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Trump digs votes - The Effect of Trump's Coal Campaign on the Presidential Ballot in 2016

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JEL: D72, P16, P18, R11

Keywords: U.S. Presidential Election 2016, Coal Production, Durbin Model

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1. Introduction

Donald Trump promised in his 2016 Presidential campaign to end the 'war on coal' and put U.S. miners back to work. The peak of his coal campaign was probably a speech at the Charleston Civic Center on May 5, 2016, in Charleston, West Virginia, in the Appalachian coal region. He wore a miner's hard hat and promised the crowd new job opportunities.[1] This speech happened just a few weeks after his rival, the Democratic nominee Hillary Clinton, stated in a speech in Columbus, Ohio, as part of a longer statement, that her government would "put a lot of coal miners and coal companies out of business."[2] Trump capitalized on Clinton's statement, taken out of context, to build his campaign for coal and jobs and secure a significant number of votes.

In this paper, we investigate the effect of this campaign pledge on the Republicans' vote share at the county level. In particular, we first introduce an event study model as a two-way fixed effects difference-in-differences specification. Then, we study the Republicans' vote share in areas more or less 'exposed' to coal mining, using coal production in a county as the main predictor. We aim to understand whether the electoral support for the Republicans increased more in counties characterized by coal extraction on a larger scale, and that should also be more sensitive to the coal recovery electoral campaign pledge. We model electoral outcomes in a reduced form, where the share of votes obtained by the Republican party depends on the economic and institutional characteristics of the counties. Identification is obtained by incorporating spatially lagged explanatory variables and controlling for spatially autocorrelated error terms while absorbing state-specific effects and counties' pre-election characteristics among the controls.

U.S. coal production is mainly concentrated in two large regions. In the eastern Appalachian region (especially Alabama, Pennsylvania, Kentucky, Virginia, and West Virginia), mining is underground and labour-intensive. In contrast, the Western Powder River Basin region (mainly North Dakota, Wyoming, and Montana) is characterised by surface mining, which is less labour-intensive.

U.S. coal production fell by one-third between 2011 and 2016, and the impact on employment was even more dramatic: from 130,000 workers in 2011 to less than 70,000 in 2016 (Houser *et al.* (2017)). The collapse of the coal industry also had downstream effects on whole communities where coal companies are located, reducing employment, wealth, and tax revenues, finally resulting in service cuts. These communities represent an interesting quasi-natural experiment, as they were differently exposed to the coal industry crisis, depending on the varying degrees of economic dependence on coal production. We aim to precisely exploit these differences in exposure to the coal industry collapse to estimate the effect on the presidential vote outcome.

[1] `https://www.washingtonpost.com/video/politics/trump-receives-warm-welcome-in-coal-country/2016/05/06/9259c5ea-1327-11e6-a9b5-bf703a5a7191_video.html`

[2] `https://www.npr.org/2016/05/03/476485650/fact-check-hillary-clinton-and-coal-jobs?t=1652451309596`

We find a positive effect of coal production in a county on the Republican vote share. If the coal output in a county rises by an additional one million short tons (approximately corresponding to one standard deviation), the vote share of the Republican party significantly increases by 0.064-0.094 percentage points.A short ton is a unit of weight commonly used in the United States and Canada, equal to 2,000 pounds or approximately 907.185 kilograms.

To estimate the populist effect of Donald Trump, we substitute in our model the Republicans' vote share in 2016 with the difference between the vote share of Donald Trump in 2016 and Mitt Romney in 2012. We learn that Donald Trump receives disproportionately more votes in the Midwest Counties and the Rust Belt. In this populist model, the effect of an additional one million short tons is a significant increase in the Republicans' vote share by 0.080-0.116 percentage points.

To test the validity of our estimates, we apply several robustness checks. First, we use the inverse-distance weighting matrix not only for estimation but also for spatial clustering. Second, we replace coal output in short tons with binary variables to examine non-linear effects of coal production. Finally, we replace the overall coal output of a county with the output per employed worker and the output per working hour. Naturally, the different specifications lead to slightly different results. However, the positive relationship between coal production and Trump's electoral share remains.

To the best of our knowledge, this paper is the first to focus on the impact of coal production in a county on the political outcome. Furthermore, we consider spillover effects and apply spatial clustering to avoid biased estimates due to trade, migration, and information flows between counties.

In the empirical political economy literature, there is extensive debate on the impact of economic conditions on presidential voting (Lewis-Beck & Stegmaier (2000), Besley & Case (2003)). Generally, high unemployment and difficult economic conditions benefit Democratic candidates (Rees *et al.* (1962), Wright (2012), Burden & Wichowsky (2014)). Simultaneously, economic shocks, such as rising import competition or energy transition, explain ideological polarization, expanding support for both far-left and far-right views (Autor *et al.* (2020)). An extensive literature empirically investigates the rise of populist parties in many high-income countries, with many authors finding that economic insecurity, financial distress, and low income are among the driving forces of the increasing support for 'populist' policies (Acemoglu *et al.* (2013), Guiso *et al.* (2017)). We contribute to this literature by empirically establishing the role of economic distress and campaign promises (that exploit this distress) in presidential elections. We focus on the coal industry, which serves as an excellent case study.

The paper is organised as follows. The next section describes the U.S. coal industry, while Section 3 details the main variables introduced in the empirical analysis and the data sources. In Section 4, we present our empirical strategy and address identification issues. Section 5 presents our results and robustness checks, and discusses our findings in detail. Section 6 concludes.

2. The U.S. Coal Industry

This section documents a few facts about the U.S. coal industry. Employment in the U.S. coal industry declined for decades with a slight increase in the 2000s, as illustrated in *Figure* 1. We observe a peak in June 1985 with 177.8 thousand employed miners and a decline to 49.6 thousand just before the presidential election in October 2016. During Donald Trump's presidency, nothing has changed significantly in terms of employment in the coal industry. In the first three years of the Trump Administration, the decline in employment stalled, only to continue to decline a bit further at the end of his presidency.

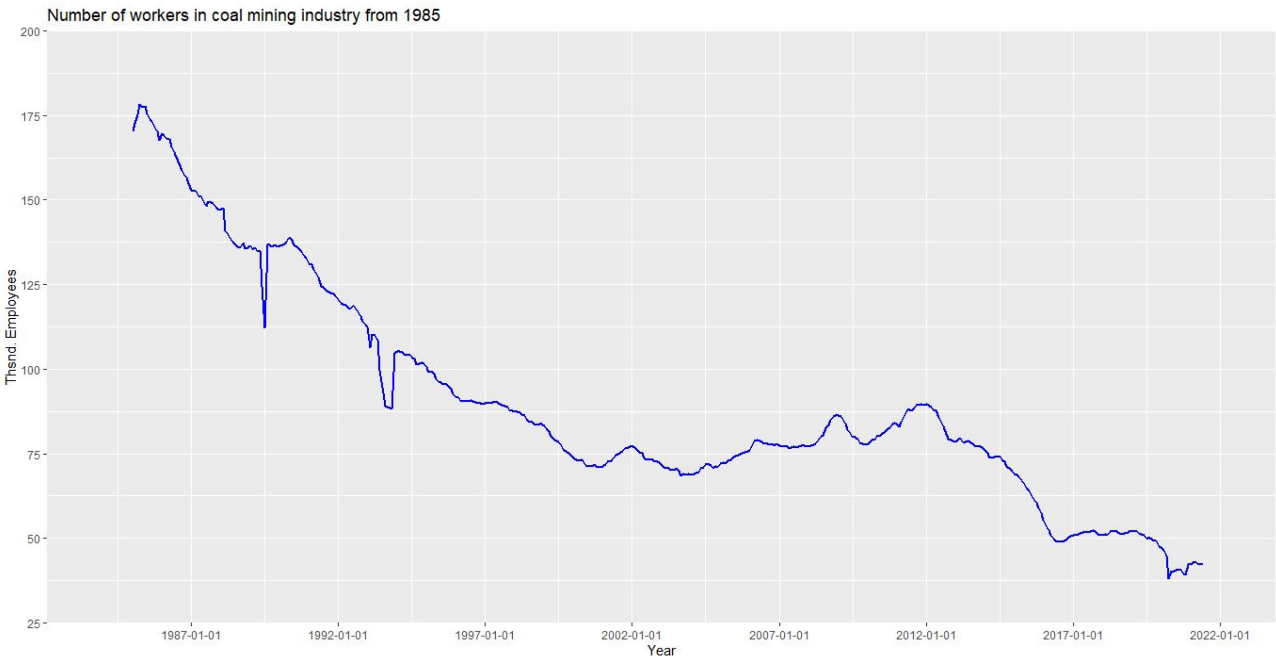

Figure 1: *Seasonally adjusted number of employees in the coal mining industry since 1985*

Data Source: FRED[3]

The decline in employment coincides with a decrease in coal consumption. Coal consumption increased over decades, reaching its peak level in 2005 at 22.8 Quadrillion British thermal units (Btu) (equivalent to 1.2 billion short tons).[4] Since then, coal consumption in the U.S. has been on the decline. This is primarily due to the decreasing use of coal as a source of electric energy (see *Figure* 2). Furthermore, Davis *et al.* (2021) point out that coal-based electric generating capacity has decreased since 2011 due to more stringent environmental regulations, increased use of renewable energies, a lower price for natural gas, and lower peak electricity prices.

[3] https://fred.stlouisfed.org/series/CES1021210001

[4] https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T01.03#/?f=A&start=1949&end=2020&charted=1-13

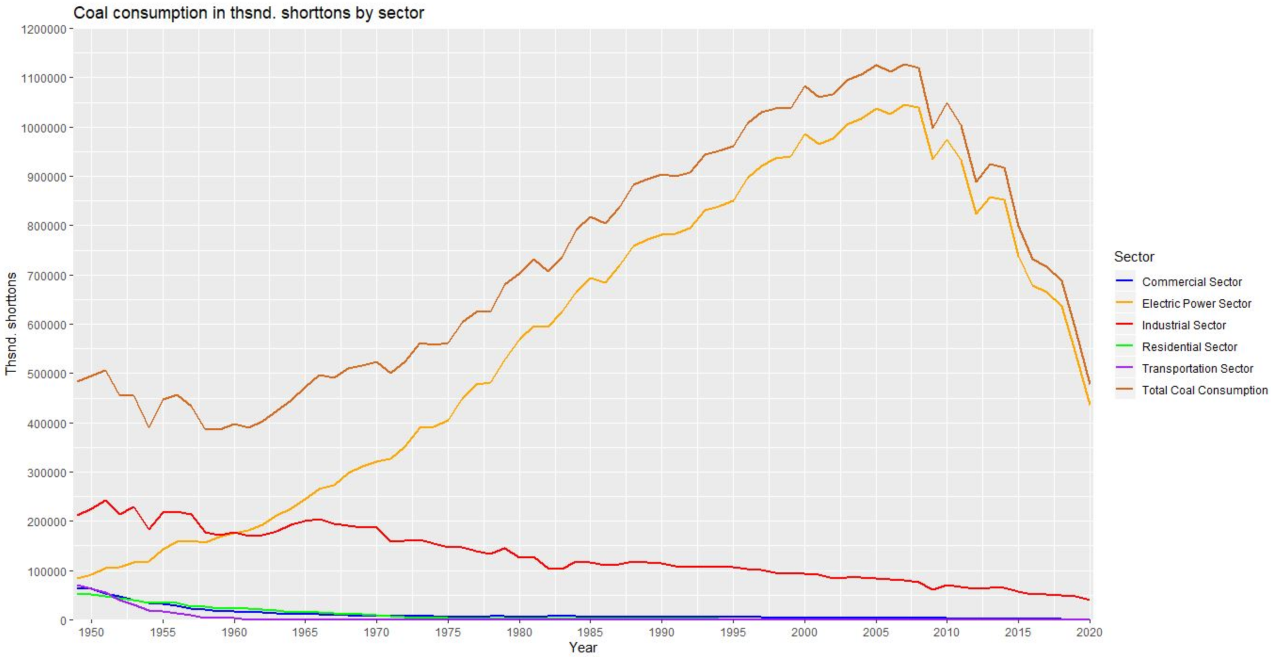

Figure 2: *Annual coal consumption by sector since 1949*

Data Source: EIA[5]

Together with coal consumption, coal production has decreased. In fact, in 2020, coal production in the U.S. fell below the level of 1985, as displayed in *Figure* 3. As mentioned before, lower natural gas prices led to higher demand for natural gas and, correspondingly, less demand for coal in the U.S. and internationally. The COVID-19 pandemic also contributed to the decline in 2020. U.S. coal mines temporarily shut down to prevent the further spread of the coronavirus. Consequently, U.S. coal exports decreased by 26% in 2020 compared to 2019.

The Trump Administration did not halt the decline of the U.S. coal industry, but it must be acknowledged that it was not due to a lack of effort. Bloomberg reports that the Trump administration spent over one billion U.S. dollars on the coal industry during its legislative period. Environmental rules were also relaxed, and attempts were made to prevent the closure of power plants.[7]

3. Data

The attempt to revive the U.S. coal industry was unsuccessful, but was Trump's prominent election pledge in 2016 with the well-known slogan "Trump digs coal" successful at the ballot boxes? As mentioned above, we aim to analyse the effect of this pledge on the ballot outcome of the 2016 Presidential election at the county level.

[5]`https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T06.02#/?f=M&start=197301&end=202104&charted=1-5-12-13-14-15`

[6]`https://www.eia.gov/todayinenergy/detail.php?id=48696`

[7]`https://www.bloomberg.com/news/features/2020-09-03/trump-s-broken-coal-promises-could-cost-him-2020-`

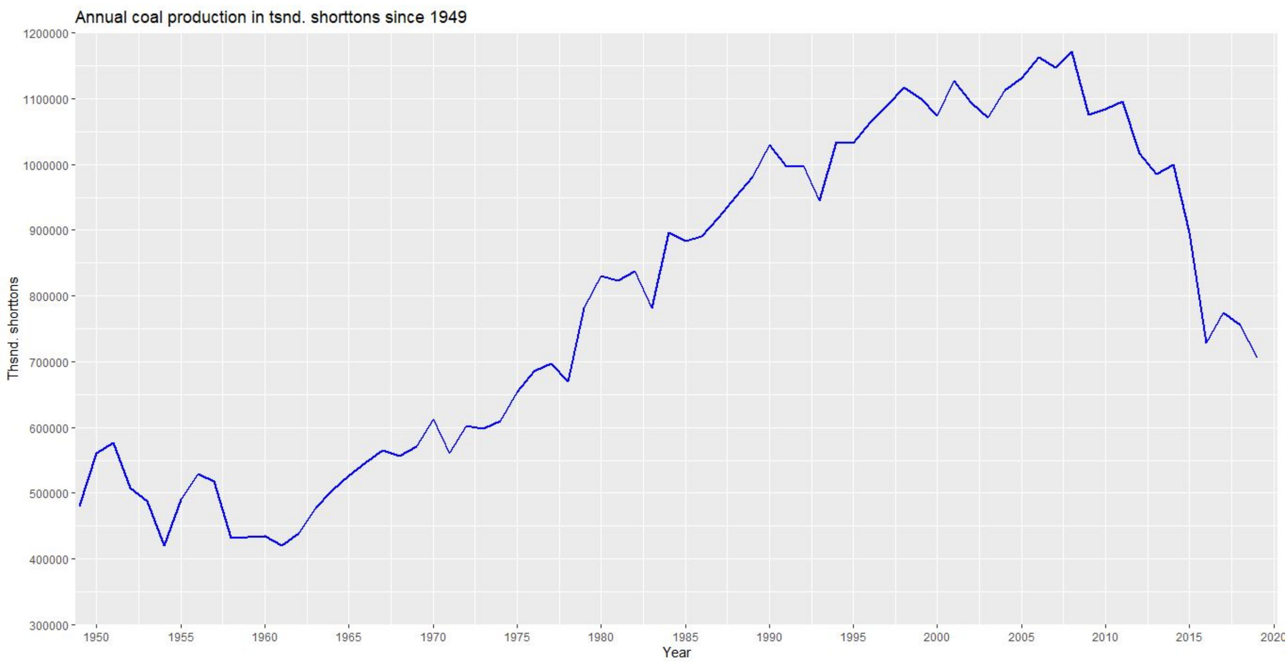

Figure 3: *Annual coal production since 1949*

Data Source: EIA [6]

3.1. Electoral Results and Coal Production Data

The dependent variable is the percentage of votes for the Republicans. Data on the 2016 ballot outcomes are sourced from Harvard Dataverse, providing election data from 2000 collected by the MIT Election Data and Science Lab.[8] We calculate the Republicans' percentage of votes by dividing the total number of votes for the Republicans by the total number of votes and multiplying by 100.

Our empirical strategy (further details in *Section* 4) enables us to estimate two distinct effects of each explanatory variable on the electoral outcome: the local effect and the spillover effect. The local effect quantifies the change in the Republicans' share in a given county when the explanatory variable of that county changes. The spillover effect quantifies the change in the Republicans' share in a given county when the explanatory variable of neighbouring counties changes.

The primary variable of interest is coal output. Data on coal output, coal employment, and hours worked for active and inactive mines (both surface and underground) and preparation plants are obtained from the U.S. Energy Information Administration (EIA).[9] County-level coal production is computed as follows: for each county, coal output is aggregated across 'active', 'active, men working, not producing', 'permanently abandoned', and 'temporarily closed' plants that operated at least one mine in 2016. Inactive plants ('permanently abandoned' and 'temporarily closed') are also included for three reasons. First, they produced a non-negative output

[8] `https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/VOQCHQ`
[9] `https://www.eia.gov/coal/data.php#production`

quantity and employed non-negative input amounts but closed in 2016. Second, the EIA notes that some mines may have been erroneously designated as 'permanently abandoned.' Third, counties with relevant plants may have been influenced by Trump's campaign pledge to boost coal production in the U.S. Given Trump's election pledge and the perceived significance of coal regions in Donald Trump's victory, a positive effect is anticipated (Goetz *et al.* (2019)).

The impact of spillovers from neighbours is ambiguous. On the one hand, economic benefits from trade support Donald Trump and the Republicans. Nevertheless, gains from trade are limited due to the relatively simplistic supply chains characterising of the coal industry, as the primary buyer of coal is the electricity sector (refer to *Figure* 2). On the other hand, environmental disadvantages (e.g. emissions, pollution) may offset economic benefits to some extent, particularly in closer regions. Additionally, inhabitants of a given county might fear the opening of a power plant in their locality. Furthermore, coal mining counties are often neighbours, suggesting that a given coal county might not be significantly concerned about whether its neighbour also hosts a coal mine.

Building on existing literature (e.g., Steinmayr (2021)), we also incorporate a control for the Republicans' percentage of votes in the preceding 2012 ballot (Obama vs. Romney). This variable reflects the county's general ideological preference, and we anticipate a positive impact. It is constructed in a manner analogous to the methodology used for the Republicans' percentage of votes in 2016, utilizing the same dataset. The spillover effect of this variable is expected to be negative, given that Republicans typically perform better in rural states situated close to the geographical center of the U.S. The further away from the center, the less influential the Republicans are anticipated to be.

As in Monnat & Brown (2017), Alaska is excluded from our dataset due to the lack of election data for those counties.[10] Additionally, Cambell/Wyoming (FIPS: 56005) is excluded as it represents an extreme outlier regarding coal output.[11] Finally, to incorporate changes in commuting zone-specific import penetrations by China (see *Subsection* 3.2), Hawaii is also omitted, as the import penetration data by Autor *et al.* (2020) do not cover this state.

