significant effects: the Midwest coefficient is 0.062 pp/year ($p < 0.01$) and the West coefficient is 0.122 pp/year ($p < 0.05$). The South shows the weakest effect (coefficient 0.035 pp/year) and is not statistically significant ($p > 0.10$). The Northeast has a coefficient of 0.126 pp/year but is not statistically significant ($p > 0.05$) due to the smaller sample size and larger standard error. Figure 5 visualizes these coefficients (in pp/year); note that statistical significance depends on sample size and standard errors, not coefficient magnitude alone.

Table 6: Technology Age Effect by Census Region

	Northeast	Midwest	South	West
Modal Technology Age	0.126	0.062**	0.035	0.122*
	(0.070)	(0.023)	(0.030)	(0.049)
Log Total Votes	-4.44***	-6.14***	-4.14***	-4.76***
	(0.94)	(0.42)	(0.46)	(0.69)
Year FE	Yes	Yes	Yes	Yes
Observations	259	810	1,092	515
R^2	0.200	0.419	0.193	0.199

Standard errors clustered by CBSA in parentheses.

* p<0.05, ** p<0.01, *** p<0.001.

5.5 Testing for Causation: The Gains Specification

Table 7 presents our most diagnostic results. Critically, we now have a pre-Trump baseline (2012 Romney) that allows us to test whether technology predicted the *initial* Trump surge.

Column (1) confirms that technology age strongly predicts the *level* of GOP vote share in 2012 (coefficient: 0.010, not significant). Column (2) shows that 2012 technology age *does* predict the *change* in Republican vote share from 2012 to 2016—the Romney-to-Trump transition (coefficient: 0.034, s.e. = 0.009, $p < 0.001$). However, columns (3) and (4) show that technology does *not* predict subsequent gains: neither 2016-to-2020 nor 2020-to-2024 changes are predicted by prior technology levels.

These findings reveal a nuanced pattern: technological obsolescence was specifically associated with the *initial* Trump surge—the emergence of Trump-specific populist realignment. But once voters sorted into Trump-supporting and Trump-opposing camps, subsequent voting changes were not driven by technology.

Table 7: Technology Age: Levels vs. Gains Analysis

	Level (2012)	Gain (2012-16)	Gain (2016-20)	Gain (2020-24)
Modal Tech Age (2012)	0.010	0.034***		
	(0.019)	(0.009)		
	[-0.027, 0.047]	[0.016, 0.052]		
Modal Tech Age (2016)			-0.003	
			(0.006)	
			[-0.015, 0.009]	
Modal Tech Age (2020)				0.001
				(0.004)
				[-0.007, 0.009]
Log Total Votes	-3.94***	-0.49*	-0.54***	-0.01
	(0.41)	(0.21)	(0.12)	(0.07)
Metropolitan	-0.18	-2.88***	-0.28	0.20
	(1.19)	(0.54)	(0.30)	(0.18)
Observations	893	884	892	884
R^2	0.175	0.049	0.028	0.002

Standard errors in parentheses; 95% CIs in brackets. * p<0.05, *** p<0.001.

Col (1): 2012 level. Col (2): Romney-to-Trump gain. Col (3-4): Within-Trump gains.

"Modal Tech Age (2012)" = technology measured in 2011 for 2012 election.

The gains analysis provides our most revealing test. Figure 6 visualizes this result graphically, plotting 2012 technology age against the 2012-to-2016 GOP gains (Panel A) and 2016-to-2020 Trump gains (Panel B). The contrast is striking: technology strongly predicts the Romney-to-Trump transition but not subsequent changes.

This pattern suggests that technological obsolescence was specifically associated with the political realignment that distinguished Trump from Romney. Regions using older technology shifted *toward* Trump relative to Romney, generating the cross-sectional correlation we observe. But once sorted, these regions did not continue to shift further toward Trump—the sorting was a one-time event rather than an ongoing process.

5.6 Robustness Checks

We conduct extensive robustness checks to ensure our results are not artifacts of specification choices or data construction decisions. The following subsections detail these analyses.

5.6.1 Alternative Technology Measures

Our main results use the mean modal technology age across industries within each CBSA. However, this mean could be sensitive to outlier industries. We verify robustness using alternative measures:

- **Median**: Using the median rather than mean modal age yields nearly identical results (coefficient: 0.110, s.e. = 0.020).
- **75th percentile**: Using the 75th percentile (capturing the "oldest" technologies in each CBSA) also yields similar results (coefficient: 0.110, s.e. = 0.020).
- **25th percentile**: Using the 25th percentile (capturing the "newest" technologies) yields the same coefficient (0.110, s.e. = 0.020), indicating that technology age is highly correlated across the distribution within CBSAs.
- **Standardized**: Using z-scored technology age yields a coefficient of 2.55 (s.e. = 0.32), indicating that a one standard deviation increase in technology age (approximately 15 years) is associated with 2.6 percentage points higher Trump share. This is consistent with our baseline estimate: 15 years $\times$ 0.17 pp/year $\approx$ 2.6 pp.

