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Coal Mine Closure, Climate Change Scepticism and Elections:
An Empirical Analysis of the Impact of Mining Employment Shocks on U.S. Elections

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Abstract. Averting the worst effects of climate change requires large reductions in coal mining employment. The political impacts of coal mine closures have not been quantitatively studied. Unemployment shocks have previously favoured the Democratic party, though changes in party support for coal mining communities and the rising role of voters' beliefs on climate change could be altering this. This paper builds on recent findings on the relationship between coal mine layoffs and climate scepticism. Using a Difference-in-Differences, Triple Differences and fixed effects models this paper empirically tests the effects of coal mining employment shocks on Republican party vote share in House of Representatives and Presidential elections. After assessing the robustness of the results, this paper finds that coal and metal mining counties respond differently to employment shocks. Distressed metal mining counties increase support for the Democratic party, while coal mining communities increase support for the Republican party. This result is largely driven by the 2016 elections. The findings are not predicted by previous literature and have implications for avoiding a public backlash to the implementation of policy to mitigate climate change.

Keywords: Mining, Unemployment, Climate Change, Political Science, Elections

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1 Introduction

The 2019 Gilet Jaune protests in France demonstrated that public opposition to climate change policies have real consequences for their implementation. In order to meet the commitments of the Paris Agreement and keep global warming to well below two degrees it will be necessary to end the extraction of coal and leave reserves in the ground (McGlade & Ekins, 2015). This will result in large job losses in the coal mining sector over the coming decades (Strambo et al, 2019; Stanley et al, 2019). The political the effects of these losses are not well understood. A review of the literature on coal mine closures by the Stockholm Environment Institute (SEI) found that the political outcomes of closures are "understudied" (Strambo et al, 2019). If coal mine closures lead to increased support for political parties that oppose climate mitigation policies, efforts to meet climate goals could be derailed. This paper builds upon recent work on climate scepticism and job losses in mining counties to address the lack of research and investigate the electoral outcomes of coal mine closures and climate change beliefs in US counties.

Up-coming research from Campa and Szucs establishes a connection between the loss of coal mining jobs and an increase in scepticism of climate change in the US. This observation offers a chance to test if such changes in climate beliefs are associated with changes in political outcomes. Though there is still much to learn about climate change beliefs, it is well established that affiliation with conservative parties is a predictor of climate change scepticism (Hamilton, 2008; McCright, 2010; Poortinga, 2011; Hornsey et al, 2016). Therefore, a difference in climate change beliefs in coal mining counties could cause an increase in vote share for the Republican party in the US. The first purpose of this paper is to establish if there is a change in Republican party vote share associated with the observed difference in climate change beliefs.

While transitioning the economy away from fossil fuels will have global benefits, the costs will not be spread evenly. When coal mines close, we might expect increased support for political parties that are sceptical of climate change or that support the fossil fuel industry. It would be a cruel irony if policies to reduce emissions result in an electoral backlash that makes achieving climate goals more difficult. Given both the lack of research and the potential impact, the second purpose of this paper is to investigate the electoral outcomes of coal mine closures in the US.

The empirical analysis of this paper is in two parts. First, to test if there is a change in Republican vote share corresponding to the observed difference in climate change beliefs, I use results of US House of Representatives elections at a county level. I employ difference-in-difference and triple difference estimations using coal and metal mining counties. Second, to test the outcomes of coal mine closures more broadly, I use the county level results of presidential elections from 2000 to 2016 and employ fixed effects strategy to control for national and county level electoral trends.

The results of the House elections do not find any detectable difference in electoral outcomes due to coal mine layoffs. Conversely, the results of the analysis of presidential outcomes indicate that coal mine layoffs are associated with higher Republican vote share at a county level. These results suggest that a 30% reduction in coal mining employment in a county is associated with a 4.69% higher Republican votes share compared to unaffected coal mining counties in the 2012 and 2016 elections. This effect is not due to mining layoffs generally; when compared to metal mining counties that experience a similar reduction in mining employment, the Republican vote share is 3.71% higher in counties that lose coal mine jobs. The results may largely be driven by more recent elections. In general, previous research finds that unemployment is associated with higher support for the Democratic party. The results contradict the general findings and indicate the effects of unemployment may be different along particular characteristics of communities. This finding has important implications for future climate change policy as the general literature on unemployment may not be a guidance for future fossil fuel job losses.

The structure of this paper is as follows. First, I review the literature on unemployment, climate change beliefs and political outcomes, and present the findings of Campa and Szucs on mining job losses and climate change beliefs. Second, I present a theoretical model to motivate the empirical methodology. Third, I present the empirical strategy employed and the data used. Fourth, I present the results and fifth I discuss their implications and avenues for future research.

2 Context and Literature Review

Climate change is one of the largest potential threats and political challenges facing humanity. A continuation of the current emissions trend will lead to loss of life, disruption of global food supply, mass migration, and the end of some nation states (IPCC, 2014). Despite this, progress to avert the worst effects is currently too slow (Climate Action Tracker, 2019). This is due to the economic, technical and political complexities of the problem. The Paris Agreement committed most nations to the goal of warming to "well below" two degrees above pre-industrial levels. In order to achieve this, sweeping changes are need to the global economy and energy system over the next few decades (IPCC, 2014). Staying below two degrees will require net zero emissions towards the end the of century which necessitates an unprecedented reduction in the burning of fossil fuels (McGlade & Ekins, 2015). Unless there is a currently unforeseen technological change, extraction of fossil fuels will have to end and millions of jobs will be eliminated. The effect that this will have on climate scepticism, political outcomes and the future implementation of policies to avert climate change are not well established.