3.2. Further Control Variables

In addition to our main variables, we incorporate a range of controls to account for county-level economic conditions. First, we include the unemployment rate in percentage points (Rodríguez-Pose *et al.* (2021), Steinmayr (2021), Halla *et al.* (2017), Madestam *et al.* (2013)), using data provided by the U.S. Department of Agriculture.[12] The literature suggests an ambiguous effect

[10] Election data is only available for districts that are a combination of multiple counties (boroughs).

[11] In this county, 257.54 million short tons are produced, compared to the second-highest value of 29.79 million short tons. Including this observation does not alter the results significantly, as almost identical coefficients are observed.

[12] `https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/`

of the unemployment rate. On one hand, voters in high-unemployment counties may prefer Democrats, expecting them to maintain welfare programs. On the other hand, these voters might favour Trump, anticipating his ability to restore existing jobs and create new ones (Goetz *et al.* (2019)). Additionally, populist parties tend to benefit from high unemployment rates (Algan *et al.* (2017)). Spillovers from neighbouring counties may negatively impact the dependent variable in a given county, as higher unemployment rates signal weak economic performance in the entire region. A widespread economic downturn, however, may make voters more inclined to support Democrats who are perceived as better equipped to address such crises through expansive fiscal policies.

Second, we introduce the percentage of workers in manufacturing over the total workforce, measured in percentage points (Steinmayr (2021), Autor *et al.* (2020), Ochsner & Roesel (2020), Goetz *et al.* (2019), Halla *et al.* (2017)). We obtain this variable from the U.S. Census.[13] If not specified otherwise, all subsequent variables are sourced from the same U.S. Census dataset.[14] The impact of the share of manufacturing workers is ambiguous. Although this group remains an important target for the Democrats, the observed trend of blue-collar workers voting for right-wing extremists is widespread (Rydgren & Tyrberg (2020), Adorf (2018), Stockemer *et al.* (2018)). Furthermore, Clinton was perceived as a representative of Wall Street rather than U.S. workers. These factors might favour a positive impact of this variable on the dependent variable. The spillover effect is also ambiguous. On one hand, a county may benefit from positive effects spreading from manufacturing and job impacts in neighbouring counties. On the other hand, prosperous counties attract young, highly educated individuals, potentially Democrats, and workers (e.g. engineers) from other counties. Moreover, thriving counties also attract firms, suggesting adverse backwash effects on the dependent variable.

Third, we control for poverty (Goetz *et al.* (2019)) by introducing the percentage of households living below the poverty line. A negative effect on our dependent variable is anticipated, given Republicans' historical opposition to welfare state expansions. Its spillover is expected to impact the dependent variable negatively, for similar reasons as the spillover of unemployment.

Fourth, we incorporate the percentage of people benefiting from either public or private social insurance over the total population (Goetz *et al.* (2019)). We expect a positive effect for two reasons. First, higher-income counties are likely to have more people affording social insurance, and wealthier counties tend to lean towards Republican voting. Second, a larger share of inhabitants benefiting from social insurance, whether public or private, suggests a smaller complement (those lacking social insurance) who might prefer Democrats, indicating a positive

[13] `https://www.census.gov/data.html`

[14] While annual data are not available, we use the five-year estimates by the U.S. Census. They are released annually and the averages over the previous five years (in our case from 2011 to 2015). Since the availability of five-year estimates is better than the availability of one-year and three-year estimates, we pick the five-year estimates. Since they are predicted for longer time horizons, they capture trends and developments in relevant variables that have accumulated over time and might influence political outcomes. They are values in the sense that values are generated from surveys (University of Washington (2024)).

impact on Trump's percentage of votes. However, as booming counties attract high-skilled workers, the spillover effect is expected to have a negative influence.

As a final economic control variable, we incorporate the growth rate of import penetration from China at the commuting zone level, as provided by Autor *et al.* (2020). Given Donald Trump's frequent use of anti-China rhetoric during his campaign, we anticipate a positive effect. The spillover effect, however, might be negative, as high import penetration from China is associated with weak economic performance.

We also incorporate controls for socio-demographic characteristics. Firstly, we include the proportion of females in the total population (Rodríguez-Pose *et al.* (2021), Steinmayr (2021), Autor *et al.* (2020), Goetz *et al.* (2019), Halla *et al.* (2017)). This variable is calculated by dividing the number of women by the total population. Due to sexual harassment allegations against Donald Trump and his pejorative reactions, we anticipate a negative impact. Additionally, in many countries globally, women tend to vote for left-wing parties (Goetz *et al.* (2019)).

Next, we introduce the proportion of Black households over the total number of households (Rodríguez-Pose *et al.* (2021), Goetz *et al.* (2019), Madestam *et al.* (2013)). Given Trump's several racist comments and the significant representation of Black people in the Democrat's electorate, this variable is expected to decrease the Republicans' percentages of votes (Goetz *et al.* (2019)). Its spillover might have a positive effect, as voters might feel estranged when observing a growing share of African-Americans in neighbouring counties, thereby increasing their tendency to vote for Trump.

We also incorporate the proportion of Hispanics over the total number of inhabitants (Autor *et al.* (2020), Goetz *et al.* (2019), Madestam *et al.* (2013)). Calculated in the same way as the share of females, we expect a negative impact (Goetz *et al.* (2019)). Similar to the share of Black people, a positive effect is anticipated for its spillover.

Fourth, the proportion of adults with at least a bachelor's degree over the total number of adults controls for the county's education level. Generally, more educated individuals tend to vote more strongly for the Democrats, suggesting a negative impact (Rodríguez-Pose *et al.* (2021), Steinmayr (2021), Autor *et al.* (2020), Goetz *et al.* (2019), Scala & Johnson (2017), Barone *et al.* (2016), Mendez & Cutillas (2014)).

Since young people constitute a crucial target demographic for the Democrats, we anticipate a negative effect of this variable, controlling for the county's age distribution (Rodríguez-Pose *et al.* (2021), Steinmayr (2021), Autor *et al.* (2020), Halla *et al.* (2017), Mendez & Cutillas (2014)). Additionally, given that young people are generally more mobile than older generations (e.g., for study or work) and actively communicate their ideas and views, spillovers might negatively impact Trump's percentage of votes. The variable is constructed using the annual population estimates from the U.S. Census, summing the number of people aged up to 30 and dividing it by the total population.

For the same reason, we include the proportion of individuals aged over 60 in the total population. Similar to the proportion of young people, this variable is derived from the annual population estimates of the U.S. Census. We anticipate a positive effect on the Republicans' share of votes, as older generations typically align more strongly with the Republican party (Pew Research Center (2018)). Spillover effects are unclear. Older generations are generally less mobile than younger ones and do not communicate their ideas and views as frequently or publicly, suggesting potentially insignificant spillovers.

Finally, we control for the quality of public infrastructure and urbanization by incorporating the popularity of public means of transport. We calculate the proportion of workers (aged 16 and above) commuting to work by public transport over the number of workers (aged 16 and above) who do not work from home. This variable also serves as a proxy for urbanization. We expect a negative impact, as cities constitute a significant part of the Democrats' electorate. The spillover effect is ambiguous. On one hand, spillovers might have a positive impact if local public transport networks are loosely connected, leading to frustration and envy. On the other hand, inhabitants of neighbouring counties may observe the benefits of a good public infrastructure when working there. Overall, we anticipate a positive impact. Major cities with well-developed public infrastructure are primarily located on the East and West coasts. However, the Republicans have garnered more votes in counties far from the coasts (e.g., fly-over states), indicating a positive impact that increases with the distance cutoff.[15]

As in other studies (e.g. Rodríguez-Pose *et al.* (2021), Goetz *et al.* (2019)), all the covariates are from the year 2016. The one exception is the data from Autor *et al.* (2020) as they focus on the change in import competition from 2002 to 2010.

3.3. Descriptive Evidence

Summary statistics are presented in *Table* 1. The entire county-level dataset comprises 3,107 observations.

Figures 4 and 5 depict maps illustrating the percentages of votes for Donald Trump and Mitt Romney on the 2016 and 2012 ballots. The brighter the county's colour, the higher these percentages. Coal-producing counties are outlined in green. Higher percentages of votes for the Democrats are evident in coastal regions, where larger cities are located. In contrast, Trump was successful in the Midwest, Mid-Atlantic, South East, and the eastern parts of the

[15] Other variables, such as average and median household income, the relative sizes of different age cohorts and race groups, and employment shares of other industries, are not included due to strong multicollinearity, as suggested by high bivariate correlation coefficients and variance inflation factors. In comparison to Goetz *et al.* (2019), voter turnout is excluded, as it can be classified as another outcome of the ballot, suggesting it as a poor control in the sense of Angrist & Pischke (2009)

Variable	Unit	Mean (SD)	Min - Med - Max	IQR (CV)	VIF
Political Variables:					
Share Republican 2016	Percentage Points	63.28 (15.67)	4.09 < 66.34 < 96.03	20.43 (0.25)	NA
Share Republican 2012	Percentage Points	59.6 (14.83)	5.98 < 60.78 < 95.86	19.98 (0.25)	3.65
Difference Percentages of Votes between 2016 (Trump) and 2012 (Romney)	Percentage Points	3.67 (5.72)	-37.62 < 3.67 < 23.12	6.58 (1.56)	NA
Coal Variables:					
Coal Output	Mill. Shorttons	0.14 (1.17)	0 < 0 < 29.79	0 (8.21)	1.08
Average Number of Coal Workers hired by Mines	Integer	13.19 (91.59)	0 < 0 < 2287	0 (6.94)	NA
Average Number of Working Hours used by Mines	Integer	28273.42 (199560)	0 < 0 < 5019915	0 (7.06)	NA
Coal Output per Worker	Thsnd. Shorttons per Worker	9.01 (7.19)	0.47 < 7.65 < 51.9	7.67 (0.8)	NA
Coal Output per Working Hour	Shorttons per Working Hour	4.5 (3.7)	0.38 < 3.49 < 25.5	3.49 (0.82)	NA
Economic Controls:					
Share Manufacturing	Percentage Points	12.33 (7.13)	0 < 11.5 < 48.3	10 (0.58)	2.43
Unemployment Rate	Percentage Points	5.21 (1.83)	1.7 < 4.9 < 24.1	2.1 (0.35)	2.62
Share Poverty	Percentage Points	15.91 (6.27)	3.4 < 14.9 < 48.6	7.7 (0.39)	4.09
Share Insurance	Percentage Points	87.82 (5.11)	53.41 < 88.47 < 97.88	6.6 (0.06)	3.06
Growth Rate Import Penetration from China	Percentage Points	0.76 (0.68)	-0.26 < 0.63 < 6.08	0.64 (0.89)	1.50
Demographic Controls:					
Share Female	Percentage Points	49.93 (2.21)	30.16 < 50.34 < 56.78	1.58 (0.04)	1.51
Share Black People	Percentage Points	9.1 (14.57)	0 < 2.27 < 86.18	9.79 (1.6)	4.16
Share Latino	Percentage Points	9.35 (13.75)	0.52 < 4.14 < 96.24	7.27 (1.47)	3.31
Share Education	Percentage Points	21.55 (9.44)	0 < 19.2 < 78.5	10.5 (0.44)	3.09
Share Young	Percentage Points	37.17 (5.28)	13.06 < 36.77 < 68.47	5.64 (0.14)	7.08
Share Old	Percentage Points	25.27 (5.54)	6.73 < 24.95 < 65.61	6.7 (0.22)	6.86
Share Public Transport	Percentage Points	1 (3.25)	0 < 0.35 < 64.42	0.68 (3.27)	1.54
Note:	'Mean' denotes the average, 'SD' the standard deviation, 'Min' the minimum value, 'Med' the median, 'Max' the maximum value, 'IQR' the interquartile range and 'CV' the coefficient of variation. The last column 'VIF' displays the variance inflation factors of the variables included in the regression of the Republicans' percentage of votes excluding the spillovers. They are computed manually from the R^2s of simple OLS regressions of each covariate on the other covariates and state dummies. Variance inflation factors of the controls, except for the groups of age classes, vary between 1.08 and 4.09 not suggesting multicollinearity. For the age categories, VIFs are higher, since they sum up to one together with the share of middle-aged persons.				

Table 1: *Descriptive statistics*

West, North, and South West. Notably, states in the Rustbelt, the coal, and industrial region (e.g. Michigan, Ohio, Pennsylvania) were significant epicentres of Trump's victory. *Figure* 6 illustrates the difference in the Republicans' percentages of votes between 2016 and 2012. In the relevant counties, Trump was even more successful than Romney in 2012, suggesting that Trump's campaign pledges proved to be an effective tool in gaining votes in counties affected by declining manufacturing and coal mining. Furthermore, the Republicans won the election in many other coal-producing counties in Wyoming, Illinois, and the Appalachians (e.g. Kentucky, Pennsylvania, and West Virginia). On the other hand, Romney received higher percentages in Arizona and Utah.

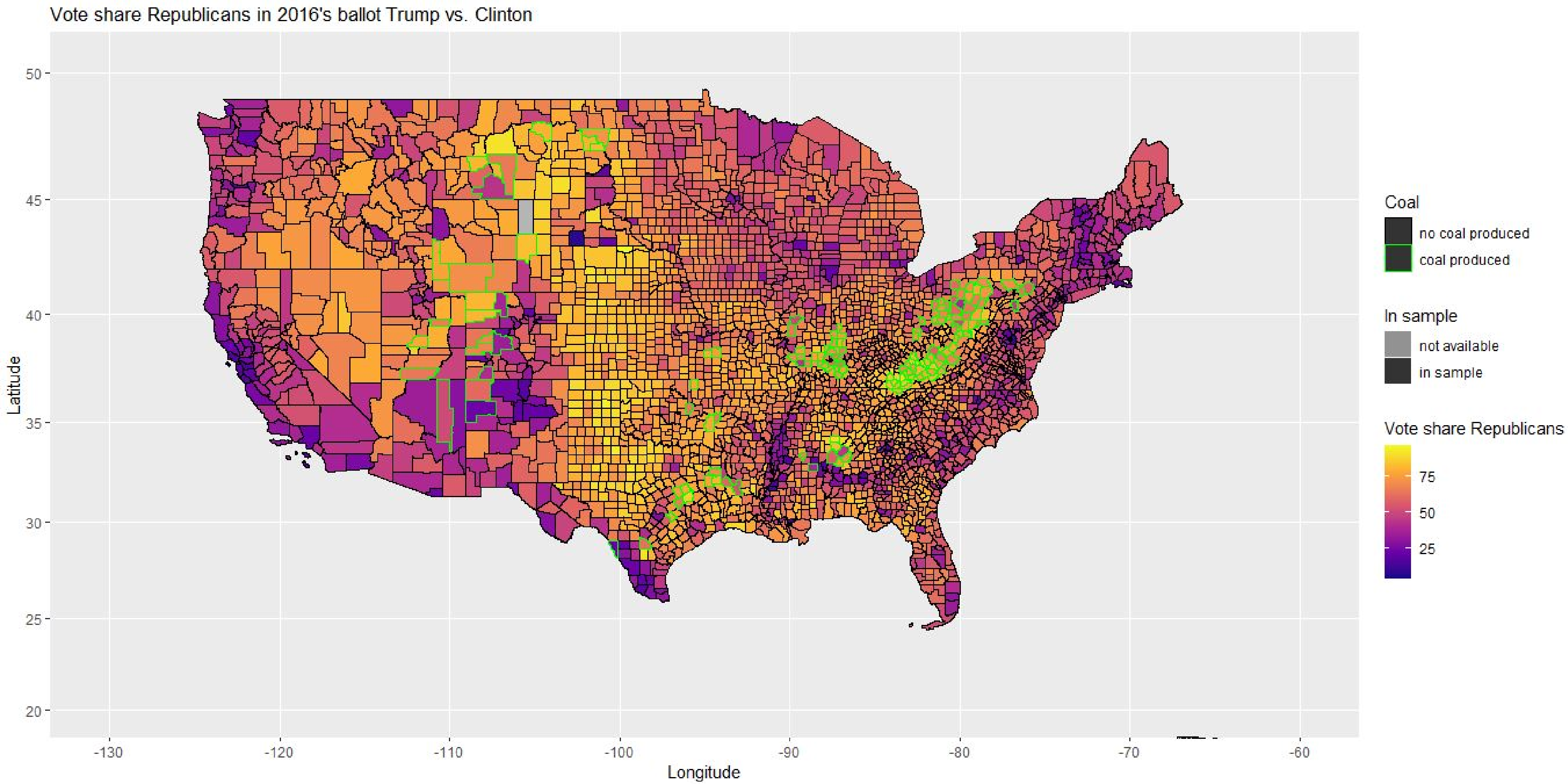

Figure 4: *Republicans' percentage of votes in the 2016 ballot: Trump vs. Clinton*

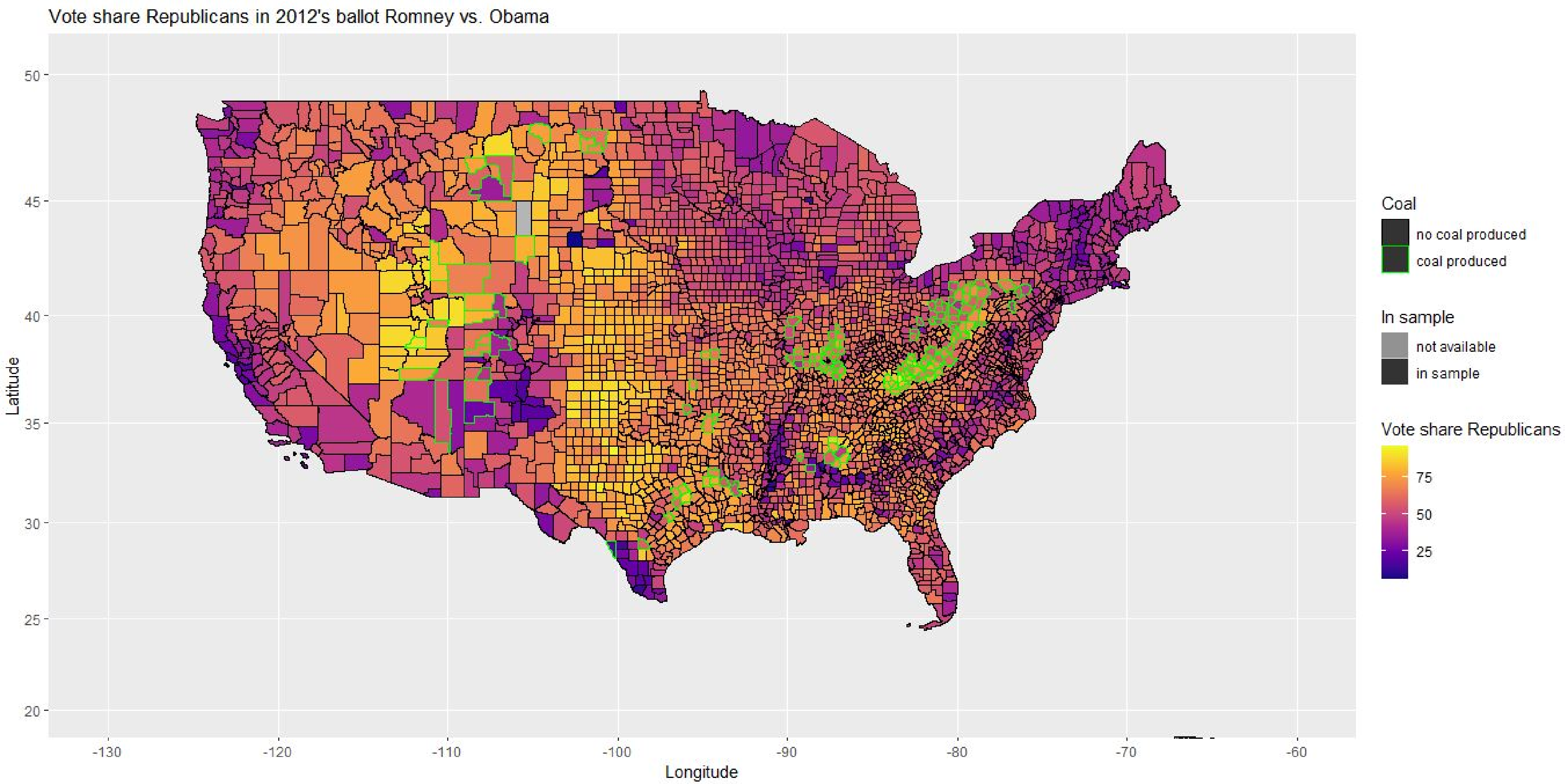

Figure 5: *Republicans' percentage of votes in the 2012 ballot: Romney vs. Obama*