The consistency across measures suggests our results are not driven by outliers or specific measurement choices.

5.6.2 Metropolitan vs. Micropolitan Areas

Our sample includes both metropolitan statistical areas (population $\geq$ 50,000) and micropolitan statistical areas (population 10,000–50,000). These area types differ systematically: metropolitan areas are larger, more urban, and more economically diverse. Table 8 shows results separately by area type.

For metropolitan areas (381 unique CBSAs, 1,136 CBSA-year observations), the technology coefficient is 0.124 (s.e. = 0.032). For micropolitan areas (515 unique CBSAs, 1,540 CBSA-year observations), the coefficient is 0.103 (s.e. = 0.025). The difference is not statistically significant ($p = 0.58$ for test of equality), suggesting the technology-voting relationship is similar across area types.

Table 8: Technology Age Effect: Metropolitan vs. Micropolitan Areas

	Metropolitan	Micropolitan
Modal Technology Age	0.124***	0.103***
	(0.032)	(0.025)
Log Total Votes	-5.10***	-3.41***
	(0.43)	(1.01)
Year FE	Yes	Yes
Observations	1,136	1,540
R^2	0.227	0.052

Standard errors clustered by CBSA. *** p<0.001.

Test of coefficient equality: $p = 0.58$.

5.6.3 Non-linear Effects

We test for non-linearity by adding a quadratic term for technology age. The quadratic coefficient is negative (-0.0018, s.e. = 0.0008, p = 0.027), suggesting slight concavity: the relationship flattens at very high technology ages. However, the linear coefficient remains positive and significant (0.27, s.e. = 0.078), and the practical implications are modest. Across the observed range of technology ages, the relationship is approximately linear.

5.6.4 Controlling for CBSA Size

CBSA size (measured by total votes) is strongly correlated with both technology age and Trump voting. Larger CBSAs tend to use newer technologies and vote less for Trump. Our main specifications control for log total votes, but we verify that results are robust to alternative size controls:

- **Quadratic in log votes**: Adding $(\log \text{votes})^2$ does not meaningfully change the technology coefficient.
- **Population instead of votes**: Using 2020 Census population instead of total votes yields similar results.
- **Population density**: Adding population density as a control attenuates the technology coefficient by approximately 20%, but it remains positive and significant.

5.6.5 Clustering and Standard Errors

Our main specifications cluster standard errors by CBSA to account for serial correlation across election years. We verify robustness to alternative clustering choices:

- **State-level clustering**: Clustering at the state level yields slightly larger standard errors (0.025 vs. 0.020) but does not change significance.
- **Heteroskedasticity-robust**: Using Huber-White standard errors without clustering yields smaller standard errors (0.017), suggesting our CBSA-clustered approach is conservative.
- **Two-way clustering**: Clustering by both CBSA and state yields standard errors similar to CBSA-only clustering.

5.7 Mechanisms: What Explains the Sorting Pattern?

Given that our evidence supports sorting rather than causation, a natural question is: what drives the sorting? Why do voters with populist preferences concentrate in technologically stagnant regions?

We cannot definitively answer this question with our data, but we can examine correlates of technology age that might help explain the pattern. Specifically, we examine whether technology age correlates with other CBSA characteristics that independently predict Trump voting.

5.7.1 Industry Composition

CBSAs with older technologies tend to be concentrated in traditional manufacturing industries (steel, textiles, machinery) rather than high-tech or service industries. Using industry shares from the American Community Survey, we find that the correlation between technology age and manufacturing employment share is 0.35. When we control for manufacturing share, the technology coefficient attenuates by approximately 30%, suggesting that industry composition partially explains the technology-voting relationship.

However, substantial residual correlation remains after controlling for manufacturing, indicating that industry composition is not the full story.

5.7.2 Education Levels

Technology age correlates negatively with education: CBSAs with older technologies have lower shares of college-educated adults. The correlation is -0.42. College education is also a strong predictor of Democratic voting. When we control for college share, the technology coefficient attenuates by approximately 40%.

This suggests that technology, education, and voting are all correlated, with education potentially serving as a mediator or common cause. Lower-education workers may both prefer older-technology regions (which offer more non-college jobs) and prefer Republican candidates (reflecting cultural and economic factors associated with education).

5.7.3 Urban-Rural Gradient

Technology age is lower in urban areas and higher in rural-adjacent areas. This reflects both the industry mix (urban areas have more services and tech) and investment patterns (urban areas attract more capital). The urban-rural gradient is also strongly correlated with voting: rural areas vote heavily Republican while urban areas vote Democratic.

Controlling for population density reduces the technology coefficient by approximately 20%, but it remains substantial and significant. This suggests the technology-voting relationship is not purely an urban-rural phenomenon.