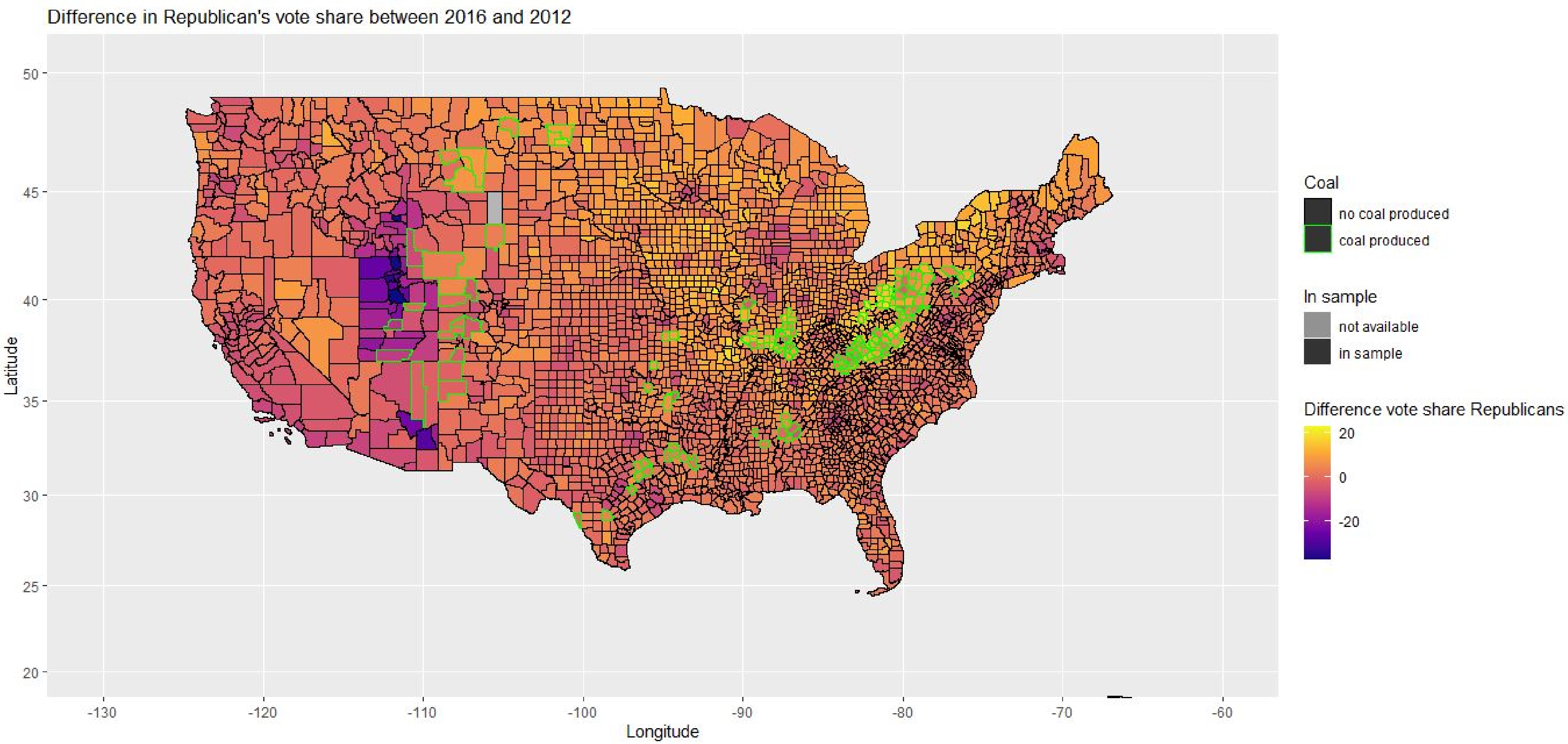

Figure 6: *Difference in Republicans' percentage of votes between 2016 and 2012*

4. Empirical strategy

Trump's promise to revive the US coal industry was an exogenous event, easily understood by the electorate and heavily publicized, especially in the campaign's final months. We employ a twofold empirical strategy to examine the effect of this campaign promise on the election outcome. First, we use an event study model to show the change in Republican Party share in coal counties in 2016 relative to other presidential election years. We then employ a cross-sectional county-based research design that compares counties with more coal-dependent economies to counties whose economies are unaffected by coal production. Identification is achieved by including spatially lagged explanatory variables and controlling for spatially autocorrelated error terms, while including state-specific effects and county pre-election characteristics among the controls.

First, we estimate the following equation:

$$\begin{aligned} r_{c,t} = & \beta_{2004} D_{2004} + \beta_{2008} D_{2008} + \beta_{2016} D_{2016} + \beta_{2020} D_{2020} + \\ & \delta_{2004} D_{2004} \cdot Coal_c + \delta_{2008} D_{2008} \cdot Coal_c + \delta_{2016} D_{2016} \cdot Coal_c + \\ & \delta_{2020} D_{2020} \cdot Coal_c + \alpha_c + \epsilon_{c,t} \end{aligned} \tag{1}$$

where $r_{c,t}$ is the Republican Party's share of votes in county c and election year t, for $t \in 2004, 2008, 2012, 2016, 2020$. Fixed effects for counties α_c are included to control for confounding omitted variables that vary across counties. Dummies for every election year D are formed, except for the year 2012 that serves as the baseline. These dummies absorb confounding factors that vary over time but are common across counties. $Coal$ is an indicator variable for the presence of coal production in county c. It equals one, if the county produces coal, and is zero otherwise. The status as a coal county does not change over time. The event date corresponds to 2016, when the campaign promise to revive coal production was made. We have observations for three presidential election years before the event (2004, 2008, and 2012) and one presidential election year after the event (2020). The error term is ϵ. The event study model in equation (1) is a two-way fixed effects difference-in-differences specification. The treated group consists of counties with some positive coal production in the year under consideration, while the control group is represented by counties with zero coal production, within the same state of the coal counties. Therefore, the dummies for the election years are interacted with the dummy indicating coal counties.[16] The treatment, represented by the campaign promise, takes place in 2016.

The δ are our main coefficients of interest and they estimate the treatment impact, that we define in reference to year 2012 (and the dummy variable for year 2012, D_{2012}, is omitted). We

[16] The dummy indicating coal counties is captured by the county fixed effects α because it is time-invariant.

use cluster robust standard errors at the level of counties c to control for autocorrelation within counties.

Next, we exploit variation in the size of the coal industry across counties and the timing of elections (2012 and 2016). We measure county-level coal 'exposure' as the annual coal production. The variation in coal production will generate differential responses in the electoral choices of the counties to the exogenous electoral promise. Our baseline specification takes the following form:

$$r_c^{2016} = \alpha + \beta\, Coal_c + \gamma\, r_c^{2012} + \psi'\, X_c + \sigma'\, D_s + \epsilon_c \tag{2}$$

where r_c^{2016} represents the Republicans' percentage of votes in a given county c located in a particular state s in 2016, Coal_c is the coal output in millions of short tons in the same county c. The coefficient of interest is β, describing the impact of coal production on county electoral outcomes. r_c^{2012} is the Republicans' percentage of votes in the same county c in 2012. X_c denotes an $N \times K$ matrix, including county-level controls as explained in *Section* 3.2, where N and K are the numbers of observations and variables, respectively. D_s covers state dummies controlling for unobserved state-specific heterogeneity, such as state-specific preferences, policies (e.g., states differ in legislation on early and postal voting), and other characteristics (e.g., swing states). Finally, ϵ_c defines the error term.

Even after conditioning on our control variables, the OLS estimation of equation (2) may produce biased coefficients if spatial patterns in the data are omitted from the equation. Equation (2) implicitly assumes that the stable unit treatment value assumption (SUTVA) is satisfied, but such an approach neglects trade, migration, and information flows between counties, resulting in biased estimates.[17] If this is the case, the residuals in equation (2) will be spatially autocorrelated. To check whether OLS generates biased coefficients, we test whether the residuals are spatially correlated using the test by Moran (1948) (Dall'erba & Le Gallo (2008), Ertur *et al.* (2006)).

To perform the test, we construct inverse distance matrices using various cutoffs, following the approach by Fingleton (1999). First, we compute the deciles of the distances between all pairs of counties. Second, we construct inverse distance matrices using the chosen deciles as cutoffs for the distance. Third, we test the residuals of the conventional OLS regression for spatial autocorrelation, employing the Moran test. The residuals are tested separately, applying each inverse distance matrix. If the Moran test consistently does not reject the null hypothesis (no spatial autocorrelation), then the results by OLS are considered consistent. Fourth, we choose the cutoff and corresponding inverse matrix that maximizes the significant Moran's I statistic to serve as the spatial weighting matrix in the spatial regression.

[17] In the literature, the assumption that the treatment of individual i only affects the outcome of the same individual i, but not the outcomes of the other $-i$ individuals is called 'SUTVA' (Wooldridge (2010)).

To assess whether the OLS estimates exhibit this inconsistency using the test by Moran (1948), we employ a various types of spatial weighting matrices W: a binary queening matrix and inverse distance matrices. The queening matrix is a binary adjacency matrix, that only models interactions between direct neighbours. It is one of the simplest forms of adjacency matrices that only considers spatially limited interactions. In this matrix, there is a link between counties i and j equals one ($w_{i,j} = 1$), if county j shares a border with county i at least at one point, and is zero ($w_{i,j} = 0$) otherwise. Therefore, all the neighbors of a given county get the same weight, as it does not distinguish closer neighbors and neighbors farer away, as long as they share a border. This matrix is also used to investigate the spatial serial correlation of residuals for the case in which economic flows should only focus on the closest neighbors. The matrix is constructed from shapefiles obtained from the U.S. Census Bureau.[18]

The inverse-distance matrices are a more complex way of modelling interactions between spatial zones that are not limited to neighbors that share a border with a given county. Additionally, they inverse-distance matrices exhibit distance decay (Basile (2009), Dall'erba & Le Gallo (2008), Ertur *et al.* (2006), Pede *et al.* (2007)). Circle distances between every pair of counties are computed from the centroids of each polygon. The further away county j is from i, the smaller the influence (weight) of county j on i.

When constructing the inverse distance matrices, we implement various cutoffs. In other words, circles with a given radius are drawn around every county's centroid, defining the area where spillovers across counties are expected. If the distance exceeds this threshold (i.e., county j's centroid is located outside this circle around county i's centroid), it is assumed that county j does not influence county i, and thus its weight is set to zero ($w_{i,j} = 0$). On the other hand, if county j's centroid is located inside this circle, county j is assumed to impact county i and, hence, receives a weight based on the inverse distance ($w_{i,j} = \frac{1}{d_{i,j}}$). For the error terms, we set $w_{\epsilon,i,j} = 1$ if county j's centroid is located within the circle around county i's centroid and zero otherwise. The cutoffs are defined based on the deciles of the Pythagorean distances between the mass points of every pair of counties: 447 (first decile), 667 (second decile), 856 (third decile), 1,039 (fourth decile), 1,228 (fifth decile, median), 1,432 (sixth decile), 1,667 (seventh decile), 1,977 (eighth decile), 2,496 (ninth decile), and 4,578 (tenth decile, maximum) km.

The Moran's I statistics are consistently significant, indicating that the OLS residuals suffer from inconsistency due to spatial autocorrelation. The inverse distance matrix with the first decile cutoff (447 km) generates the highest statistically significant Moran's I statistic.

To address the spatially autocorrelated residuals, we must consider spillover effects and spatial clustering to establish a link between coal production and the Republicans' percentage of votes at the county level (Scala & Johnson (2017)). Therefore, we estimate a spatial Durbin Error model, as illustrated in Equation (3):

[18] `https://www2.census.gov/geo/tiger/TIGER2016/COUNTY/?sec_ak_reference=18.e0fd717.1515267074.5aed87d`

$$r_c^{2016} = \alpha + \beta\, Coal_c + \rho_1\, W\, Coal_c + \gamma\, r_c^{2012} + \rho_2\, W\, r_c^{2012} + \psi'\, X_c + \rho_3\, W\, X_c + \sigma'\, D_s + \epsilon_c$$
$$with\;\; \epsilon_c = \lambda\, W_\epsilon\, \epsilon_c + \eta_c \tag{3}$$

where W and W_ϵ define the spatial weight matrix for the coal output, covariates, and error term, respectively. ϵ_c denotes the error term, which consists of a spatially correlated component and an independent but heteroskedastically distributed innovation η_c. We estimate this model using the three-step proceudre proposed by Kelejian & Prucha (1999). Further details are provided in *Appendix* C.

The coefficients β, γ, and ψ quantify the effect of coal and other covariates in county i on the dependent variable in the same county, i.e., the local effect. In contrast, the coefficients ρ_1, ρ_2, and ρ_3 measure the degree to which the dependent variable of the given county is influenced by the coal production and values of other covariates in its neighboring counties, i.e., the spillover effect.

In a spatial Durbin Error model, only spatial spillovers of the covariates and errors are introduced, but no spatial lag of the dependent variable is considered. There are two main reasons for this modelling. First, strategic interactions and coordination between counties on ballot outcomes are unlikely, suggesting the exclusion of the spatial lag of the dependent variable. Second, the characteristics of one county plausibly influence the Republicans' vote share in other counties via trade and migration flows. For instance, coal production in a given county does not only create jobs in the same county but also in neighbouring ones.

We employ various specifications of equation (3), primarily differing in the definition of the weighting matrices. The approach by Fingleton (1999) suggests using the inverse distance weighting matrix with a cutoff of 447 km for the spatial regression. Given the large cutoff, we extend the approach by Fingleton (1999), incorporating additional cutoffs from 150 to the first decile 447 km.[19]

All matrices are row-normalized, implying that the influence of county i on the other $-i$ counties decreases with the number of neighbours. First, row sums are calculated. Second, each cell is divided by its respective row sum. Subsequently, the matrices are multiplied by the relevant vectors to obtain $W\,$Coal, $W\, r^{2012}$, and $W\, X$. In other words, normalization facilitates interpretation, and the resulting products are interpretable as distance-weighted averages of the underlying variables (Weiss *et al.* (2015)).

W_ϵ is a binary weighting matrix used to incorporate spatial clustering of the residuals. In this matrix, a link between counties i and j equals one if the distance between the counties is smaller

[19]The supplementary cutoffs include 150, 200, 250, 300, 350, and 400 km. 150 km is the lowest possible threshold; below this value, some counties become isolated as islands without any neighbours.

than the corresponding cutoff. In other words, the link is one if county j lies inside the circle around the centroid of county i. The radius of this circle is the relevant cutoff. The link is zero if county j lies outside the same circle.

The coefficient of interest is β in equation (3) for the coal variable. The estimates may be biased, if unobserved county characteristics affecting political outcomes are also correlated with the coal output. We argue that simultaneity issues are unlikely, as winning votes by promoting coal mining and supporting mine operators to relocate is a challenging political endeavour. Stricter environmental legislation, opposition from residents, high wage costs, and the lengthy construction times required for relocation and capacity building are among the hurdles such a political pledge might face. Moreover, more feasible alternatives exist to garner votes in the relevant counties. Hence, in the short run, coal output can reasonably be classified as an exogenous variable. Furthermore, the previous governments showed little interest in coal counties, which are Republican strongholds in regions crucial for the Republican party (e.g., Midwest, South-West, Central-East, and South-East). Additionally, omitted variable biases are addressed by including a comprehensive set of controls and state dummies. Controlling for pre-election counties' characteristics and including state-fixed effects, which absorb systematic differences in economic performance across states, alleviates the simultaneity issue substantially. In our main specification, we thus estimate equation (3) controlling for spatially autocorrelated error terms while absorbing state-specific effects and pre-election characteristics among the controls.

We expect that the coefficient for coal production has a positive sign due to the electoral pledge. Coal mining is an important industry in the coal counties. If it is declining, income and employment may decrease. Therefore, parties and politicians such as Donald Trump supporting the coal industry will be favored in relevant counties. However, the spillover effect is ambiguous. On one hand, closer neighbours benefit from increased employment and economic growth, while on the other hand, they may suffer from pollution. Furthermore, more liberal Republican voters might generally oppose the support of coal mining. The farther away the neighbours, the weaker the effects on economic prosperity and pollution. For medium cutoffs, we expect positive coefficients, as pollution merely implies regional disadvantages that are outweighed by economic advantages. For larger thresholds, advantages and disadvantages may again compensate each other, as more distant counties neither substantially benefit nor lose from coal mining in a given county.

Following the approach of Rodríguez-Pose *et al.* (2021) and Goetz *et al.* (2019), we also introduce an alternative specification where the dependent variable is the difference between the percentages of all votes received by Donald Trump in 2016 and Mitt Romney in 2012:

$$\begin{aligned} &r_c^{2016} - r_c^{2012} = \alpha + \beta\, Coal_c + \rho_1\, W\, Coal_c + \psi'\, X_c + \rho_2\, W\, X_c + \sigma'\, D_s + \epsilon_c \\ &with\ \ \epsilon_c = \lambda\, W_\epsilon\, \epsilon_c + \eta_c. \end{aligned} \tag{4}$$

In this specification, the coefficients quantify the extent to which Donald Trump appeals to voters in a county when the value of a given covariate rises by one unit, beyond merely being the Republican candidate. Results remain robust when using a different reference election. We re-estimate the same equations but deduct the Republicans' shares of votes in 2004 and 2008 from the same share in 2016. Overall, results barely change.

Considerations about identification are presented in *Appendix* B.

5. Results and Discussion

5.1. Results of the Event Study

Figure 7 shows the estimated δ coefficients and their 95%-confidence intervals from equation (1).

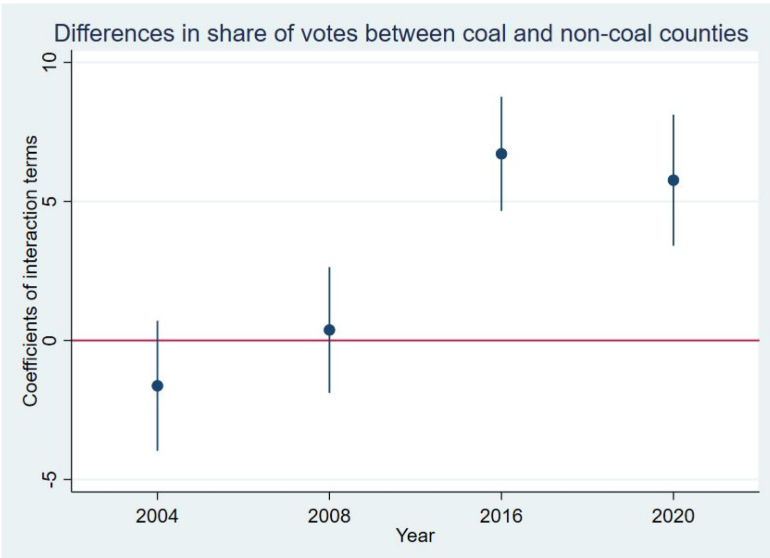

Figure 7: *Estimated coefficients and confidence intervals for the event study regression*

The coefficients of the interaction terms with the years 2004 and 2008 are insignificant, suggesting that the Republicans' shares of votes do not systematically differ between coal and non-coal counties. Only starting from the year 2016 in which Donald Trump has run for office the first time the differences in the shares of votes turn significant. Starting from the year 2016, the Republican Party becomes more successful in coal counties than in non-coal coal counties. As can be seen from the figure, the Republicans' shares of votes in the treatment group are on average significantly higher than in the control group. In fact, Trump's candidature spurred the Republicans' success in these counties. We interpret this result as some *prima facie* evidence of a sudden increase in the Republican Party's share of votes in coal counties in 2016, related to the pledge, since the shares of votes do not significantly differ across coal and non-coal counties in the years before he has run for presidency.

In the next section, we present the estimation results for identifying the differential responses of counties' electoral choices to the exogenous electoral promise. In particular, we focus on the 2012-2016 electoral outcomes and estimate the effect of the size of coal production, which differs across coal counties, as well as spillover effects.

5.2. Results of the Core Models

5.2.1. Explaining the Republicans' Percentages of Votes

Table 2 provides the estimation results for equations (2) and (3). In every regression, the dependent variable is the county-level Republicans' percentage of votes in 2016. Column (1) displays the estimates of the simple OLS model with standard errors clustered at the state level, excluding spatial spillovers. In columns (2)-(8), inverse distance matrices are employed to incorporate the spatial spillovers of the covariates. In relevant columns, spatial clustering is introduced by using the binary pendants of the inverse distance matrices. For instance, column (2) shows the regression estimates using the inverse distance matrix with a cutoff of 150 km. Its binary pendant is used to include the spatial clustering of the residuals. In these columns, standard errors are robust.

In Column (1), the Ordinary Least Squares (OLS) estimated coefficient for coal output (measured in millions of short tons) is positive and statistically significant. If the coal output in county i increases by one million short tons (approximately one standard deviation), the percentage of votes for Republicans significantly increases by 0.1 percentage points in 2016.

As outlined in *Section* 4, the Ordinary Least Squares (OLS) estimates are inconsistent if the residuals are spatially autocorrelated. To check whether this holds true for the OLS regression at hand, we apply the test by Moran (1948). In doing so, we employ various spatial weighting matrices. First, we use a binary queen matrix. Second, we apply inverse distance matrices with various cutoffs.

Cutoffs are selected following the approach by Fingleton (1999). As discussed in *Section* 4, these cutoffs are based on the distances between the centroids of each pair of counties: 447 km (first decile), 667 km (second decile), 856 km (third decile), 1,039 km (fourth decile), 1,228 km (median, fifth decile), 1,432 km (sixth decile), 1,667 km (seventh decile), 1,977 km (eighth decile), 2,496 km (ninth decile), and 4,578 km (maximum, tenth decile).

We use each weighting matrix separately to test the residuals. The first two blocks in *Table* 3 display the results of the Moran tests. Column (1) provides the type of the matrix, column (2) the implemented cutoff, column (3) the Moran's I statistics, and column (4) the test's p-value. All tests detect spatial correlation in the OLS residuals. Hence, there is a spatial pattern in the data that is not accounted for in the OLS regression shown in column (1) in *Table* 2. Consequently, OLS can be biased and must be interpreted cautiously.

	OLS	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X								
Coal Output	0.100**	0.077**	0.064**	0.078***	0.089***	0.089***	0.094***	0.090***
	(0.044)	(0.032)	(0.031)	(0.030)	(0.033)	(0.034)	(0.035)	(0.035)
Share Republican 2012	0.838***	0.818***	0.823***	0.818***	0.821***	0.822***	0.821***	0.821***
	(0.019)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Manufacturing	−0.007	0.017*	0.019**	0.020**	0.018*	0.016*	0.017*	0.017*
	(0.016)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Unemployment Rate	0.038	0.049	0.038	0.035	0.045	0.041	0.026	0.035
	(0.064)	(0.048)	(0.049)	(0.046)	(0.047)	(0.048)	(0.049)	(0.049)
Share Poverty	−0.026	−0.045**	−0.038**	−0.036**	−0.037**	−0.038**	−0.034*	−0.036**
	(0.032)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
Share Insurance	0.059*	0.070***	0.062***	0.054***	0.055***	0.057***	0.061***	0.062***
	(0.035)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Import Penetration	0.094	0.189***	0.183**	0.185***	0.196***	0.188**	0.152**	0.158**
	(0.075)	(0.070)	(0.071)	(0.068)	(0.073)	(0.074)	(0.071)	(0.071)
Share Female	−0.149***	−0.135***	−0.134***	−0.144***	−0.140***	−0.138***	−0.143***	−0.144***
	(0.043)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Share Black People	−0.159***	−0.183***	−0.179***	−0.183***	−0.180***	−0.178***	−0.180***	−0.180***
	(0.014)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)
Share Latino	−0.114***	−0.115***	−0.109***	−0.111***	−0.106***	−0.105***	−0.104***	−0.103***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Share Education	−0.405***	−0.396***	−0.389***	−0.386***	−0.387***	−0.388***	−0.388***	−0.386***
	(0.018)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Share Young	−0.049	−0.068*	−0.073*	−0.074**	−0.084**	−0.082**	−0.073**	−0.072**
	(0.063)	(0.037)	(0.038)	(0.036)	(0.038)	(0.038)	(0.036)	(0.036)
Share Old	0.098*	0.071**	0.074**	0.081***	0.068**	0.069**	0.080***	0.079**
	(0.049)	(0.030)	(0.031)	(0.030)	(0.031)	(0.031)	(0.030)	(0.031)
Share Public Travel	−0.009	−0.041	−0.054*	−0.056*	−0.046	−0.046	−0.065*	−0.072*
	(0.019)	(0.028)	(0.032)	(0.034)	(0.034)	(0.034)	(0.036)	(0.037)
Intercept	27.402***	40.584***	55.573***	49.044***	61.453***	77.737***	89.324***	125.749***
	(6.072)	(10.144)	(11.370)	(14.335)	(15.483)	(18.570)	(22.514)	(26.511)
$W_X X$								
Coal Output		0.182	0.225	0.535	0.238	0.705	1.242*	1.998***
		(0.188)	(0.292)	(0.350)	(0.398)	(0.489)	(0.720)	(0.758)
Share Republican 2012		−0.014	−0.033	−0.041	−0.044	−0.058*	−0.048	−0.093**
		(0.021)	(0.023)	(0.026)	(0.029)	(0.033)	(0.041)	(0.044)
Share Manufacturing		−0.014	−0.073	−0.103*	−0.069	−0.087	−0.319***	−0.351***
		(0.046)	(0.053)	(0.057)	(0.065)	(0.071)	(0.080)	(0.087)
Unemployment Rate		0.004	−0.255	−0.014	−0.339	−0.358	−0.251	−0.509
		(0.169)	(0.203)	(0.245)	(0.259)	(0.304)	(0.399)	(0.426)
Share Poverty		−0.098*	−0.181**	−0.243**	−0.256**	−0.248**	−0.336**	−0.350**
		(0.059)	(0.077)	(0.096)	(0.103)	(0.119)	(0.143)	(0.156)
Share Insurance		−0.047	−0.110	−0.030	−0.073	−0.115	−0.116	−0.262*
		(0.070)	(0.077)	(0.094)	(0.106)	(0.118)	(0.118)	(0.138)
Import Penetration		−0.395	−0.338	0.280	−0.976	−0.800	1.016	1.396
		(0.376)	(0.424)	(0.573)	(0.614)	(0.678)	(0.829)	(0.913)
Share Female		0.237*	0.233	0.184	0.382*	0.260	0.055	−0.277
		(0.136)	(0.160)	(0.227)	(0.222)	(0.256)	(0.322)	(0.370)
Share Black People		0.039**	0.047**	0.051**	0.048*	0.061**	0.044	0.029
		(0.017)	(0.022)	(0.021)	(0.025)	(0.027)	(0.030)	(0.034)
Share Latino		0.007	−0.003	−0.018	0.001	−0.010	−0.051	−0.087**
		(0.021)	(0.023)	(0.032)	(0.028)	(0.030)	(0.036)	(0.041)
Share Education		−0.238**	−0.355***	−0.470***	−0.536***	−0.598***	−0.710***	−0.785***
		(0.046)	(0.055)	(0.065)	(0.069)	(0.081)	(0.103)	(0.107)
Share Young		−0.267**	−0.336**	−0.214	−0.517***	−0.603***	−0.527**	−0.545**
		(0.114)	(0.135)	(0.171)	(0.187)	(0.208)	(0.249)	(0.268)
Share Old		−0.131	−0.125	−0.055	−0.213	−0.264	−0.249	−0.254
		(0.103)	(0.116)	(0.144)	(0.156)	(0.173)	(0.205)	(0.224)
Share Public Transport		0.184**	0.280***	0.451***	0.404***	0.490***	0.767***	0.890***
		(0.075)	(0.098)	(0.121)	(0.134)	(0.143)	(0.159)	(0.177)
$W_\epsilon \epsilon$		0.025***	0.014***	0.013***	0.009***	0.008***	0.010***	0.010***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.977	0.978	0.977	0.978	0.977	0.977	0.978	0.976

Note: The dependent variable is the percentage of votes for Republicans in all specifications. In Column (1), standard errors are clustered at the state level. The standard errors in Columns (2)-(8) are robust. Standard errors are displayed in parentheses below the coefficients. Alaskan and Hawaiian counties, as well as Campbell/Wyoming, are excluded. The baseline for the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

To avoid this problem, we estimate spatial Durbin Error models. These models have the advantage of directly incorporating spatially lagged explanatory variables and a spatial error term into the election model.

To perform the spatial regression, the spatial weighting matrix has to be defined. According to Fingleton (1999), the matrix that generates the highest significant Moran's *I* statistics should be applied to perform the estimation.

The highest significant Moran's *I* statistics are generated by the inverse distance matrix with a cutoff of 447 km (first decile). Given the long pairwise distances between U.S. counties, the deciles and, thus, the cutoffs are relatively large. As explained in *Section* 4, we extend the approach by Fingleton (1999) by involving additional cutoffs from 150 km to the first decile, 447 km. They include 150, 200, 250, 300, 350, and 400 km. The results are shown in *Table* 3. When introducing these new cutoffs up to the first decile, the highest significant Moran's *I* statistics is now produced by the inverse distance matrix with a cutoff of 200 km. Thus, we employ this matrix to estimate the spatial Durbin models. Nevertheless, we apply the other spatial weighting matrices with cutoffs from 150 to 447 km (first decile) as robustness checks.

Type	Cutoff	*Moran's* I *statistic*	$p - value$
Binary			3,107 observations
Queening	none	660.83 * **	0.000
Inverse distance (deciles as cutoffs)			3,107 observations
Inverse distance	447 km (first decile)	896.34 * **	0.000
Inverse distance	667 km (second decile)	521.31 * **	0.000
Inverse distance	856 km (third decile)	431.18 * **	0.000
Inverse distance	1,039 km (fourth decile)	442.00 * **	0.000
Inverse distance	1,228 km (median, fifth decile)	462.74 * **	0.000
Inverse distance	1,432 km (sixth decile)	445.80 * **	0.000
Inverse distance	1,667 km (seventh decile)	422.80 * **	0.000
Inverse distance	1,977 km (eighth decile)	428.68 * **	0.000
Inverse distance	2,496 km (ninth decile)	402.05 * **	0.000
Inverse distance	4,578 km (maximum, tenth decile)	394.34 * **	0.000
Inverse distance (cutoffs from 150 to 447 km)			3,107 observations
Inverse distance	150 km	1, 385.84 * **	0.000
Inverse distance	200 km	1, 496.95 * **	0.000
Inverse distance	250 km	1, 385.14 * **	0.000
Inverse distance	300 km	1, 313.28 * **	0.000
Inverse distance	350 km	1, 198.65 * **	0.000
Inverse distance	400 km	1, 022.06 * **	0.000
Note:	The table examines whether the residuals of the Ordinary Least Squares (OLS) regression displayed in Column (1) of *Table* 2 are spatially autocorrelated. To investigate this issue, the test by Moran (1948) is employed. The first block displays the results of the test applying the binary queening matrix, while the second block provides the results of the tests employing inverse distance weighting matrices with cutoffs as the deciles of the pairwise distances. Given the generally significant test statistics, the residuals of the OLS regression can be considered spatially autocorrelated. The approach by Fingleton (1999) proposes to apply the inverse distance matrix with a cutoff of 447 km. However, this cutoff is still quite large. Therefore, the third block provides the results of the tests by Moran (1948) that apply inverse distance matrices with cutoffs ranging from 150 to 447 km.		
	*p<0.1; **p<0.05; ***p<0.01		

Table 3: *Results of the Moran tests*

The results of the spatial Durbin Error models are displayed in Columns (2)-(8) in *Table* 2. Our results allow for the computation of local and spillover effects. The local effect measures the change in the Republicans' share when a county characteristic (e.g., coal production) changes in a particular county. The corresponding estimated coefficients are in the top panel of *Table* 2. The spillover effect measures the impact on the Republicans' voting share of a particular county from changing an exogenous variable (e.g., coal production) in another county. The corresponding estimated coefficients are in the bottom panel of *Table* 2. The local effect of coal production is in the range of 0.064-0.094: if coal output in county i rises by one million short tons, the Republicans' share significantly increases by 0.064-0.094 percentage points in 2016.

Row-normalisation of the spatial weighting matrices allows us to interpret the spillover coefficients as the effects of changes in weighted averages. When the distance-weighted average of coal production of county i's neighbours located within the circle around its centroid is increased by one million short tons, the dependent variable in county i increases by 0.182-1.998 percentage points. Spillovers, however, significantly affect the dependent variable in only two out of eight models, suggesting that benefits and disadvantages from pollution compensate for each other within shorter distances. Within given regions (up to 350 km), the relatively small gains from trade do not sufficiently exceed environmental disadvantages. These spillover patterns are reasonable for two further reasons. First, the supply chain of the coal industry is quite simplistic. Coal is mined and then transported to a coal-fired power plant. As shown before, the electricity industry is by far the most important consumer of coal. Given the simplistic supply chains, economic benefits from trade might not be that large. Second, neighbouring coal counties constitute a coal region (Appalachian). If neighbour j produces coal, this fact might be irrelevant to county i if it also produces coal because there will be no trade, and the pollution in county i comes primarily from the county's mines themselves. That will make spillovers within coal regions weaker.

Overall, we find that coal-producing counties indeed show a stronger tendency to vote for Trump than other counties, confirming the hypothesis that Trump has been more successful in these counties due to his election pledges.

As expected, the Republicans' percentage of votes on the 2012 ballot significantly increases the same party's outcome in 2016, suggesting some degree of persistence of preferences. In comparison, the spillover is mostly negative and insignificant. Hence, spillovers in votes from neighbouring counties in the previous ballot are limited.

Next, the unemployment rate does not significantly affect Trump's percentage of votes. The same is true for its spillover.

Plausibly, a more dominant manufacturing industry significantly positively impacts the dependent variable, as Trump's agenda, compared to that of Clinton, has been more pro-business (e.g., the pledge to reduce corporate taxes). On the other hand, the spillover's impact is significantly negative, suggesting that neighbouring counties' booming manufacturing sectors might absorb businesses, jobs, and highly-skilled workers, causing income losses, unemployment, and poverty. Such a decline would support the Democrats.

On the other hand, poverty significantly reduces the Republicans' share of votes. Its spillover is also significantly negative because high poverty rates in neighbouring counties might raise worries and anxiety in county i, spurring its inhabitants to vote for the Democrats due to the Republicans' restrictive social policy.

In comparison, the share of socially insured people significantly increases Trump's share of voters, as a larger share coincides with robust economic development. The effect of its spillover only significantly differs from zero in three regressions.

For the growth rate of import penetration, we find a positive effect on Donald Trump's vote share in every model, except for the simple OLS model. The spillover effect is not uniform but never significant.

As expected, the findings confirm that females, Black People, Hispanics, better-educated, and younger people vote less for Trump. While the spillover of females does not significantly affect the dependent variable, the share of Black households significantly raises it in five models, suggesting that voters in a given county might be concerned about an increasing share of Black people at the cost of the share of whites. In comparison, the share of Latinos in neighbouring counties does not show an effect. The share of people with a bachelor's degree or more and the share of young people always show a significantly negative effect because well-educated and young people are more mobile and communicate their ideas more openly, more frequently, and with a greater reach (especially through social media).

Confirming the generation gap in American politics, older generations support the Republicans more strongly than younger generations. As expected, spillover effects do not significantly deviate from zero.

Furthermore, the share of workers aged above 16 traveling to work by public means of transport significantly decreases Trump's share of votes in four models, as the quality of living tends to be higher in relevant counties, implying a smaller pool of frustrated voters prone to Trump. Additionally, the spillover is significantly positive and rises with the cutoff, suggesting that counties far away from the coasts (where there are big cities with good public transport systems) vote more intensively for the Republicans.

Lastly, the spillovers of the residuals are significantly positive. Thus, a positive shock to the dependent variable is likely to affect the outcomes of neighbouring counties similarly because the same or similar shocks might also affect them.

5.2.2. Examination of Populism Effects

Table 4 presents the results for the populist equation (4). Column (1) displays OLS results with standard errors clustered at the state level. Columns (2)-(8) present the regression estimates for the Spatial Durbin Error models using the inverse distance matrices.

Once again, the residuals of the equation estimated using OLS, as shown in Column (1), exhibit spatial autocorrelation. As previously, the cutoffs of the inverse distance matrices are based on the deciles of the pairwise distances. Likewise, the inverse distance matrix with a cutoff of 447 km (first decile) generates the highest significant Moran's I statistics. Since this cutoff is already a large number, we introduce additional cutoffs from 150 to 447 km (first decile) to assess whether the residuals maintain spatial autocorrelation. When adding these additional cutoffs, then the inverse distance matrix with a cutoff of 200 km generates the highest significant Moran's I statistics like before. Therefore, we again employ this matrix for the spatial regression but use the other inverse distance matrices with cutoffs ranging from 150 to 447 km as robustness checks.