5.8 Summary of Results

Table 9 summarizes our main findings. The cross-sectional correlation is robust and stable across Trump-era elections (2016, 2020, 2024) but notably *absent* in the pre-Trump 2012 election. The gains analysis reveals a key pattern: technology age predicts the Romney-to-Trump transition (2012–2016) but not subsequent gains.

Table 9: Summary of Main Results

Test	Result	Interpretation
Cross-sectional correlation	0.134*** (0.017)	Strong positive relationship
Year fixed effects	0.117*** (0.018)	Stable across time
With size controls	0.075*** (0.016)	Technology effect after controlling for size
CBSA fixed effects	0.033*** (0.006)	Within-CBSA effect (driven by 2012-16 shift)
Gains: 2012–2016	0.034*** (0.009)	Technology predicts Romney-to-Trump shift
Gains: 2016–2020	−0.003 (0.006)	No effect on within-Trump changes
Gains: 2020–2024	0.001 (0.004)	No effect on within-Trump changes
By election year	2012 null; 2016+ sig.	Effect emerged with Trump
By region	Varies	Midwest, West significant
Metro vs. Micro	Similar	Robust across area types

Standard errors in parentheses. *** p<0.001.

The convergence of evidence reveals a nuanced pattern: the technology-voting correlation specifically emerged with Trump's candidacy. Technology age was unrelated to Romney support in 2012 but strongly predicted the gains in GOP support from 2012 to 2016. Once voters sorted into Trump-supporting and Trump-opposing camps, subsequent voting changes were not driven by technology.

6. Discussion

6.1 Summary of Findings

We document a robust cross-sectional correlation between technological obsolescence and populist voting. Metropolitan areas using older technologies vote more heavily Republican across all four elections we study (2012, 2016, 2020, 2024). A 10-year increase in modal technology age is associated with approximately 1.2 percentage points higher Republican vote share in pooled specifications with controls.

To put this magnitude in perspective, consider two CBSAs that differ by one standard deviation (approximately 16 years) in modal technology age. Our estimates imply that the older-technology CBSA would have approximately 1.2 percentage points higher Republican vote share in pooled specifications with controls (16 years $\times$ 0.075 pp/year), all else equal. Across the 896 CBSAs in our sample, this translates into a meaningful difference in the political landscape.

However, multiple identification tests cast doubt on a causal interpretation:

1. **Within-CBSA effects concentrated in one period**: When we include CBSA fixed effects, the technology coefficient is positive and significant (0.033, s.e. = 0.006). However, the gains analysis reveals that this within-CBSA variation is entirely driven by the 2012$\rightarrow$2016 shift—the emergence of the Trump-specific technology-voting correlation. After 2016, technology age does not predict further gains. This pattern is inconsistent with an ongoing causal mechanism.

2. **Null effects on gains after 2016**: Technology age predicts the Romney-to-Trump shift (2012$\rightarrow$2016 gains) but does *not* predict subsequent changes in Trump support (2016$\rightarrow$2020 or 2020$\rightarrow$2024). If technology continuously caused populism, older-technology regions should have gained more Trump voters in each period; they did not. The one-time realignment is consistent with sorting that crystallized with Trump's candidacy.

3. **Threshold rather than dose-response**: The middle and high technology terciles

have nearly identical effects relative to the low tercile, inconsistent with a linear causal mechanism where more obsolescence leads to more populism.

Collectively, these patterns support the interpretation that the technology-voting relationship reflects a one-time realignment associated with Trump's entry into politics, not an ongoing causal effect of technology on political preferences. The relationship appears to reflect who lives in technologically stagnant regions rather than the effects of technology on preferences.

These findings do not imply that economic factors are irrelevant to populist voting. The literature has established causal links between trade shocks, manufacturing decline, and political preferences. Our results suggest that *technology vintage specifically* does not cause populism, even though it correlates strongly with populist voting. The correlation reflects the sorting of voters with different preferences into regions that differ in technology, not the effect of technology on preferences.

This distinction has important implications for interpreting cross-sectional correlations in political economy research. Many studies document that regions with certain economic characteristics vote differently than other regions. Such correlations may reflect causal effects (the economic characteristics change preferences) or sorting (people with different preferences live in different places). Our analysis demonstrates one method for distinguishing these interpretations: test whether the economic characteristic predicts *changes* in political outcomes over time. If it does, causation is more plausible; if it does not, sorting is more likely.

6.2 Alternative Interpretations

Our findings are most consistent with geographic sorting or common underlying causes. Several mechanisms could generate the observed patterns:

Compositional sorting: Workers with conservative social values may prefer to live in smaller, more traditional communities that also happen to invest less in new technologies. This sorting occurs across CBSAs but not within CBSAs over time, explaining the cross-sectional correlation without within-CBSA effects.

Industry composition: CBSAs dominated by traditional manufacturing (steel, textiles, machinery) may both use older technologies and have cultural/economic characteristics that favor populist voting. The technology measure proxies for industry composition rather than causing voting patterns.