Regarding the coefficient of interest for coal production, Donald Trump was more successful in 2016 than Romney in 2012 in a given county when more coal is produced. When coal output increases by one million short tons, the difference in percentages significantly increases by 0.080-0.116 percentage points. This suggests that Trump's campaign pledge played a role. Voters in coal-producing counties may have believed that Trump, as a businessman, could keep his promise. However, spillovers are insignificant. Hence, the output of neighbouring counties has no significant impact on the outcome in a given county. Trump has also focused more intensively on the coal counties themselves and less on their neighbours. Moreover, the simplistic supply chains and the clustering of coal counties also decrease spillover effects.

In comparison, the effect of the unemployment rate turns significantly positive, suggesting that Trump won a larger percentage of votes than Romney in counties with a higher unemployment rate. Plausibly, voters had more confidence in Trump because he might have been able to create new jobs due to his vocational background.

The same holds for poverty shares. While higher poverty did not significantly reduce Donald Trump's share of votes, he received more votes than Romney, suggesting that the electorate might have believed Trump would be more capable of reducing poverty through job creation than Mitt Romney. Its spillover is still significantly negative, indicating that Trump's margin over Romney declined when more neighbouring counties suffered from poverty. In other words, if poverty is a geographically widespread problem in a given region, voters preferred the Democrats and Mitt Romney.

While Trump has been more successful than Romney in counties with a strong manufacturing sector, as suggested by three models, the spillover is now significantly positive. Although the percentages of votes decrease when neighbouring counties benefit from a robust manufacturing industry, as shown in *Table* 2, Donald Trump has still been more successful in the given county than Mitt Romney. The reason might be that Trump's campaign also covered the revitalisation of the Rust Belt. Given the complex supply chains (long and geographically widespread) characterising the manufacturing sectors, positive shocks spread out more broadly geographically, benefiting larger regions.

In comparison, the share of socially insured people becomes insignificant, suggesting that a higher share generally favours the Republican party, as Trump has not significantly benefited

	OLS	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
X								
Coal Output	0.116**	0.089**	0.080**	0.091**	0.106***	0.103**	0.107**	0.104**
	(0.047)	(0.037)	(0.036)	(0.037)	(0.041)	(0.041)	(0.043)	(0.044)
Share Manufacturing	0.024	0.025**	0.023**	0.022**	0.017	0.015	0.016	0.016
	(0.020)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Unemployment Rate	0.202**	0.164***	0.149***	0.140***	0.142***	0.138**	0.142**	0.155***
	(0.010)	(0.056)	(0.056)	(0.054)	(0.054)	(0.056)	(0.056)	(0.057)
Share Poverty	0.067	0.082***	0.076***	0.082***	0.084***	0.083***	0.079***	0.075***
	(0.051)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)
Share Insurance	0.025	0.036	0.026	0.022	0.024	0.026	0.028	0.031
	(0.041)	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Import Penetration	0.123	0.230***	0.244***	0.249***	0.233***	0.234***	0.223***	0.233***
	(0.099)	(0.083)	(0.081)	(0.082)	(0.084)	(0.086)	(0.087)	(0.087)
Share Female	−0.066	−0.030	−0.032	−0.030	−0.030	−0.031	−0.033	−0.034
	(0.055)	(0.033)	(0.033)	(0.034)	(0.034)	(0.035)	(0.034)	(0.035)
Share Black People	−0.065***	−0.068***	−0.066***	−0.065***	−0.065***	−0.066***	−0.065***	−0.063***
	(0.014)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
Share Latino	−0.057***	−0.070***	−0.064***	−0.064***	−0.060***	−0.058***	−0.057***	−0.055***
	(0.015)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)
Share Education	−0.311***	−0.319***	−0.316***	−0.315***	−0.317***	−0.318***	−0.318***	−0.317***
	(0.019)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Young	−0.111	−0.131***	−0.127***	−0.138***	−0.140***	−0.140***	−0.137***	−0.135***
	(0.087)	(0.047)	(0.046)	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
Share Old	0.049	0.007	0.017	0.011	0.010	0.013	0.014	0.015
	(0.066)	(0.036)	(0.036)	(0.036)	(0.035)	(0.036)	(0.036)	(0.036)
Share Public Transport	0.015	0.000	−0.002	0.002	0.014	0.024	0.030	0.028
	(0.040)	(0.031)	(0.034)	(0.035)	(0.036)	(0.035)	(0.035)	(0.036)
Intercept	11.597**	19.074**	18.664	11.210	16.311	28.707	45.909*	66.522**
	(5.754)	(8.837)	(12.110)	(14.458)	(17.051)	(20.264)	(24.875)	(28.461)
$W_X X$								
Coal Output		0.303	0.406	0.382	0.057	0.445	0.491	1.117
		(0.223)	(0.288)	(0.365)	(0.474)	(0.592)	(0.714)	(0.753)
Share Manufacturing		0.096**	0.141**	0.170**	0.237***	0.277***	0.274***	0.356***
		(0.047)	(0.060)	(0.071)	(0.081)	(0.091)	(0.099)	(0.106)
Unemployment Rate		0.141	0.154	0.250	0.174	0.200	0.169	−0.085
		(0.141)	(0.182)	(0.220)	(0.259)	(0.299)	(0.350)	(0.404)
Share Poverty		0.008	−0.068	−0.159*	−0.234**	−0.285**	−0.325**	−0.315*
		(0.059)	(0.074)	(0.092)	(0.113)	(0.130)	(0.151)	(0.175)
Share Insurance		0.005	0.053	0.142	0.109	0.099	0.068	−0.019
		(0.066)	(0.088)	(0.109)	(0.130)	(0.141)	(0.155)	(0.170)
Import Penetration		−0.782**	−1.554***	−2.001***	−2.947***	−3.436***	−3.399***	−3.562***
		(0.385)	(0.480)	(0.637)	(0.749)	(0.846)	(0.950)	(1.028)
Share Female		0.236*	0.285	0.380	0.542**	0.494	0.518	0.382
		(0.130)	(0.182)	(0.240)	(0.263)	(0.305)	(0.364)	(0.419)
Share Black People		−0.030	−0.027	−0.015	0.014	0.037	0.036	0.025
		(0.020)	(0.024)	(0.030)	(0.031)	(0.032)	(0.035)	(0.038)
Share Latino		0.057***	0.062**	0.074**	0.085***	0.099***	0.116***	0.129***
		(0.018)	(0.025)	(0.031)	(0.031)	(0.033)	(0.036)	(0.039)
Share Education		−0.062	−0.117**	−0.195***	−0.234***	−0.264***	−0.337***	−0.367***
		(0.040)	(0.053)	(0.063)	(0.067)	(0.076)	(0.086)	(0.093)
Share Young		−0.449***	−0.532***	−0.575***	−0.746***	−0.923***	−1.222***	−1.381***
		(0.125)	(0.164)	(0.201)	(0.231)	(0.254)	(0.276)	(0.294)
Share Old		−0.168	−0.182	−0.181	−0.261	−0.339*	−0.450**	−0.451*
		(0.109)	(0.139)	(0.163)	(0.187)	(0.204)	(0.226)	(0.246)
Share Public Transport		0.049	0.074	0.111	0.074	0.079	0.136	0.230
		(0.079)	(0.098)	(0.117)	(0.132)	(0.140)	(0.154)	(0.169)
$W_\epsilon \epsilon$		0.021***	0.014***	0.011***	0.010***	0.009***	0.008***	0.007***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.779	0.756	0.759	0.758	0.750	0.748	0.733	0.708

Note: In all specifications, the dependent variable is the difference between the Republicans' percentage of votes in 2016 and 2012. All standard errors, in parentheses, take into account heteroskedasticity. Alaskan and Hawaiian counties, as well as Campbell/Wyoming, are excluded. The baseline for the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

Table 4: *Spatial Durbin regressions on the difference in the Republicans' percentage of votes between 2016 and 2012.*

more from it than Romney did in 2012.

Plausibly, the growth rate of import penetration spurs Trump's margin, as he has intensified trade conflicts with China. Thus, the campaign against China also turned out to be a successful tool. Spillover effects are significantly negative, as trade restrictions damage neighbouring counties and their industries, given the complex system of supply chains.

Similar to the share of socially insured people, the share of women loses significance. The Republican vote share generally suffers from a higher proportion of women independent of the candidate, implying that scandals about sexual harassment have not significantly affected Trump's probability of winning.

As seen in *Table* 2, higher shares of Black people, Hispanics, highly-educated, and young people generally decrease the Republicans' chances of winning. However, Donald Trump has been even more unpopular in these groups than Mitt Romney. This might be due to his response to the Black-Lives-Matter movement and racist comments. Conversely, the spillover of the share of Hispanics becomes significantly positive. Hence, Trump's strategy of stoking fears of Hispanics ('wall to Mexico') has proven successful, as Trump received more votes in counties whose neighbours are home to larger shares of Hispanics.

On the other hand, older generations backed the Republican party, but not Trump in particular, as suggested by the insignificant impact. Trump has not been more or less successful in urban counties as well.

As shown in Goetz *et al.* (2019), the results remain robust when using the Republicans' share of votes in previous ballots (e.g. 2008, 2004) instead of the one in 2012 as the reference values.

5.3. Robustness Checks

5.3.1. Republicans' Percentage of Votes

The assumption that all counties within the great circle around a given county's centroid respond the same way to a shock in the same county might be quite restrictive. Therefore, we apply the inverse distance matrices instead of their binary counterparts to account for spatial clustering of the residuals. The results remain robust. Nevertheless, the local impact of manufacturing and the spillover effects of coal, poverty, shares of Black people, and young people lose some significance. The reason is that the counties inside a given circle are not assumed to respond identically anymore. On the one hand, this flexibilisation might enhance accuracy, but on the other hand, it is likely that shocks such as his dispute with John McCain will affect counties inside a given circle identically due to the high media interest and frequent television reports.

Secondly, we substitute the continuous coal output measure with a set of binary variables representing different size groups to account for the non-linear effects of coal production. Accordingly, we generate six dummy variables for the following six class sizes: (i) no coal production, (ii) coal production in the range of 0-1 million short tons, (iii) 1-3 million short tons, (iv) 3-5 million short tons, (v) 5-9 million short tons, and (vi) more than nine million short tons. We then re-estimate equations (2) and (3), including the set of dummies for class size, and the results are presented in *Table* C.1.2 in *Appendix* C.1.

Furthermore, we substitute coal output with output per employed worker and per working hour. Both variables represent average products of labour measuring productive efficiency. Output per worker is measured in thousand short tons per employee, while output per working hour is measured in short tons per working hour. The coefficients of interest are all positive but imprecisely estimated in some specifications. However, both local and spillover effects are consistent with our results when using different coal production measures. Additionally, the spillovers become significant, suggesting that the productivity of coal mining is a more relevant criterion for neighbouring counties than the output itself.

Detailed estimation results for the use of the inverse-distance matrix for modelling spatial clustering, for different coal output categories, as well as for different output measures can be found in *Tables* C.1.1, C.1.2, C.1.3, and C.1.4 in *Appendix* C.1.

5.3.2. Populism Effects

Finally, we conduct the same robustness checks for the populist equation (4). Results remain consistent across different specifications and the various coal measures adopted. Estimates can be found in *Appendix* C.2, and in *Tables* C.2.1, C.2.2, C.2.3, and C.2.4.

5.4. Discussion

Our results are generally in line with the existing literature. Regarding the variable of interest, coal output, Goetz *et al.* (2019) also find a significantly positive impact of the share of employment in the coal industry, both in a base and in a populist model. Despite using different measures, the magnitudes of their coefficients and ours are comparable

Similarly, Steinmayr (2021) observes a significantly positive impact of the right-wing party's percentage of votes in the previous ballot on the share of the same party in the ballot of interest.

Goetz *et al.* (2019) find an insignificant negative effect of the share of manufacturing in both models. In contrast, we obtain significantly positive effects, attributed to the inclusion of spatial spillovers. For instance, when conducting OLS regressions, as illustrated in the first columns of *Tables* 2 and 4, the variable's impact is also insignificantly negative. This result underscores the necessity of controlling for spatial spillovers to avoid omitted variable biases.

In equation (3), the unemployment rate is deemed insignificant, while in the populist equation, it significantly raises the difference in votes, consistent with findings by Rodríguez-Pose *et al.* (2021) and Goetz *et al.* (2019). When estimating the simple OLS model without accounting for spillovers, the effect remains insignificantly positive, as observed in Rodríguez-Pose *et al.* (2021). However, it becomes significantly negative, aligning with Goetz *et al.* (2019), when the Republicans' percentage of votes in the 2012 election is excluded. This highlights the importance of including the outcome of the previous ballot to mitigate omitted variable bias.

We observe that higher poverty shares significantly decrease the Republicans' share of votes. This finding contrasts with other studies, some of which report insignificant effects (Goetz *et al.* (2019)) or negative effects (Rodríguez-Pose *et al.* (2021)).

The share of insured people significantly increases the Republicans' percentage of votes. Goetz *et al.* (2019) observed a significantly positive effect of the share of uninsured people on the same dependent variable. However, in the populist equation, its effect is found to be insignificant. The difference in conclusions may be attributed to the limitation in the number of covariates, as suggested by the variance inflation factors. The exclusion of spillovers does not alter the results. Furthermore, excluding the outcome of the 2012's ballot does not change the conclusion.

The positive effect of the growth of import penetration is, to some extent, consistent with Autor *et al.* (2020). They found that the same variable increased the growth of the Republicans' probability of winning, while it insignificantly decreased the growth of the party's share of votes in nearby counties (spillovers). Two reasons account for this disparity. First, dependent variables are differently defined (levels vs. first differences). Second, in the OLS regressions excluding the spillovers, its impact is also insignificant. Hence, the inclusion of the spillovers may address omitted variable biases.

Next, the share of females significantly decreases the dependent variable in the regression of Trump's percentage of votes, as in Goetz *et al.* (2019), but turns insignificant in the populist equation. In the simple OLS equation, the impact, however, remains insignificant, implying that the smaller number of covariates contributes to this conclusion.

Like Rodríguez-Pose *et al.* (2021), Goetz *et al.* (2019), and Scala & Johnson (2017), we also observe a significant negative impact of Black households, a significantly negative effect of the share of Hispanics, and significantly negative impacts of the shares of people aged up to 30 years, comparable to their share of millennials, and a significant negative impact of highly educated people.

Lastly, confirming the existence of a generation gap, older generations support the Republican party, contradicting Goetz *et al.* (2019), who found a negative effect on Trump's share of votes.

However, it's important to note that older generations do not particularly support Trump, as evident from the results of the populist equation, which align with the findings of this study.

6. Conclusions

Our results support the assertion that presidential campaigns significantly influence vote shares. We present an event study model and a spatial model to quantify the magnitude of these effects, accounting for local and spillover effects and addressing biases such as omitted variables in OLS specifications.

Our analysis demonstrates the success of Donald Trump's coal resurgence pledge at the ballot boxes during the 2016 Presidential campaign, particularly in coal regions and their surrounding areas.

Utilizing a spatial Durbin Error model, we identify a robust positive effect of coal production in a county on Donald Trump's vote share in that county. In our baseline model, this positive effect ranges from 0.064 to 0.100 percentage points per additional million short tons of coal production. This effect is even more pronounced in our populist model, where we estimate the vote difference between Mitt Romney in 2012 and Donald Trump in 2016, incorporating the county's coal production and additional control variables. An additional coal production of one million short tons significantly increased the Republicans' vote share by 0.080 to 0.116 percentage points.

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Appendices

A. Estimation Method

Both Maximum Likelihood (ML) and GLS-2SLS-GMM techniques produce consistent estimates. According to Lee (2004), ML is asymptotically efficient and consistent if certain regularity conditions are satisfied. However, this holds true only under homoskedastic errors, while GLS-2SLS-GMM also generates efficient and consistent estimates under heteroskedasticity (Arraiz *et al.* (2010), Badinger & Egger (2011), Drukker *et al.* (2013b), Kelejian & Prucha (1998), Kelejian & Prucha (1999), Kelejian & Prucha (2010)). Furthermore, Gibbons & Overman (2012) criticise MLE for assuming prior knowledge of the data-generating processes, which is not typical in empirical studies. Given these issues, we choose GLS-2SLS-GMM, taking into account heteroskedasticity.

Empirical studies employing instrumental variables techniques follow Kelejian & Prucha (1999), who use spatial lags of all covariates as instruments. Kelejian & Prucha (1999) suggest a procedure consisting of three steps.

In the first step, consistent estimators for all coefficients are obtained through a Two-Staged Least Square (2SLS) estimation. The coefficients are combined into the single vector $\delta = (\alpha, \gamma, \beta', \rho')'$, and an estimator is obtained by $\tilde{\delta} = (\tilde{Z}'Z)^{-1}\tilde{Z}'y$, where Z is the matrix containing the covariates and the spatially lagged covariates, $\tilde{Z} = P_{H_1}Z$, $P_{H_1} = H_1(H_1'H_1)^{-1}H_1'$, and $H_1 = X_f$, where X_f is a matrix containing the covariates and their spatial lags. Spatial clustering in the residuals is ignored, as only asymptotically efficient and consistent estimators of the listed coefficients are required.

In the second step, coefficient λ is obtained with GMM by solving the sample equivalent of the population moment conditions using the residuals obtained from the first step (Badinger & Egger (2011), Drukker *et al.* (2013a), Kelejian & Prucha (1998), Kelejian & Prucha (1999), Kelejian & Prucha (2004), Kelejian & Prucha (2010)).

$$\begin{aligned} \frac{1}{N}\, E[\eta' W_\epsilon \eta] &= 0 \\ \frac{1}{N}\, E[\eta' B_\epsilon \eta] &= 0 \\ with\, B_\epsilon &= W_\epsilon' W_\epsilon - diag(W_\epsilon' W_\epsilon) \end{aligned} \tag{A5}$$

In the third step, the estimator $\tilde{\lambda}$ is used to apply a Cochrane-Orcutt transformation, as illustrated in equation (A6).

$$
\begin{aligned}
y_{nt} &= Z_*(\lambda)\delta + \eta \\
with\, y_{nt} &= (I_n - \sum_{s=1}^{S} \lambda W_\epsilon) y \\
and\, Z_*(\lambda) &= (I_n - \sum_{s=1}^{S} \lambda W_\epsilon) Z
\end{aligned}
\tag{A6}
$$

I_n and S denote an $n \times n$ identity matrix and the order of spatial lags of the error term (in our case, $S = 1$).

By using the instrument matrix H_2 and substituting λ with the estimator $\tilde{\lambda}$, the GS2SLS estimator of δ is

$$
\begin{aligned}
\hat{\delta} &= \{\widehat{Z_*(\tilde{\lambda})}' Z_*(\tilde{\lambda})\}^{-1} \widehat{Z_*(\tilde{\lambda})}' y_*(\tilde{\lambda}) \\
with\, y_*(\tilde{\lambda}) &= (I_n - \sum_{s=1}^{S} \tilde{\lambda} W_\epsilon) y \\
and\, Z_*(\tilde{\lambda}) &= (I_n - \sum_{s=1}^{S} \tilde{\lambda} W_\epsilon) Z \\
and\, \widehat{Z_*(\tilde{\lambda})} &= P_{H_2} Z_*(\tilde{\lambda}) \\
and\, P_{H_2} &= H_2 (H_2' H_2)^{-1} H_2'
\end{aligned}
\tag{A7}
$$

where H_2 comprises the linearly independent columns, defined as $H_2 = [H_1, W_\epsilon H_1]$.

B. Identification

Regarding identification, several issues need consideration.

First, the 'reflection problem', as outlined by Manski (1993) and discussed by Pinske & Slade (2010) and Gibbons & Overman (2012), is generally challenging to assess. The central question is whether the correlation between the percentages of votes for Republicans in neighbouring counties is directly caused by a correlation with the percentages of votes or by a correlation with the characteristics of neighbouring counties, implying an indirect correlation through percentages of votes, or both (Weiss *et al.* (2015)). While we assume that there is no strategic interaction in voting behaviour among people in neighbouring counties, the characteristics of a given county can influence its neighbours via trade and migration flows, suggesting a spatial Durbin model.

Second, the correlation in Republicans' percentages of votes can stem from both spatial correlation between Republicans' percentages of votes and spatial clustering of the residuals. To disentangle these effects, we follow Weiss *et al.* (2015) by accounting for the spatial clustering of residuals. Consequently, the model must be correctly specified, particularly regarding the spatial weight matrices applied to the residuals. While we present arguments in favor of our specification and the decision on the design of the spatial weight matrices, it's important to note that testing whether the underlying assumptions about the nature of spatial clustering of errors are correct is not feasible.

Third, the sample is incomplete due to the absence of election data for Alaskan counties. However, Kelejian & Prucha (2010) show that the GLS-2SLS-GMM estimator remains asymptotically normal and consistent, provided the number of missing observations in the dependent variable is not too large. Given that there is only one coal-producing county in Alaska, this issue can be neglected.

C. Results of Robustness Checks

C.1. Republicans' Percentage of Votes

Table C.1.1 displays the estimation results when using the inverse-distance matrix for modelling spatial clustering.

Table C.1.2 shows the estimation results for the re-estimation of equations (2) and (3), including the set of dummies for class size in coal production.

Once again, the residuals of the equation estimated using OLS, as shown in column (1), exhibit spatial autocorrelation. Among all deciles, the inverse distance matrix with a cutoff at the first decile (447 km) generates the highest significant Moran's I statistics. Given that this cutoff is already quite large, additional cutoffs ranging from 150 to 447 km are added to examine whether the residuals display spatial autocorrelation. Similar to the previous analysis, the inverse distance matrix with a cutoff of 200 km produces the highest significant Moran's I statistics. Therefore, this matrix is used for the spatial regression, while the other inverse distance matrices with cutoffs ranging from 150 to 447 km are employed as robustness checks.

We observe that for small amounts of coal production, Trump's percentage of votes does not significantly differ from those in non-coal-producing counties. Conversely, the dependent variable is higher for counties that produce larger amounts of coal. Plausibly, in these relevant counties, coal mining serves as a more crucial source of income, influencing local economic conditions and, therefore, favouring the Republican party.

In comparison, the interpretation of spillovers is not straightforward, as some spillovers exhibit very large coefficients.

	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
X							
Coal Output	0.062*	0.035	0.063**	0.073**	0.068**	0.070**	0.067*
	(0.034)	(0.041)	(0.032)	(0.032)	(0.033)	(0.035)	(0.035)
Share Republican 2012	0.820***	0.831***	0.820***	0.819***	0.820***	0.821***	0.822***
	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Manufacturing	0.016*	0.007	0.018*	0.015	0.015	0.015	0.015
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Unemployment Rate	0.029	−0.002	−0.004	0.018	0.018	0.015	0.023
	(0.048)	(0.053)	(0.056)	(0.056)	(0.058)	(0.060)	(0.061)
Share Poverty	−0.043**	−0.042**	−0.039**	−0.038**	−0.034**	−0.040**	−0.040**
	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Share Insurance	0.065***	0.054***	0.051**	0.055***	0.061***	0.063***	0.067***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
Import Penetration	0.218***	0.204***	0.209***	0.199***	0.165**	0.170**	0.182**
	(0.074)	(0.073)	(0.072)	(0.071)	(0.072)	(0.072)	(0.073)
Share Female	−0.140***	−0.150***	−0.151***	−0.149***	−0.148***	−0.147***	−0.145***
	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Share Black People	−0.179***	−0.168***	−0.176***	−0.180***	−0.179***	−0.178***	−0.178***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Latino	−0.117***	−0.111***	−0.118***	−0.111***	−0.112***	−0.110***	−0.108***
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Share Education	−0.391***	−0.389***	−0.384***	−0.386***	−0.387***	−0.388***	−0.387***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Share Young	−0.065*	−0.060*	−0.080**	−0.085**	−0.082**	−0.081**	−0.083**
	(0.037)	(0.034)	(0.034)	(0.035)	(0.036)	(0.036)	(0.036)
Share Old	0.070**	0.079***	0.063**	0.064**	0.068**	0.063**	0.060**
	(0.030)	(0.029)	(0.029)	(0.029)	(0.030)	(0.030)	(0.030)
Share Public Transport	−0.048*	−0.043	−0.042	−0.041	−0.044	−0.040	−0.044
	(0.028)	(0.030)	(0.032)	(0.034)	(0.034)	(0.034)	(0.035)
Intercept	40.732***	46.996***	56.913***	67.433**	81.251***	77.513**	84.847**
	(8.325)	(14.830)	(18.685)	(26.284)	(30.905)	(35.591)	(37.201)
$W_X X$							
Coal Output	0.005	−0.239	0.283	0.034	−0.239	−0.871	−0.403
	(0.153)	(0.487)	(0.402)	(0.545)	(0.668)	(0.863)	(0.888)
Share Republican 2012	−0.028	−0.067**	−0.083**	−0.067*	−0.074*	−0.087*	−0.122**
	(0.020)	(0.028)	(0.033)	(0.036)	(0.038)	(0.046)	(0.049)
Share Manufacturing	−0.062	−0.169***	−0.204***	−0.229***	−0.281***	−0.353***	−0.346***
	(0.042)	(0.059)	(0.069)	(0.085)	(0.100)	(0.105)	(0.112)
Unemployment Rate	−0.103	0.018	0.028	0.237	0.156	−0.028	−0.547
	(0.143)	(0.279)	(0.318)	(0.420)	(0.527)	(0.631)	(0.625)
Share Poverty	−0.062	−0.065	−0.117	−0.211	−0.172	−0.117	−0.046
	(0.061)	(0.085)	(0.107)	(0.137)	(0.162)	(0.174)	(0.193)
Share Insurance	−0.074	−0.106	−0.079	−0.043	−0.003	0.073	0.081
	(0.057)	(0.089)	(0.100)	(0.118)	(0.135)	(0.145)	(0.149)
Import Penetration	−0.318	0.338	0.051	−0.250	−0.006	−0.223	−0.315
	(0.318)	(0.484)	(0.599)	(0.713)	(0.849)	(0.934)	(1.020)
Share Female	0.158	−0.127	−0.118	−0.036	−0.179	0.033	−0.085
	(0.115)	(0.204)	(0.293)	(0.295)	(0.329)	(0.361)	(0.393)
Share Black People	0.014	−0.005	−0.007	0.004	−0.007	−0.007	−0.001
	(0.017)	(0.022)	(0.026)	(0.030)	(0.033)	(0.036)	(0.043)
Share Latino	−0.015	−0.072***	−0.052*	−0.041	−0.048	−0.037	−0.036
	(0.019)	(0.022)	(0.027)	(0.032)	(0.034)	(0.036)	(0.039)
Share Education	−0.222***	−0.324***	−0.500***	−0.589***	−0.600***	−0.730***	−0.854***
	(0.045)	(0.071)	(0.091)	(0.106)	(0.120)	(0.142)	(0.148)
Share Young	−0.100	0.170	0.064	−0.226	−0.361	−0.559	−0.525
	(0.110)	(0.185)	(0.223)	(0.282)	(0.330)	(0.372)	(0.399)
Share Old	−0.041	0.224	0.191	−0.029	−0.223	−0.298	−0.221
	(0.091)	(0.153)	(0.195)	(0.243)	(0.282)	(0.338)	(0.375)
Share Public Transport	0.244***	0.414***	0.582***	0.589***	0.563***	0.629***	0.790***
	(0.074)	(0.086)	(0.113)	(0.140)	(0.164)	(0.189)	(0.219)
$W_\epsilon \epsilon$	0.685***	1.817***	1.968***	2.117***	2.243***	2.448***	2.618***
	(0.060)	(0.126)	(0.128)	(0.147)	(0.163)	(0.184)	(0.207)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.978	0.978	0.978	0.977	0.977	0.978	0.978

Note: The dependent variable is the Republicans' percentage of votes in all specifications. All standard errors, in parentheses, take into account heteroskedasticity. Alaskan and Hawaiian counties, as well as Campbell/Wyoming, are excluded. The baseline for the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

Table C.1.1: *Spatial Durbin regressions of Republicans' percentage of votes using inverse-distance ma-*

As an illustration, let us consider two scenarios. In the first situation, a specific county has no neighbouring counties with coal mines. In the second scenario, the same county has a neighbour producing between one and three million short tons. This neighbour receives a weight of 0.0003 (average weight). In column (8) of Table C.1.2, the weighted average increases from zero to 0.0003, indicating a rise in the dependent variable by $26.682 \cdot 0.0003 = 0.008$ percentage points.

Moreover, this specification distinguishes spillover effects resulting from different class sizes. For instance, spillover effects from neighbouring counties with lower coal production significantly increase a given county's dependent variable in some models. For smaller outputs, economic benefits may outweigh concerns regarding pollution and emissions. Similarly, the spillovers from the third and fourth class sizes show a significant impact. Concerning the former (coal production between three and five million short tons per year), its spillovers are significantly negative. Thus, residents in a given county might fear that coal mines of a similar class category might open in their county in the future due to possible liberalizations and the resulting pollution. Nonetheless, the economic advantages may not be large enough to compensate for these downsides. Conversely, the spillover of the fourth dummy (coal production in the range of 5-9 million short tons) is only significant in three out of eight models. Hence, for neighbouring counties, environmental disadvantages might be too large to be compensated by economic gains from trade.

In *Tables* C.1.3 and C.1.4, the estimation results for the alternative measures of coal output (output per employed worker and output per working hours) are presented.

The residuals of the OLS regressions, as shown in column (1) of both tables, exhibit spatial autocorrelation. When using deciles as cutoffs for the inverse-distance matrices, the highest significant Moran's I statistic is produced by the first decile (447 km). Similarly, including cutoffs from 150 km to the first decile suggests choosing the inverse-distance matrix with a cutoff of 200 km to perform the spatial regression, as this matrix generates the highest significant Moran's I statistics. Nevertheless, other inverse distance matrices with cutoffs ranging from 150 to 447 km are applied as robustness checks.

The results are robust, as both coal output per worker and coal output per working hour significantly boost the Republicans' share of votes. In comparison, the spillover effects turn significant, suggesting that the productive efficiency of coal mining tends to be more relevant than simple output quantities.

C.2. Difference in Republicans' Percentage of Votes Between 2016 and 2012

The following tables present the results for the respective populist equations.

	OLS	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X								
$I\{Coal\ Output \in [0,1)\}$	−0.174	0.200	−0.062	−0.094	−0.141	−0.080	−0.007	−0.048
	(0.496)	(0.295)	(0.284)	(0.280)	(0.286)	(0.282)	(0.282)	(0.286)
$I\{Coal\ Output \in [1,3)\}$	−0.020	0.486	0.142	0.163	0.239	0.493	0.502	0.431
	(0.483)	(0.372)	(0.428)	(0.413)	(0.445)	(0.457)	(0.451)	(0.450)
$I\{Coal\ Output \in [3,5)\}$	−0.111	−0.591	−0.593	−0.327	−0.342	−0.596	−0.604	−0.539
	(0.824)	(0.709)	(0.679)	(0.671)	(0.684)	(0.710)	(0.697)	(0.711)
$I\{Coal\ Output \in [5,9)\}$	1.290	1.175*	1.170	0.899	1.418**	1.706**	1.620**	1.647**
	(0.853)	(0.686)	(0.727)	(0.676)	(0.699)	(0.740)	(0.749)	(0.731)
$I\{Coal\ Output \geq 9\}$	1.780***	1.837***	1.548**	1.567***	1.582***	1.708***	1.842***	1.869***
	(0.346)	(0.615)	(0.623)	(0.521)	(0.583)	(0.651)	(0.650)	(0.572)
Share Republican 2012	0.838***	0.819***	0.824***	0.819***	0.822***	0.824***	0.823***	0.825***
	(0.019)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Manufacturing	−0.007	0.016*	0.018*	0.020**	0.017*	0.016*	0.018*	0.017*
	(0.015)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Unemployment Rate	0.045	0.064	0.052	0.037	0.057	0.065	0.047	0.065
	(0.062)	(0.048)	(0.049)	(0.046)	(0.047)	(0.048)	(0.050)	(0.048)
Share Poverty	−0.025	−0.045**	−0.038**	−0.036**	−0.037**	−0.037**	−0.039**	−0.047**
	(0.030)	(0.018)	(0.019)	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)
Share Insurance	0.060*	0.071***	0.063***	0.055***	0.056***	0.061***	0.062***	0.060***
	(0.035)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)
Import Penetration	0.093	0.187***	0.175**	0.184***	0.201***	0.188**	0.149**	0.192**
	(0.076)	(0.070)	(0.072)	(0.068)	(0.073)	(0.074)	(0.071)	(0.075)
Share Female	−0.148***	−0.135***	−0.136***	−0.143***	−0.139***	−0.139***	−0.144***	−0.143***
	(0.041)	(0.028)	(0.029)	(0.028)	(0.029)	(0.029)	(0.028)	(0.029)
Share Black People	−0.160***	−0.183***	−0.179***	−0.182***	−0.180***	−0.178***	−0.178***	−0.176***
	(0.014)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)
Share Latino	−0.114***	−0.116***	−0.110***	−0.111***	−0.107***	−0.106***	−0.107***	−0.104***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)
Share Education	−0.404***	−0.396***	−0.389***	−0.385***	−0.386***	−0.388***	−0.388***	−0.387***
	(0.017)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Share Young	−0.049	−0.072*	−0.074*	−0.075**	−0.084**	−0.079**	−0.071*	−0.077**
	(0.062)	(0.037)	(0.038)	(0.036)	(0.038)	(0.038)	(0.036)	(0.038)
Share Old	0.097**	0.067**	0.073**	0.081***	0.067**	0.070**	0.080***	0.066**
	(0.048)	(0.030)	(0.031)	(0.030)	(0.031)	(0.031)	(0.030)	(0.031)
Share Public Transport	−0.008	−0.040	−0.054*	−0.057*	−0.047	−0.047	−0.064*	−0.051
	(0.019)	(0.028)	(0.032)	(0.033)	(0.034)	(0.033)	(0.035)	(0.035)
Intercept	27.292***	42.079***	57.477***	46.315***	58.656***	75.670***	80.387***	134.432***
	(6.050)	(10.211)	(11.226)	(14.367)	(15.361)	(18.266)	(22.178)	(26.341)
$W_X X$								
$I\{Coal\ Output \in [0,1)\}$		−0.397	−0.824	5.909*	4.928	4.956	14.791**	7.442
		(2.251)	(2.290)	(3.576)	(4.127)	(4.759)	(5.987)	(6.198)
$I\{Coal\ Output \in [1,3)\}$		2.713	5.514	14.557**	15.044*	27.368***	38.641***	26.682**
		(3.347)	(4.579)	(6.756)	(8.099)	(10.049)	(12.541)	(13.223)
$I\{Coal\ Output \in [3,5)\}$		−11.595***	−18.562***	−11.215	−24.492**	−54.216***	−58.653***	−60.893***
		(3.755)	(7.096)	(10.911)	(11.568)	(15.220)	(18.730)	(16.660)
$I\{Coal\ Output \in [5,9)\}$		4.924*	5.068	7.959	9.611	21.413*	24.824	34.571**
		(2.748)	(6.686)	(9.711)	(11.527)	(12.118)	(16.341)	(16.488)
$I\{Coal\ Output \geq 9\}$		3.319	10.271	7.630	−1.927	10.778	21.119	18.469
		(4.458)	(6.571)	(8.478)	(11.087)	(14.008)	(16.960)	(16.834)
Share Republican 2012		−0.013	−0.036	−0.044*	−0.042	−0.049	−0.044	−0.153***
		(0.021)	(0.024)	(0.025)	(0.029)	(0.033)	(0.041)	(0.046)
Share Manufacturing		−0.024	−0.082	−0.109*	−0.081	−0.090	−0.313***	−0.135
		(0.047)	(0.052)	(0.059)	(0.065)	(0.072)	(0.081)	(0.085)
Unemployment Rate		0.028	−0.206	−0.091	−0.367	−0.402	−0.463	−0.452
		(0.175)	(0.198)	(0.249)	(0.260)	(0.296)	(0.387)	(0.373)
Share Poverty		−0.090	−0.165**	−0.247**	−0.236**	−0.162	−0.223	−0.207
		(0.060)	(0.075)	(0.098)	(0.105)	(0.115)	(0.141)	(0.154)
Share Insurance		−0.040	−0.123	−0.031	−0.045	−0.054	−0.020	−0.311**
		(0.067)	(0.076)	(0.090)	(0.104)	(0.110)	(0.113)	(0.147)
Import Penetration		−0.287	−0.350	0.608	−0.966	−0.865	1.319	−0.258
		(0.378)	(0.415)	(0.572)	(0.606)	(0.673)	(0.862)	(0.842)
Share Female		0.249*	0.221	0.175	0.392*	0.247	0.075	0.005
		(0.135)	(0.160)	(0.228)	(0.224)	(0.260)	(0.323)	(0.353)
Share Black People		0.034*	0.040*	0.060***	0.048*	0.044	0.049	0.023
		(0.019)	(0.022)	(0.023)	(0.027)	(0.029)	(0.031)	(0.035)
Share Latino		0.006	−0.016	−0.013	0.000	−0.014	−0.026	−0.075**
		(0.021)	(0.023)	(0.031)	(0.028)	(0.029)	(0.033)	(0.036)
Share Education		−0.242***	−0.343***	−0.464***	−0.525***	−0.557***	−0.686***	−0.795***
		(0.047)	(0.054)	(0.066)	(0.068)	(0.081)	(0.102)	(0.104)
Share Young		−0.311***	−0.331**	−0.162	−0.521***	−0.673***	−0.597**	−0.902***
		(0.115)	(0.131)	(0.171)	(0.184)	(0.202)	(0.243)	(0.235)
Share Old		−0.173	−0.149	−0.007	−0.237	−0.375**	−0.263	−0.491**
		(0.107)	(0.116)	(0.151)	(0.156)	(0.171)	(0.206)	(0.209)
Share Public Transport		0.187**	0.284***	0.446***	0.407***	0.492***	0.745***	0.738***
		(0.075)	(0.098)	(0.122)	(0.133)	(0.143)	(0.158)	(0.175)
$W_\epsilon \epsilon$		0.024***	0.013***	0.013***	0.009***	0.008***	0.010***	0.006***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.077	0.977	0.978	0.977	0.978	0.978	0.977	0.974

Note: The dependent variable is the Republicans' percentage of votes in all specifications. All standard errors, in parentheses, take account of heteroskedasticity. Alaskan and Hawaiian counties, as well as Campbell/Wyoming, are excluded. The baseline for the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