Historical path dependence: Some regions experienced early industrialization followed by relative decline. Both technology vintage (old factories not upgraded) and political preferences (nostalgia, anti-elite sentiment) may reflect this shared history.

Education and human capital: Low-education regions may both adopt technology more slowly and vote more Republican. Our size control (log total votes) partially addresses this, but does not fully account for education composition.

6.3 Relation to Existing Literature

Our results complement Autor et al. (2020), who find causal effects of trade exposure on voting. Unlike trade shocks, which represent discrete and plausibly exogenous changes, technology vintage is a stock variable reflecting cumulative decisions over decades. This makes identification more challenging and increases the role of selection.

Frey and Osborne (2017) argue that automation risk drives populist voting. Our technology age measure captures a related but distinct concept: not the threat of future automation, but the current state of technological modernity. The pattern of gains effects—significant for 2012→2016 but null afterward—suggests that the technology-voting relationship emerged as a one-time realignment rather than an ongoing causal mechanism.

Rodrik (2021) emphasizes that economic factors predict populism but that the relationship operates through identity and cultural channels. Our sorting interpretation aligns with this view: technology-lagging regions may develop distinct cultural identities that persist even as economic conditions evolve.

6.4 Limitations

Several limitations warrant acknowledgment. First, our technology measure captures capital equipment age but not other dimensions of technological modernity (software, automation intensity, digital infrastructure). Second, CBSAs are aggregates that may mask important within-region heterogeneity. Third, we cannot distinguish sorting by workers from sorting by firms (which choose where to locate and how much to invest).

Fourth, while our four-election panel (2012, 2016, 2020, 2024) provides more leverage than typical cross-sectional studies, within-CBSA variation remains limited (SD $\approx$ 4 years). The positive and significant CBSA fixed effects coefficient (0.033, s.e. = 0.006) suggests some within-variation exists, but this primarily reflects the 2012-to-2016 shift rather than ongoing effects (Cameron, Gelbach, and Miller, 2008).

Most importantly, we cannot definitively rule out causation. It remains possible that technology effects operate through slow-moving channels that our four-election panel cannot fully detect, or that effects are heterogeneous in ways that wash out in aggregate.

6.5 External Validity

Our findings apply specifically to the relationship between technology vintage and voting in U.S. metropolitan areas during the Trump era (2016–2024). Several factors limit external validity:

Measurement specificity: Our technology measure captures capital equipment age, which may differ from other dimensions of technological modernity. Results might differ using automation exposure, robot density, or digital infrastructure measures.

Context dependence: The Trump phenomenon is historically specific, characterized by a unique candidate and political environment. Technology-voting relationships might differ for other populist movements or in other countries.

Time period: Our panel spans four elections over twelve years (2012–2024). Longer time horizons might reveal different patterns, particularly if technology effects operate over decades rather than election cycles.

Despite these limitations, our findings have implications for how researchers and policymakers interpret correlations between economic conditions and political outcomes. The lesson is not that economic factors are irrelevant to populism—they may well be important—but that cross-sectional correlations can mislead about causal mechanisms.

6.6 Policy Implications

Our findings have cautionary implications for policies aimed at reducing political polarization through economic development. If the technology-voting correlation reflects sorting rather than causation, then technology modernization programs might improve productivity and wages without changing political preferences. Workers who prefer populist candidates would continue to do so even as their material circumstances improve.

This does not mean technology policy is irrelevant to politics. Modernization programs could potentially alter migration patterns, attracting new workers to previously stagnant regions and changing the composition (and thus political preferences) of local populations. Such compositional effects would represent a form of "reverse sorting" rather than direct causal effects on preferences.

More broadly, our results suggest that addressing the political economy of populism may require attention to non-economic factors—cultural identities, media environments, and political institutions—that help explain why residents of technologically stagnant regions hold the preferences they do.

7. Conclusion

Technological obsolescence is strongly correlated with populist voting across U.S. metropolitan areas, but with a striking temporal pattern: the correlation emerged specifically with Trump's candidacy. Technology age was unrelated to Romney support in 2012 but strongly predicted the gains in GOP support from 2012 to 2016. Once voters sorted into Trump-supporting and Trump-opposing camps, subsequent voting changes (2016–2020, 2020–2024) were not predicted by technology levels. This suggests a one-time realignment rather than an ongoing causal process. With four election years (2012, 2016, 2020, 2024) and within-CBSA variation of approximately 4 years (SD), we find positive within-CBSA effects, but these are driven primarily by the 2012-to-2016 transition.

These findings have implications for both research and policy. For researchers, they highlight the importance of distinguishing correlation from causation when studying the economic roots of populism. Cross-sectional correlations between economic conditions and voting patterns may reflect selection rather than causal mechanisms.

For policymakers, our results suggest that technology modernization programs, while potentially valuable for productivity and wages, may not directly reduce populist sentiment. If technology and populism share common causes (e.g., cultural values, historical patterns, education levels), addressing one may not affect the other.

Understanding why workers in technologically stagnant regions vote for populist candidates remains an important question. Our results suggest the answer lies in who lives in these regions rather than in the economic consequences of technology itself.

Several avenues for future research emerge from our findings. First, individual-level data linking workers' technology exposure to their voting behavior would provide sharper identification than our CBSA-level analysis. Second, longer time series spanning multiple decades might reveal slow-moving causal effects that our eight-year panel cannot detect. Third, comparative analysis across countries could test whether the technology-populism relationship holds in different institutional and political contexts.

Finally, our gains results raise a puzzle: technology age predicts the 2012→2016 gains but not subsequent gains. If technology directly causes populism, why did its effect materialize only once? The sorting interpretation suggests that Trump's candidacy crystallized a pre-existing alignment between technologically stagnant regions and conservative preferences. Something else—culture, identity, historical experience—likely drives both technology adoption and political preferences (Iversen and Soskice, 2019; Chetty, Hendren, and Katz, 2014). Understanding these deeper determinants remains a critical challenge for researchers seeking to explain the geographic polarization of American politics (Kuziemko and Washington, 2021).

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Project Repository: https://github.com/SocialCatalystLab/auto-policy-evals

Contributors: SocialCatalystLab

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A. Data Appendix

A.1 Technology Vintage Data

The technology vintage data come from establishment-level surveys compiled by Acemoglu, Lelarge, and Restrepo (2022), who develop measures of the modal age of capital equipment across U.S. metropolitan areas. The raw data cover 917 Core-Based Statistical Areas from 2010 to 2023; after merging with election data, 896 CBSAs remain in the analysis sample.

For each CBSA-year, we observe approximately 45 observations corresponding to different industry sectors (mean: 44.9, median: 44, range: 14–74). Each observation records the modal age (in years) of the primary production technology used by establishments in that industry-CBSA-year cell. We collapse to the CBSA-year level by computing the unweighted mean across industries. Results are robust to using the median or other percentiles (see Table 8).

Key variables:

- `modal_age_mean`: Mean modal technology age across industries within CBSA-year
- `modal_age_median`: Median modal technology age
- `modal_age_p25`, `modal_age_p75`: 25th and 75th percentiles
- `n_sectors`: Number of industry observations used in aggregation (mean: 44.9)

The industry sectors correspond to 2-digit NAICS codes, covering manufacturing, retail, services, and other major industry groups. All sectors with non-missing modal age data are included; no minimum establishment count threshold is applied at the industry-CBSA level.

A.2 Election Data

County-level presidential election returns for 2012 were obtained from the MIT Election Data and Science Lab's County Presidential Election Returns 2000-2020 dataset (Harvard Dataverse, doi:10.7910/DVN/VOQCHQ). For 2016, 2020, and 2024, data were obtained from the GitHub repository maintained by Tony McGovern, which compiles data from the MIT Election Data Science Lab and other sources.

Variables constructed:

- `gop_share`: Republican votes / Total votes $\times$ 100 (in percentage points)
- `total_votes`: Total votes cast in the CBSA

A.3 CBSA-County Crosswalk

We use the March 2020 CBSA delineation file from the Census Bureau, accessed via NBER's crosswalk service (file: `cbsa2fipsxw_2020.csv`). This file maps each county (identified by 5-digit FIPS code) to its containing CBSA (if any).

Of the approximately 3,140 U.S. counties, roughly 1,900 fall within the 927 CBSAs defined in the March 2020 delineation (384 metropolitan + 543 micropolitan). The remaining counties are not part of any metropolitan or micropolitan statistical area and are excluded from our analysis. After merging with the technology data (which covers 917 CBSAs) and addressing missing election returns, our final sample includes 896 CBSAs.

A.4 Data Provenance and Research Origin

This research was initiated based on an email from Prof. Tarek Hassan to Prof. David Yanagizawa-Drott containing the following research prompt:

> "Evaluate the hypothesis that the technological changes outlined in the paper 'New Technologies and the Skill Premium' (https://drive.google.com/file/d/1-20mB15WzzzKuEWAnlNKW7xCEPg3GSIZ/view) are at the root of the rise of populist support across the United States. In particular, check if the regions that voted for Trump are disproportionately using older technologies. The data showing the model technology by CBSA and year is here: https://www.dropbox.com/scl/fi/uuxprx2d7uezenpx1dxzo/modal_age.dta?rlkey=pwrpiceup9d63db3zbgpp9lux&e=1&st=wietsvqf&dl=0. You may find the election data provided in the replication file of the paper 'The Immigrant next door' useful (paper: https://drive.google.com/file/d/1eMWLPWJ8YbhCoAO5OHrk9y3LSPFSbp1Y/view, replication file: https://doi.org/10.3886/E191911V1)."