Table C.1.2: *Spatial Durbin regressions of Republicans' percentage of votes using dummies for categories of coal output amounts*

	OLS	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X								
Coal Output per Employee	0.046	0.038*	0.027	0.034*	0.034*	0.036*	0.045**	0.042**
	(0.029)	(0.020)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Share Republican 2012	0.838***	0.818***	0.823***	0.819***	0.821***	0.822***	0.821***	0.821***
	(0.020)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Manufacturing	−0.007	0.017*	0.019**	0.019**	0.017*	0.016	0.017*	0.017*
	(0.016)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Unemployment Rate	0.037	0.047	0.037	0.033	0.044	0.042	0.026	0.037
	(0.064)	(0.048)	(0.049)	(0.046)	(0.047)	(0.048)	(0.049)	(0.049)
Share Poverty	−0.026	−0.044**	−0.039**	−0.036**	−0.037**	−0.038**	−0.035*	−0.037**
	(0.032)	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
Share Insurance	0.059*	0.070***	0.062***	0.054***	0.055***	0.057***	0.062***	0.063***
	(0.035)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)
Import Penetration	0.093	0.190***	0.184**	0.188***	0.200***	0.193***	0.160**	0.167**
	(0.075)	(0.070)	(0.071)	(0.068)	(0.073)	(0.074)	(0.071)	(0.071)
Share Female	−0.149***	−0.136***	−0.134***	−0.145***	−0.140***	−0.138***	−0.143***	−0.144***
	(0.043)	(0.028)	(0.029)	(0.028)	(0.029)	(0.029)	(0.028)	(0.029)
Share Black People	−0.159***	−0.183***	−0.179***	−0.183***	−0.180***	−0.179***	−0.180***	−0.181***
	(0.014)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)
Share Latino	−0.113***	−0.115***	−0.109***	−0.111***	−0.106***	−0.105***	−0.104***	−0.103***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Share Education	−0.405***	−0.396***	−0.389***	−0.386***	−0.387***	−0.388***	−0.388***	−0.388***
	(0.018)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Share Young	−0.048	−0.068*	−0.073*	−0.074**	−0.085**	−0.082**	−0.074**	−0.073**
	(0.063)	(0.037)	(0.038)	(0.036)	(0.038)	(0.038)	(0.036)	(0.036)
Share Old	0.099*	0.072**	0.074**	0.081***	0.067**	0.069**	0.079***	0.079**
	(0.049)	(0.030)	(0.031)	(0.030)	(0.030)	(0.031)	(0.030)	(0.031)
Share Public Transport	−0.009	−0.041	−0.054*	−0.055	−0.045	−0.045	−0.064*	−0.071*
	(0.019)	(0.028)	(0.032)	(0.033)	(0.034)	(0.034)	(0.036)	(0.037)
Intercept	27.428***	40.122***	54.753***	46.659***	59.650***	76.395***	85.141***	119.552***
	(6.072)	(10.199)	(11.363)	(14.317)	(15.562)	(18.668)	(22.347)	(26.165)
$W_X X$								
Coal Output per Employee		0.108	0.141	0.410**	0.341**	0.453**	0.706**	1.065***
		(0.087)	(0.123)	(0.159)	(0.161)	(0.193)	(0.295)	(0.298)
Share Republican 2012		−0.013	−0.032	−0.041	−0.043	−0.058*	−0.047	−0.092**
		(0.021)	(0.024)	(0.026)	(0.029)	(0.033)	(0.041)	(0.044)
Share Manufacturing		−0.009	−0.068	−0.082	−0.038	−0.059	−0.284***	−0.303***
		(0.047)	(0.053)	(0.058)	(0.066)	(0.072)	(0.080)	(0.088)
Unemployment Rate		0.000	−0.261	−0.066	−0.387	−0.382	−0.324	−0.610
		(0.170)	(0.204)	(0.248)	(0.261)	(0.307)	(0.405)	(0.424)
Share Poverty		−0.095	−0.174**	−0.232**	−0.237**	−0.233*	−0.317**	−0.321**
		(0.059)	(0.078)	(0.096)	(0.105)	(0.121)	(0.144)	(0.156)
Share Insurance		−0.042	−0.102	−0.011	−0.055	−0.106	−0.082	−0.219
		(0.070)	(0.077)	(0.092)	(0.106)	(0.119)	(0.117)	(0.136)
Import Penetration		−0.405	−0.364	0.275	−1.095*	−0.953	0.826	1.118
		(0.377)	(0.424)	(0.568)	(0.618)	(0.684)	(0.834)	(0.911)
Share Female		0.238*	0.236	0.151	0.359	0.252	0.040	−0.284
		(0.136)	(0.159)	(0.227)	(0.222)	(0.258)	(0.323)	(0.369)
Share Black People		0.040**	0.046**	0.058***	0.055**	0.066**	0.051*	0.038
		(0.018)	(0.022)	(0.021)	(0.026)	(0.027)	(0.030)	(0.034)
Share Latino		0.009	−0.000	−0.009	0.011	−0.003	−0.038	−0.069*
		(0.021)	(0.023)	(0.031)	(0.028)	(0.030)	(0.035)	(0.040)
Share Education		−0.235***	−0.352***	−0.460***	−0.526***	−0.589***	−0.700***	−0.766***
		(0.047)	(0.056)	(0.066)	(0.069)	(0.081)	(0.103)	(0.108)
Share Young		−0.272**	−0.344**	−0.190	−0.510***	−0.604***	−0.515**	−0.529**
		(0.114)	(0.135)	(0.171)	(0.186)	(0.207)	(0.247)	(0.267)
Share Old		−0.133	−0.130	−0.022	−0.193	−0.251	−0.214	−0.209
		(0.103)	(0.117)	(0.146)	(0.156)	(0.171)	(0.203)	(0.223)
Share Public Transportation		0.180**	0.276***	0.442***	0.398***	0.487***	0.755***	0.871***
		(0.075)	(0.098)	(0.121)	(0.134)	(0.144)	(0.159)	(0.176)
$W_\epsilon \epsilon$		0.534***	0.025***	0.014***	0.013***	0.009***	0.008***	0.010***
		(0.037)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	
Observations	3107	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.977	0.977	0.978	0.977	0.977	0.977	0.977	0.976

Note: The dependent variable is the Republicans' percentage of votes in all specifications. All standard errors, in parentheses, take account of heteroskedasticity. Alaskan and Hawaiian counties, as well as Campbell/Wyoming, are excluded. The baseline for the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

Table C.1.3: *Spatial Durbin regressions of Republicans' percentage of votes using coal output in thsnd. short tons per average number of employees hired by coal mines*

	OLS	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X								
Coal Output per Working Hour	0.086	0.079**	0.056	0.070*	0.071*	0.075**	0.091**	0.087**
	(0.055)	(0.038)	(0.038)	(0.036)	(0.037)	(0.037)	(0.036)	(0.037)
Share Republican 2012	0.838***	0.818***	0.823***	0.819***	0.821***	0.822***	0.821***	0.821***
	(0.020)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Manufacturing	−0.007	0.017*	0.019**	0.020**	0.017*	0.016	0.017*	0.017*
	(0.016)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Unemployment Rate	0.037	0.047	0.037	0.034	0.044	0.042	0.024	0.035
	(0.063)	(0.048)	(0.049)	(0.046)	(0.047)	(0.048)	(0.049)	(0.049)
Share Poverty	−0.026	−0.045**	−0.039**	−0.037**	−0.037**	−0.039**	−0.035*	−0.037**
	(0.032)	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)	(0.018)	(0.018)
Share Insurance	0.059*	0.070***	0.062***	0.054***	0.055***	0.057***	0.061***	0.062***
	(0.035)	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)
Import Penetration	0.094	0.191***	0.184***	0.188***	0.201***	0.193***	0.160**	0.166**
	(0.075)	(0.070)	(0.071)	(0.068)	(0.073)	(0.074)	(0.071)	(0.070)
Share Female	−0.150***	−0.136***	−0.135***	−0.145***	−0.141***	−0.139***	−0.144***	−0.145***
	(0.043)	(0.028)	(0.029)	(0.028)	(0.029)	(0.029)	(0.028)	(0.028)
Share Black People	−0.159***	−0.183***	−0.179***	−0.183***	−0.180***	−0.179***	−0.180***	−0.181***
	(0.014)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)
Share Latino	−0.113***	−0.115***	−0.109***	−0.110***	−0.106***	−0.105***	−0.104***	−0.103***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Share Education	−0.405***	−0.395***	−0.389***	−0.386***	−0.387***	−0.388***	−0.388***	−0.386***
	(0.018)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Share Young	−0.048	−0.068*	−0.073*	−0.074**	−0.084**	−0.082**	−0.073**	−0.071**
	(0.063)	(0.037)	(0.038)	(0.036)	(0.038)	(0.038)	(0.036)	(0.036)
Share Old	0.099*	0.072**	0.075**	0.082***	0.068**	0.070**	0.080***	0.080***
	(0.049)	(0.030)	(0.031)	(0.030)	(0.030)	(0.031)	(0.030)	(0.031)
Share Public Transport	−0.009	−0.041	−0.054*	−0.054	−0.046	−0.046	−0.065*	−0.071*
	(0.019)	(0.028)	(0.032)	(0.033)	(0.034)	(0.034)	(0.036)	(0.037)
Intercept	27.454***	40.410***	54.936***	47.307***	59.934***	76.672***	86.234***	120.924***
	(6.076)	(10.189)	(11.387)	(14.353)	(15.579)	(18.694)	(22.405)	(26.272)
$W_X X$								
Coal Output per Working Hour		0.197	0.277	0.803**	0.625**	0.836**	1.458**	2.163***
		(0.173)	(0.243)	(0.321)	(0.317)	(0.385)	(0.603)	(0.612)
Share Republican 2012		−0.013	−0.032	−0.041	−0.044	−0.059*	−0.047	−0.091**
		(0.021)	(0.024)	(0.026)	(0.029)	(0.033)	(0.041)	(0.044)
Share Manufacturing		−0.010	−0.067	−0.078	−0.039	−0.061	−0.281***	−0.299***
		(0.047)	(0.053)	(0.059)	(0.066)	(0.072)	(0.080)	(0.088)
Unemployment Rate		0.000	−0.263	−0.063	−0.386	−0.379	−0.332	−0.605
		(0.170)	(0.204)	(0.249)	(0.261)	(0.308)	(0.408)	(0.426)
Share Poverty		−0.095	−0.174**	−0.232**	−0.239**	−0.235*	−0.313**	−0.318**
		(0.059)	(0.078)	(0.096)	(0.105)	(0.121)	(0.145)	(0.157)
Share Insurance		−0.046	−0.104	−0.014	−0.060	−0.110	−0.082	−0.220
		(0.070)	(0.077)	(0.094)	(0.106)	(0.120)	(0.118)	(0.136)
Import Penetration		−0.419	−0.380	0.217	−1.116*	−0.967	0.807	1.080
		(0.376)	(0.425)	(0.570)	(0.618)	(0.687)	(0.835)	(0.911)
Share Female		0.237*	0.234	0.152	0.363	0.255	0.018	−0.317
		(0.136)	(0.159)	(0.227)	(0.222)	(0.258)	(0.324)	(0.371)
Share Black People		0.040**	0.046**	0.057***	0.053**	0.065**	0.054*	0.041
		(0.018)	(0.022)	(0.021)	(0.026)	(0.027)	(0.030)	(0.034)
Share Latino		0.008	−0.001	−0.010	0.009	−0.004	−0.036	−0.067*
		(0.021)	(0.023)	(0.032)	(0.028)	(0.030)	(0.035)	(0.040)
Share Education		−0.236***	−0.352***	−0.459***	−0.527***	−0.590***	−0.696***	−0.760***
		(0.047)	(0.056)	(0.066)	(0.069)	(0.081)	(0.103)	(0.108)
Share Young		−0.270**	−0.341**	−0.196	−0.507***	−0.602***	−0.520**	−0.531**
		(0.114)	(0.135)	(0.171)	(0.186)	(0.208)	(0.247)	(0.266)
Share Old		−0.131	−0.127	−0.024	−0.192	−0.252	−0.213	−0.206
		(0.103)	(0.117)	(0.145)	(0.156)	(0.171)	(0.203)	(0.223)
Share Public Transport		0.180**	0.277***	0.438***	0.400***	0.488***	0.754***	0.871***
		(0.075)	(0.098)	(0.120)	(0.134)	(0.144)	(0.159)	(0.176)
$W_\epsilon \epsilon$		0.025***	0.014***	0.013***	0.009***	0.008***	0.010***	0.010***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.977	0.977	0.978	0.977	0.977	0.977	0.977	0.976

Note: The dependent variable is the Republicans' percentage of votes in all specifications. All standard errors, in parentheses, take account of heteroskedasticity. Alaskan and Hawaiian counties, as well as Campbell/Wyoming, are excluded. The baseline for the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

Table C.1.4: *Spatial Durbin regressions of Republicans' percentage of votes using coal output in short tons per working hour*

	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
X							
Coal Output	0.073	0.043	0.075*	0.093**	0.083**	0.081*	0.075
	(0.050)	(0.044)	(0.040)	(0.040)	(0.042)	(0.045)	(0.046)
Share Manufacturing	0.021*	0.018	0.025**	0.021*	0.018*	0.018*	0.016
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Unemployment Rate	0.163***	0.165***	0.142**	0.140**	0.115*	0.109*	0.123**
	(0.057)	(0.055)	(0.058)	(0.057)	(0.059)	(0.059)	(0.060)
Share Poverty	0.073***	0.067***	0.076***	0.080***	0.084***	0.077***	0.073***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Share Insurance	0.028	0.030	0.026	0.027	0.031	0.032	0.038*
	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)
Import Penetration	0.232***	0.216***	0.231***	0.213***	0.189**	0.187**	0.198**
	(0.085)	(0.082)	(0.081)	(0.081)	(0.083)	(0.085)	(0.086)
Share Female	−0.054	−0.077**	−0.067**	−0.058*	−0.049	−0.044	−0.040
	(0.034)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Share Black People	−0.062***	−0.063***	−0.063***	−0.065***	−0.065***	−0.064***	−0.063***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Share Latino	−0.071***	−0.069***	−0.072***	−0.066***	−0.064***	−0.062***	−0.059***
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Share Education	−0.317***	−0.313***	−0.308***	−0.311***	−0.314***	−0.316***	−0.317***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
Share Young	−0.160***	−0.115***	−0.136***	−0.141***	−0.139***	−0.136***	−0.136***
	(0.043)	(0.042)	(0.042)	(0.043)	(0.044)	(0.044)	(0.043)
Share Old	−0.016	0.024	0.007	0.007	0.011	0.009	0.008
	(0.034)	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Share Public Transport	−0.013	0.008	0.009	0.009	0.007	0.009	0.007
	(0.026)	(0.028)	(0.031)	(0.033)	(0.033)	(0.035)	(0.036)
Intercept	16.080	1.054	8.275	12.467	6.841	−8.463	−18.222
	(12.126)	(15.830)	(19.760)	(27.447)	(33.096)	(37.904)	(39.875)
$W_X X$							
Coal Output	0.094	−0.074	0.467	0.403	0.064	−0.616	−0.361
	(0.170)	(0.395)	(0.472)	(0.631)	(0.766)	(0.951)	(0.984)
Share Manufacturing	0.040	0.082	0.103	0.094	0.091	0.037	0.078
	(0.048)	(0.060)	(0.074)	(0.091)	(0.106)	(0.111)	(0.116)
Unemployment Rate	0.272**	0.818***	0.911***	0.970**	0.763	0.601	0.208
	(0.129)	(0.217)	(0.296)	(0.404)	(0.474)	(0.542)	(0.553)
Share Poverty	−0.056	−0.041	−0.115	−0.233	−0.226	−0.215	−0.194
	(0.071)	(0.092)	(0.119)	(0.150)	(0.177)	(0.192)	(0.212)
Share Insurance	0.046	0.161*	0.238**	0.280**	0.358***	0.473***	0.516***
	(0.074)	(0.095)	(0.099)	(0.115)	(0.136)	(0.148)	(0.162)
Import Penetration	−0.663*	−0.718	−1.208*	−1.498*	−1.761*	−2.025*	−2.374*
	(0.368)	(0.540)	(0.680)	(0.826)	(0.995)	(1.124)	(1.234)
Share Female	0.098	−0.377	−0.473	−0.225	−0.042	0.223	0.213
	(0.183)	(0.233)	(0.321)	(0.337)	(0.374)	(0.409)	(0.430)
Share Black People	0.009	−0.005	−0.006	0.001	0.004	0.021	0.053
	(0.015)	(0.019)	(0.023)	(0.027)	(0.034)	(0.039)	(0.042)
Share Latino	0.025	0.011	0.036	0.046	0.053	0.072*	0.087**
	(0.019)	(0.022)	(0.027)	(0.031)	(0.035)	(0.040)	(0.044)
Share Education	−0.121**	−0.053	−0.161**	−0.266***	−0.289**	−0.426***	−0.529***
	(0.055)	(0.060)	(0.081)	(0.103)	(0.122)	(0.144)	(0.158)
Share Young	−0.225	0.120	−0.009	−0.308	−0.462	−0.599	−0.509
	(0.173)	(0.219)	(0.267)	(0.340)	(0.388)	(0.432)	(0.455)
Share Old	−0.018	0.384**	0.370*	0.154	0.005	0.035	0.242
	(0.131)	(0.178)	(0.220)	(0.277)	(0.315)	(0.370)	(0.416)
Share Public Transport	0.192***	0.283***	0.442***	0.490***	0.492***	0.603***	0.741***
	(0.063)	(0.089)	(0.115)	(0.140)	(0.160)	(0.189)	(0.221)
$W_\epsilon \epsilon$	1.778***	1.832***	2.006***	2.072***	2.113***	2.162***	2.239***
	(0.139)	(0.116)	(0.122)	(0.134)	(0.123)	(0.116)	(0.116)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.782	0.775	0.775	0.776	0.775	0.772	0.766
Note:	The dependent variable is the Republicans' percentage of votes in all specifications. All standard errors, in parentheses, take account of heteroskedasticity. Alaskan and Hawaiian counties, as well as Campbell/Wyoming, are excluded. The baseline for the state dummies is Alabama. *p<0.1; **p<0.05; ***p<0.01						

Table C.2.1: *Spatial Durbin regressions of difference between Republicans' percentage of votes in 2016 and 2012 using inverse-distance matrices for spatial clustering of residuals.*

Similar to the previous tables, the residuals of the OLS regressions in column (1) in the following tables exhibit spatial autocorrelation. When using deciles as cutoffs for the inverse-distance matrices, the first decile at 447 km produces the highest significant Moran's I statistic. Additionally, considering cutoffs from 150 km to the first decile suggests selecting the inverse-distance matrix with a 200 km cutoff for the spatial regression, as it generates the highest significant Moran's I statistic. However, other inverse distance matrices with cutoffs ranging from 150 to 447 km are also employed as robustness checks.

	OLS	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X								
$I\{Coal\,Output \in [0,1)\}$	−0.697	−0.310	−0.468	−0.455	−0.542	−0.493	−0.409	−0.383
	(0.780)	(0.371)	(0.361)	(0.370)	(0.376)	(0.370)	(0.373)	(0.372)
$I\{Coal\,Output \in [1,3)\}$	0.057	0.549	0.387	0.397	0.497	0.812	0.921	0.838
	(0.651)	(0.487)	(0.518)	(0.544)	(0.564)	(0.577)	(0.584)	(0.575)
$I\{Coal\,Output \in [3,5)\}$	−0.382	−0.644	−0.872	−0.685	−0.684	−1.041	−1.004	−1.028
	(0.896)	(0.737)	(0.736)	(0.770)	(0.773)	(0.796)	(0.788)	(0.792)
$I\{Coal\,Output \in [5,9)\}$	1.437	1.520*	1.514*	1.500*	1.695**	1.929**	1.926**	1.803**
	(0.920)	(0.806)	(0.867)	(0.829)	(0.828)	(0.846)	(0.850)	(0.827)
$I\{Coal\,Output \geq 9\}$	2.146***	1.686***	1.643***	1.525***	1.831***	2.087***	2.399***	2.587***
	(0.289)	(0.526)	(0.603)	(0.531)	(0.546)	(0.631)	(0.675)	(0.694)
Share Manufacturing	0.023	0.022**	0.022**	0.022**	0.018	0.016	0.016	0.015
	(0.018)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Unemployment Rate	0.217**	0.182***	0.170***	0.155***	0.164***	0.172***	0.180***	0.179***
	(0.096)	(0.057)	(0.055)	(0.053)	(0.054)	(0.055)	(0.055)	(0.056)
Share Poverty	0.069	0.084***	0.077***	0.085***	0.084***	0.083***	0.076***	0.072***
	(0.048)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.019)	(0.020)
Share Insurance	0.028	0.040*	0.029	0.025	0.025	0.032	0.031	0.033
	(0.039)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
Import Penetration	0.118	0.217**	0.225***	0.251***	0.242***	0.231***	0.220**	0.223***
	(0.104)	(0.084)	(0.080)	(0.081)	(0.084)	(0.085)	(0.086)	(0.087)
Share Female	−0.064	−0.027	−0.036	−0.031	−0.029	−0.032	−0.035	−0.036
	(0.052)	(0.034)	(0.033)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)
Share Black People	−0.066***	−0.069***	−0.067***	−0.066***	−0.066***	−0.067***	−0.066***	−0.064***
	(0.012)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Share Latino	−0.058***	−0.071***	−0.066***	−0.065***	−0.063***	−0.061***	−0.061***	−0.061***
	(0.015)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Share Education	−0.311***	−0.320***	−0.315***	−0.313***	−0.316***	−0.318***	−0.319***	−0.319***
	(0.019)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Young	−0.113	−0.136***	−0.125***	−0.140***	−0.143***	−0.137***	−0.135***	−0.133***
	(0.086)	(0.047)	(0.045)	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
Share Old	0.047	0.001	0.018	0.010	0.006	0.012	0.013	0.013
	(0.063)	(0.036)	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)	(0.036)
Share Public Transport	0.016	−0.000	−0.002	−0.001	0.011	0.018	0.027	0.025
	(0.040)	(0.031)	(0.034)	(0.035)	(0.035)	(0.035)	(0.034)	(0.035)
Intercept	11.361*	21.623**	13.112	5.388	17.597	31.720	51.539**	67.466**
	(5.692)	(8.693)	(12.409)	(14.503)	(16.788)	(20.256)	(25.153)	(28.616)
$W_X X$								
$I\{Coal\,Output \in [0,1)\}$		−3.841	−3.545	−1.185	0.151	−0.272	1.434	3.600
		(2.449)	(3.201)	(4.297)	(5.477)	(6.087)	(6.579)	(7.757)
$I\{Coal\,Output \in [1,3)\}$		1.872	13.523**	20.282**	26.159***	42.733***	46.521***	44.923***
		(3.606)	(6.303)	(8.504)	(9.481)	(11.736)	(13.450)	(14.386)
$I\{Coal\,Output \in [3,5)\}$		−12.856***	−20.351**	−23.831*	−34.177**	−71.246***	−88.857***	−93.050***
		(4.313)	(8.752)	(12.170)	(13.272)	(16.778)	(18.977)	(19.511)
$I\{Coal\,Output \in [5,9)\}$		8.938***	10.859	17.324*	13.871	26.359**	31.566**	32.920*
		(2.715)	(6.747)	(9.553)	(11.691)	(12.788)	(16.044)	(17.398)
$I\{Coal\,Output \geq 9\}$		0.919	8.353	−5.446	−5.903	6.326	10.175	31.132
		(4.659)	(7.486)	(9.520)	(12.876)	(16.408)	(18.626)	(19.772)
Share Manufacturing		0.089*	0.135**	0.132*	0.196**	0.230***	0.228**	0.298***
		(0.046)	(0.062)	(0.070)	(0.079)	(0.088)	(0.097)	(0.103)
Unemployment Rate		0.177	0.227	0.293	0.213	0.171	0.081	−0.159
		(0.142)	(0.191)	(0.231)	(0.249)	(0.277)	(0.322)	(0.374)
Share Poverty		0.004	−0.062	−0.156	−0.190*	−0.159	−0.138	−0.087
		(0.058)	(0.075)	(0.097)	(0.113)	(0.123)	(0.140)	(0.166)
Share Insurance		0.003	0.080	0.201*	0.133	0.154	0.141	0.065
		(0.064)	(0.093)	(0.105)	(0.126)	(0.129)	(0.143)	(0.161)
Import Penetration		−0.620*	−1.497***	−1.923***	−2.937***	−3.367***	−3.364***	−3.509***
		(0.376)	(0.493)	(0.643)	(0.711)	(0.805)	(0.913)	(0.982)
Share Female		0.243*	0.253	0.337	0.525**	0.477	0.483	0.364
		(0.128)	(0.187)	(0.243)	(0.259)	(0.305)	(0.367)	(0.416)
Share Black People		−0.031	−0.020	−0.005	−0.002	−0.004	−0.007	−0.014
		(0.020)	(0.024)	(0.029)	(0.031)	(0.034)	(0.037)	(0.039)
Share Latino		0.055***	0.042	0.070**	0.074**	0.075**	0.091***	0.099***
		(0.017)	(0.027)	(0.030)	(0.030)	(0.032)	(0.035)	(0.037)
Share Education		−0.064	−0.105*	−0.194***	−0.232***	−0.242***	−0.301***	−0.322***
		(0.040)	(0.054)	(0.064)	(0.067)	(0.076)	(0.088)	(0.094)
Share Young		−0.494***	−0.437***	−0.514***	−0.778***	−1.026***	−1.378***	−1.494***
		(0.124)	(0.166)	(0.196)	(0.221)	(0.240)	(0.265)	(0.286)
Share Old		−0.209*	−0.141	−0.151	−0.326*	−0.521***	−0.699***	−0.676***
		(0.109)	(0.147)	(0.164)	(0.182)	(0.198)	(0.225)	(0.245)
Share Public Transport		0.060	0.103	0.135	0.089	0.098	0.135	0.218
		(0.077)	(0.100)	(0.117)	(0.131)	(0.140)	(0.154)	(0.168)
$W_\epsilon \epsilon$		0.020***	0.015***	0.011***	0.010***	0.009***	0.008***	0.007***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.780	0.764	0.769	0.766	0.763	0.763	0.748	0.730

Note: The dependent variable is the Republicans' percentage of votes in all specifications. All standard errors, in parentheses, take account of heteroskedasticity. Alaskan and Hawaiian counties, as well as Campbell/Wyoming, are excluded. The baseline for the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

Table C.2.2: *Spatial Durbin regressions of difference between Republicans' percentage of votes in 2016 and 2012 using dummies for categories of coal output amounts*

	OLS	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X								
Coal Output per Employee	0.050	0.041*	0.035	0.039*	0.043**	0.040*	0.043*	0.041*
	(0.030)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Share Manufacturing	0.024	0.024**	0.023**	0.022**	0.017	0.014	0.015	0.015
	(0.019)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Unemployment Rate	0.201**	0.162***	0.148***	0.139**	0.141***	0.139**	0.142**	0.156***
	(0.099)	(0.056)	(0.056)	(0.054)	(0.054)	(0.056)	(0.056)	(0.057)
Share Poverty	0.067	0.082***	0.076***	0.082***	0.084***	0.083***	0.078***	0.075***
	(0.051)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)
Share Insurance	0.026	0.037*	0.027	0.022	0.024	0.026	0.028	0.031
	(0.041)	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Import Penetration	0.122	0.231***	0.246***	0.252***	0.237***	0.239***	0.228***	0.236***
	(0.099)	(0.083)	(0.081)	(0.082)	(0.084)	(0.086)	(0.087)	(0.087)
Share Female	−0.066	−0.030	−0.033	−0.031	−0.030	−0.031	−0.033	−0.034
	(0.055)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Share Black People	−0.065***	−0.068***	−0.066***	−0.065***	−0.066***	−0.066***	−0.065***	−0.064***
	(0.014)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
Share Latino	−0.057***	−0.070***	−0.063***	−0.063***	−0.060***	−0.057***	−0.056***	−0.055***
	(0.015)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)
Share Education	−0.311***	−0.319***	−0.317***	−0.315***	−0.317***	−0.318***	−0.318***	−0.317***
	(0.019)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Young	−0.111	−0.131***	−0.127***	−0.139***	−0.142***	−0.141***	−0.138***	−0.137***
	(0.088)	(0.047)	(0.046)	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
Share Old	0.049	0.007	0.018	0.011	0.009	0.012	0.013	0.013
	(0.066)	(0.036)	(0.036)	(0.036)	(0.035)	(0.036)	(0.036)	(0.036)
Share Public Transport	0.016	0.000	−0.001	0.003	0.015	0.024	0.030	0.028
	(0.040)	(0.030)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Intercept	11.624**	18.591**	17.342	9.271	14.025	26.587	43.366*	62.832**
	(5.757)	(8.841)	(12.112)	(14.420)	(17.019)	(20.198)	(24.819)	(28.220)
$W_X X$								
Coal Output per Employee		0.176*	0.272**	0.392**	0.335*	0.424*	0.444	0.746***
		(0.096)	(0.128)	(0.165)	(0.190)	(0.231)	(0.279)	(0.286)
Share Manufacturing		0.098**	0.150**	0.190***	0.271***	0.313***	0.314***	0.405***
		(0.047)	(0.060)	(0.072)	(0.081)	(0.090)	(0.100)	(0.108)
Unemployment Rate		0.134	0.138	0.205	0.118	0.160	0.127	−0.138
		(0.142)	(0.183)	(0.222)	(0.259)	(0.299)	(0.349)	(0.397)
Share Poverty		0.011	−0.062	−0.143	−0.214*	−0.270**	−0.311**	−0.304*
		(0.059)	(0.074)	(0.092)	(0.113)	(0.131)	(0.152)	(0.174)
Share Insurance		0.012	0.068	0.171	0.135	0.116	0.078	−0.010
		(0.065)	(0.087)	(0.106)	(0.127)	(0.139)	(0.154)	(0.168)
Import Penetration		−0.787**	−1.594***	−2.047***	−3.023***	−3.588***	−3.566***	−3.760***
		(0.384)	(0.480)	(0.637)	(0.751)	(0.847)	(0.955)	(1.026)
Share Female		0.239*	0.280	0.349	0.510*	0.478	0.511	0.391
		(0.130)	(0.181)	(0.240)	(0.264)	(0.306)	(0.363)	(0.418)
Share Black People		−0.030	−0.025	−0.011	0.019	0.045	0.044	0.036
		(0.020)	(0.024)	(0.030)	(0.031)	(0.032)	(0.035)	(0.038)
Share Latino		0.060***	0.067***	0.084***	0.097***	0.109***	0.126***	0.142***
		(0.018)	(0.025)	(0.030)	(0.030)	(0.032)	(0.036)	(0.038)
Share Education		−0.060	−0.113**	−0.188***	−0.225***	−0.256***	−0.329***	−0.357***
		(0.041)	(0.053)	(0.063)	(0.068)	(0.076)	(0.086)	(0.093)
Share Young		−0.458***	−0.535***	−0.572***	−0.737***	−0.918***	−1.212***	−1.371***
		(0.125)	(0.164)	(0.199)	(0.230)	(0.252)	(0.275)	(0.293)
Share Old		−0.172	−0.180	−0.166	−0.236	−0.316	−0.417*	−0.409*
		(0.109)	(0.139)	(0.163)	(0.187)	(0.202)	(0.226)	(0.247)
Share Public Transport		0.046	0.067	0.102	0.068	0.078	0.136	0.232
		(0.079)	(0.098)	(0.116)	(0.131)	(0.140)	(0.153)	(0.168)
$W_\epsilon \epsilon$		0.021***	0.014***	0.011***	0.010***	0.009***	0.008***	0.007***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.780	0.757	0.759	0.759	0.751	0.749	0.733	0.708

Note: In all specifications, the dependent variable is the difference between the Republicans' percentage of votes in 2016 and 2012. All standard errors, in parenthesis, take account of heteroskedasticity. Alaskan and Hawaiian counties, and Campbell/Wyoming are excluded. The baseline of the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

Table C.2.3: *Spatial Durbin regressions of difference between Republicans' percentage of votes in 2016 and 2012 using coal output in thsnd. short tons per average number of employees hired by coal mines*

	OLS	150 km	200 km	250 km	300 km	350 km	400 km	447 km
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X								
Coal Output per Working Hour	0.090	0.075*	0.065	0.072*	0.080**	0.076*	0.082**	0.079*
	(0.058)	(0.039)	(0.040)	(0.040)	(0.040)	(0.041)	(0.041)	(0.042)
Share Manufacturing	0.024	0.024**	0.023**	0.022**	0.017	0.014	0.015	0.015
	(0.019)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Unemployment Rate	0.201**	0.162***	0.148***	0.139**	0.141***	0.139**	0.142**	0.156***
	(0.099)	(0.056)	(0.056)	(0.054)	(0.054)	(0.056)	(0.056)	(0.057)
Share Poverty	0.066	0.082***	0.075***	0.082***	0.084***	0.083***	0.078***	0.074***
	(0.051)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)	(0.019)	(0.020)
Share Insurance	0.025	0.036	0.026	0.022	0.023	0.025	0.028	0.031
	(0.041)	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)
Import Penetration	0.123	0.232***	0.246***	0.253***	0.238***	0.239***	0.228***	0.236***
	(0.099)	(0.083)	(0.081)	(0.082)	(0.084)	(0.086)	(0.087)	(0.087)
Share Female	−0.067	−0.030	−0.033	−0.031	−0.031	−0.031	−0.034	−0.035
	(0.055)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Share Black People	−0.065***	−0.068***	−0.066***	−0.065***	−0.065***	−0.066***	−0.065***	−0.064***
	(0.014)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
Share Latino	−0.057***	−0.070***	−0.063***	−0.063***	−0.060***	−0.057***	−0.056***	−0.055***
	(0.015)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)
Share Education	−0.311***	−0.319***	−0.316***	−0.314***	−0.317***	−0.318***	−0.318***	−0.317***
	(0.019)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Share Young	−0.111	−0.131***	−0.126***	−0.138***	−0.141***	−0.140***	−0.137***	−0.136***
	(0.088)	(0.047)	(0.046)	(0.045)	(0.046)	(0.046)	(0.046)	(0.046)
Share Old	0.050	0.007	0.018	0.011	0.009	0.013	0.013	0.014
	(0.066)(0.036)	(0.036)	(0.036)	(0.035)	(0.036)	(0.036)	(0.036)	
Share Public Transport	0.016	0.000	−0.001	0.003	0.015	0.024	0.030	0.028
	(0.040)	(0.031)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Intercept	11.649**	18.770**	17.804	9.926	14.385	26.988	43.634*	63.244**
	(5.761)	(8.845)	(12.118)	(14.445)	(17.041)	(20.239)	(24.869)	(28.313)
$W_X\, X$								
Coal Output per Working Hour		0.322*	0.523**	0.712**	0.568	0.731	0.842	1.450**
		(0.190)	(0.251)	(0.319)	(0.374)	(0.463)	(0.548)	(0.566)
Share Manufacturing		0.098**	0.150**	0.191***	0.268***	0.309***	0.315***	0.410***
		(0.047)	(0.060)	(0.072)	(0.081)	(0.091)	(0.100)	(0.108)
Unemployment Rate		0.135	0.135	0.208	0.128	0.172	0.135	−0.121
		(0.142)	(0.183)	(0.222)	(0.260)	(0.300)	(0.350)	(0.400)
Share Poverty		0.011	−0.060	−0.142	−0.217*	−0.273**	−0.313**	−0.307*
		(0.059)	(0.074)	(0.092)	(0.113)	(0.131)	(0.152)	(0.175)
Share Insurance		0.010	0.064	0.162	0.128	0.110	0.076	−0.014
		(0.065)	(0.087)	(0.107)	(0.128)	(0.139)	(0.154)	(0.169)
Import Penetration		−0.808**	−1.616***	−2.085***	−3.051***	−3.604***	−3.592***	−3.790***
		(0.385)	(0.481)	(0.636)	(0.753)	(0.852)	(0.959)	(1.031)
Share Female		0.238*	0.280	0.353	0.516*	0.483	0.508	0.379
		(0.130)	(0.181)	(0.240)	(0.263)	(0.306)	(0.364)	(0.420)
Share Black People		−0.030	−0.026	−0.013	0.017	0.043	0.044	0.037
		(0.020)	(0.024)	(0.030)	(0.031)	(0.032)	(0.035)	(0.038)
Share Latino		0.059***	0.066***	0.082***	0.094***	0.107***	0.125***	0.141***
		(0.018)	(0.025)	(0.031)	(0.031)	(0.033)	(0.036)	(0.038)
Share Education		−0.060	−0.112**	−0.188***	−0.225***	−0.255***	−0.327***	−0.354***
		(0.041)	(0.053)	(0.063)	(0.068)	(0.076)	(0.086)	(0.093)
Share Young		−0.455***	−0.535***	−0.571***	−0.734***	−0.917***	−1.210***	−1.365***
		(0.125)	(0.164)	(0.199)	(0.230)	(0.252)	(0.275)	(0.293)
Share Old		−0.171	−0.179	−0.167	−0.237	−0.320	−0.416*	−0.402
		(0.109)	(0.139)	(0.163)	(0.186)	(0.203)	(0.226)	(0.247)
Share Public Transport		0.047	0.068	0.103	0.069	0.077	0.136	0.233
		(0.079)	(0.098)	(0.116)	(0.131)	(0.140)	(0.154)	(0.168)
$W_\epsilon\, \epsilon$		0.021***	0.014***	0.011***	0.010***	0.009***	0.008***	0.007***
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
State Dummies	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*	*yes*
Observations	3107	3107	3107	3107	3107	3107	3107	3107
Pseudo-R squared	0.780	0.756	0.759	0.758	0.750	0.748	0.733	0.707

Note: In all specifications, the dependent variable is the difference between the Republicans' percentage of votes in 2016 and 2012. All standard errors, in parenthesis, take account of heteroskedasticity. Alaskan and Hawaiian counties, and Campbell/Wyoming are excluded. The baseline of the state dummies is Alabama.

*p<0.1; **p<0.05; ***p<0.01

Table C.2.4: *Spatial Durbin regressions of difference between Republicans' percentage of votes in 2016 and 2012 using coal output in short tons per working hour*