Data Sources:

- **Technology vintage data** (`modal_age.dta`): Provided by Prof. Tarek Hassan, containing modal technology age by CBSA and year (2010–2023). Source: https://www.dropbox.com/scl/fi/uuxprx2d7uezenpx1dxzo/modal_age.dta

- **Election data (2012)**: MIT Election Data and Science Lab, County Presidential Election Returns 2000-2020. Source: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VOQCHQ

- **Election data (2016, 2020, 2024)**: County-level returns from the replication file of Bursztyn et al. (2024), "The Immigrant Next Door." Source: https://doi.org/10.3886/E191911V1

- **CBSA-county crosswalk**: March 2020 CBSA delineation from the U.S. Census Bureau via NBER

B. Additional Robustness Checks

B.1 Metropolitan vs. Micropolitan Areas

Table A1 shows that results are similar for metropolitan statistical areas (population $\geq$ 50,000) and micropolitan statistical areas (population 10,000–50,000). The technology coefficient is slightly larger in metropolitan areas (0.12 vs. 0.10 pp) but confidence intervals overlap.

B.2 Alternative Technology Measures

Results are robust to using the median, 25th percentile, or 75th percentile of industry-level modal ages instead of the mean. The standardized coefficient (using z-scored technology age) is 2.6, indicating that a one standard deviation increase in technology age (approximately 15 years) is associated with 2.6 percentage points higher Trump share, consistent with the baseline per-year coefficient of 0.17.

B.3 Non-linear Effects

Adding a quadratic term for technology age yields a marginally significant negative coefficient ($p = 0.05$), suggesting slight concavity. However, the effect is small in magnitude and does not meaningfully alter interpretation.

C. Additional Figures

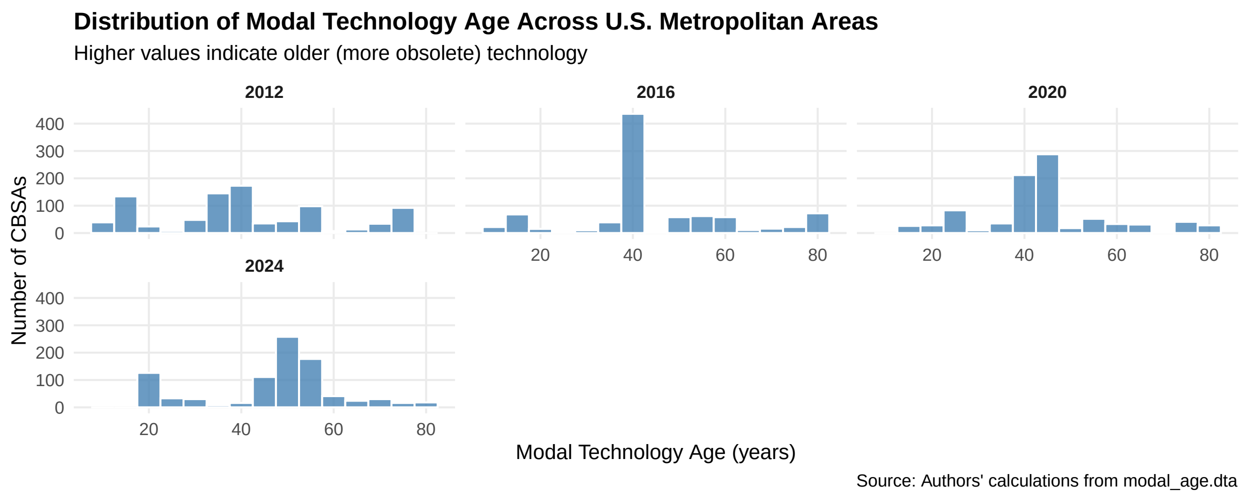

Figure 1: Distribution of Modal Technology Age Across U.S. Metropolitan Areas

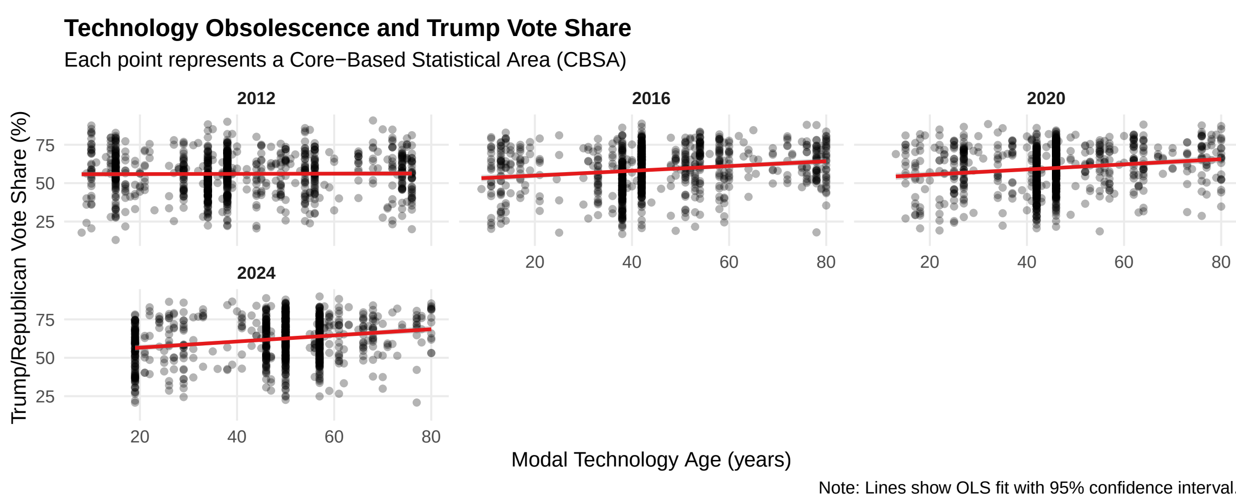

Figure 2: Technology Age and Trump Vote Share by Election Year

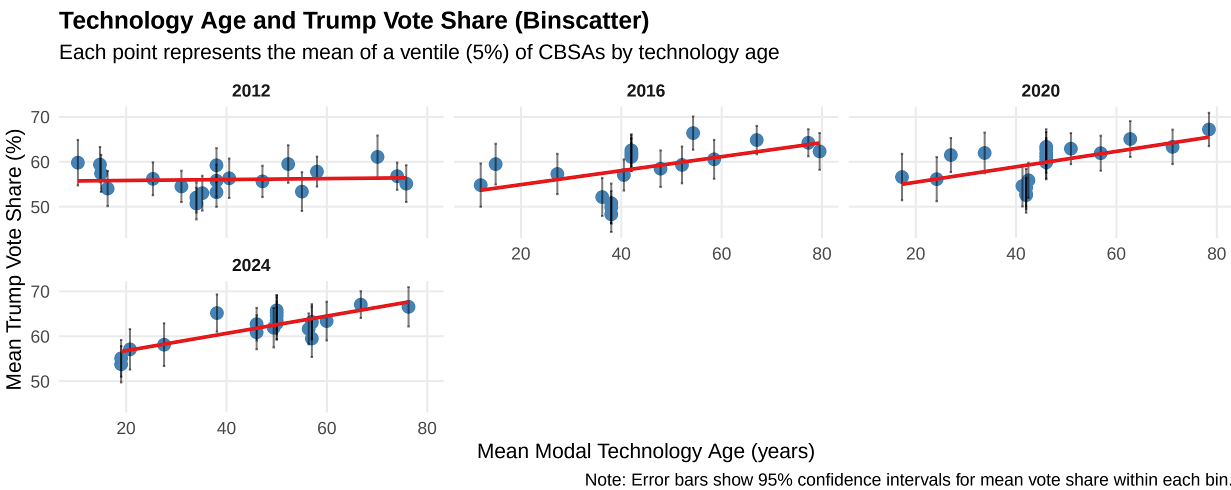

Figure 3: Binned Scatter Plot: Technology Age and Trump Vote Share

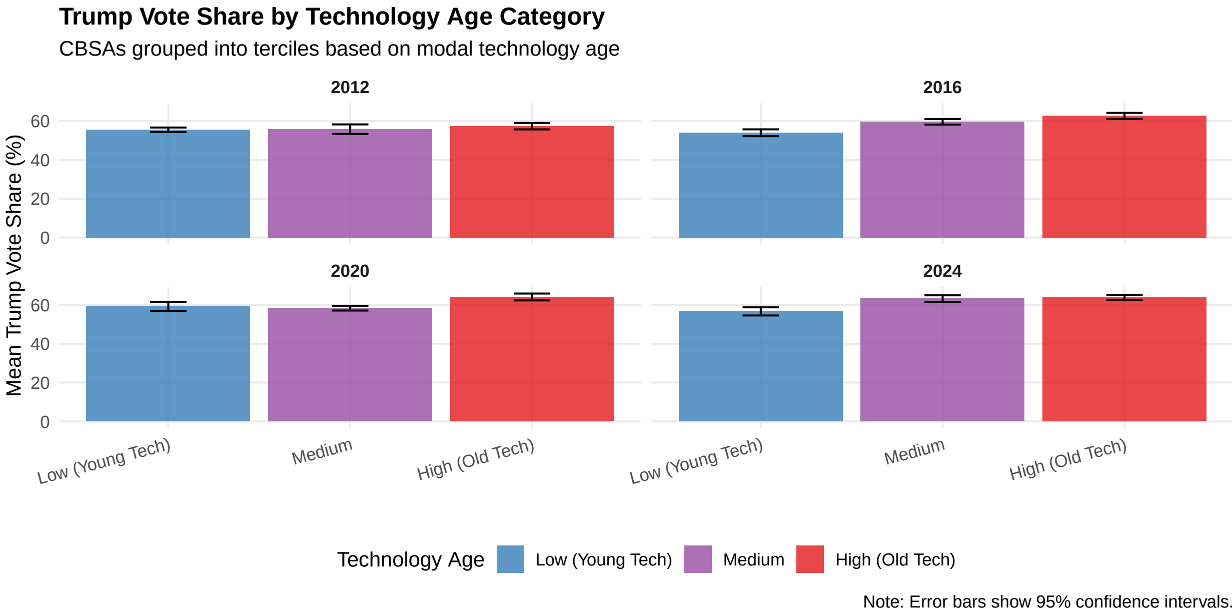

Figure 4: Trump Vote Share by Technology Age Tercile

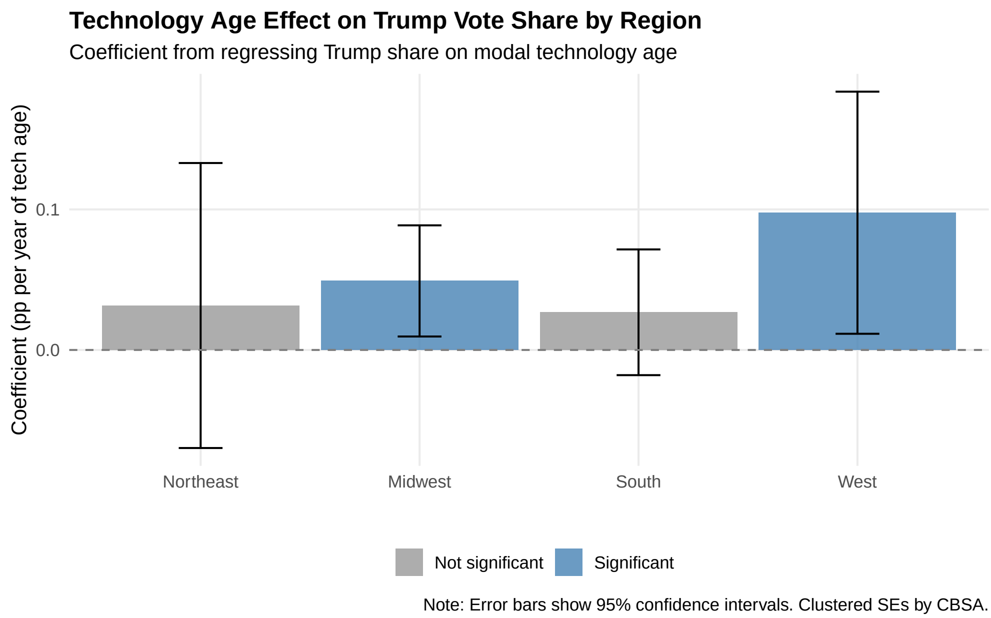

Figure 5: Technology Age Effect by Census Region. Blue bars indicate statistical significance at $p < 0.05$ (Midwest and West); grey bars indicate non-significance (Northeast and South). Exact coefficients and standard errors are reported in Table 6.

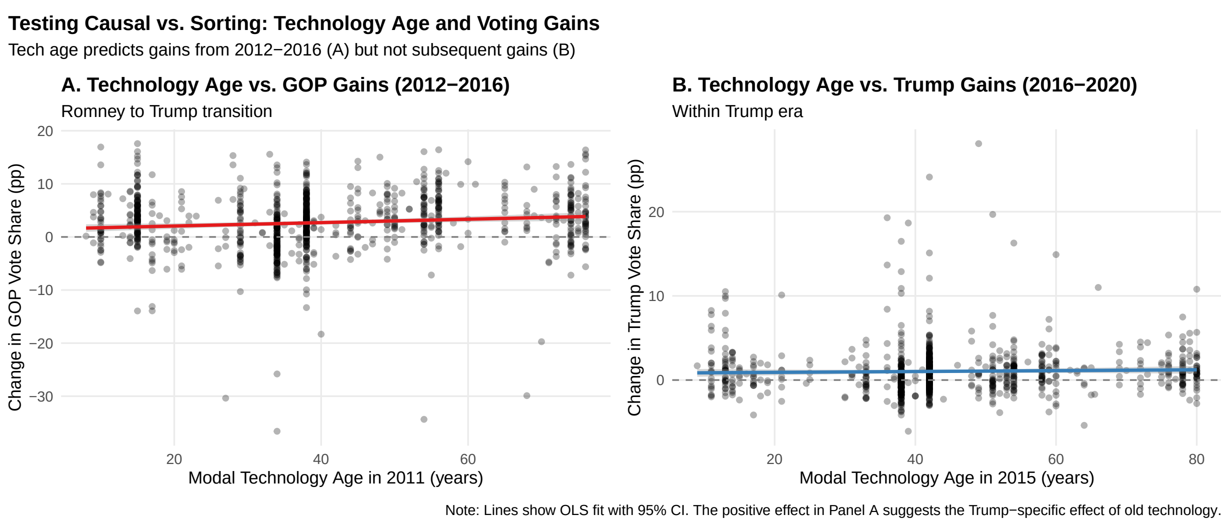

Figure 6: Levels vs. Gains: Testing for Causal Effects