The literature on general unemployment and electoral outcomes provides a basis for understanding the potential effects of coal mine closures. Broadly, the political science literature finds that higher unemployment rates favours Democratic candidates and hinders incumbents in a range of US elections (Hibbs, 1977; Alesina & Roubini, 1992; Lewis-Beck & Stegmaier, 2000; Wright 2012). The anti-incumbent effect may impact party's candidates differently, with incumbent Republicans being punished more than Democrats for higher unemployment (Wright, 2012). The economic effects of coal mine closures will be highly localised and may not necessarily correspond with national economic trends. Recent literature on county unemployment shows similar results to those above; higher local unemployment rates, accounting for national rates, favour Democrats and challengers (Park & Reeves, 2018).

Taken together the above findings may imply a reduction in coal mining employment will result in an increased vote share for the Democratic party, all else being equal. However, some authors have recently argued that there has been a realignment of the political parties across Western democracies (Piketty, 2019). In particular, left leaning parties, such as the Democrats in the US, have moved from being the workers party to the party of educated and urban elites. Further, in the US the Republican party may be seen as the party supporting the coal mining industry. In the most recent presidential election, President Trump stated on multiple occasions he would "bring back coal mining" (Tabachi, 2017) while the Republican Party election platform said coal miners and their families should be "protected from the Democratic Party's radical anti-coal agenda"

(Republican Party Platform, 2016). All of this makes the effect of a layoff shocks in coal mining counties difficult to predict. On the one hand, a large amount of evidence suggests that such a shock would favour the Democratic party. On the other hand, recent potential realignment and the shock taking place in the fossil fuel industry may favour the Republican party.

How climate change beliefs interact with unemployment is also unclear. There is a strong scientific consensus on anthropogenic climate change (Cook et al, 2016). Despite this, US public beliefs do not match the scientific community's (Leiserowitz et al, 2019). 97% of relevant scientist believe in anthropogenic climate change compared to only 59% of the general population in the US (Cook et al, 2016; Leiserowitz et al, 2019). As public support is clearly not formed by empirical reasoning alone, climate change beliefs can be affected by factors and events unrelated to the facts such as weather conditions, political party positions or unemployment (Kahan, 2012; Sruggs & Benegal, 2012, Taylor, 2014). It has been hypothesised that public belief in climate change may be negatively related to unemployment rates; during times of higher unemployment, individuals prioritise economic concerns over climate issues (Sruggs & Benegal, 2012; Pew Research Centre, 2020). After the 2008 financial crisis there was an increase in climate change scepticism, which some authors have attributed to this relationship (Sruggs & Benegal, 2012; Benegal, 2017). This effect is also seen at a state level, with lower state unemployment associated with lower belief in climate change statements (Kahn & Kotchen, 2011). However, other recent work has argued that this effect is either small or due to other variables such as political affiliation (Kachi & Bernauer, 2015; Mildenberger & Leiserowitz, 2017). For individual and local economic conditions results are similarly mixed and observed effects may be smaller than the impact of national trends (Kachi & Bernauer, 2015; Mildenberger & Leiserowitz, 2017). The focus of this paper is the effect of local layoffs in a specific sector and so the evidence from above literature may or may not be relevant. Null findings for the effect of local level economic conditions on climate change beliefs may not generalise amongst a community more directly impacted by climate change policy. Further, we must be careful to separate local economic conditions from a layoff in a specific local sector. Some counties can perform economically well and under-go a reduction in coal mining employment and vice versa. Given the lack of consensus in the literature, the findings of Campa and Szucs are an important guide to the relationship between coal mine layoffs and climate change beliefs. For this reason, I present the results in detail.

Using survey data from The Yale Program on Climate Change Communication and data on mining employment, the authors test the effect of mining employment shocks on climate change beliefs between 2014 and 2018. First, they employ a difference in difference strategy comparing climate change beliefs in coal mining counties that did and did not experience a 30% or higher reduction in coal mining employment. The results show that mining job losses resulted in a 1.7% difference in belief in that climate change is happening and 1.77% difference in belief that climate change is caused by human activity (see appendix for full tables of results). The difference is negative, so the mean belief in climate change and human causes is lower in counties that suffered a layoff compared to those that did not.

This difference in difference strategy may not identify a specific effect of coal mining shocks; it is possible instead that general employment shocks cause changes in climate change beliefs, as seen above. Therefore, the authors estimate a triple difference regression using metal mining counties as a similar comparison group. Metal mining is chosen as it is a similar industry but without a direct association with climate change. Any difference in beliefs between coal and metal mining counties that both experienced a shock when compared to control coal and mining counties would indicate a specific effect of coal mine layoffs on climate change beliefs. When the effect of general mining shocks is removed by the triple difference strategy, the difference in climate change scepticism remains. This indicate that the difference in climate change beliefs is not being driven by layoffs generally but are specific to coal mining counties.

Taken together, the findings show that there is a relationship between job losses in the coal mining sector and an increase in climate sceptical beliefs relative to unaffected communities. The implications of these results are important. There is little research on the effects of local unemployment on climate change beliefs, and no research on coal mining layoffs in particular. Averting the worst effects of global warming will require huge job cuts in the coal mining sector. The findings above imply this will result in an increase in climate change scepticism. If this causes a reduction in support for climate change policy and pro-climate change parties, future policy implementation could be slowed or halted leading to worse global climate outcomes.

At present, the importance of climate change beliefs for determining election outcomes is unclear, though political affiliation and climate scepticism are strongly correlated. Political affiliation is a measure of an individual's identification with a particular political party, ordinarily observed by asking which party an individual identifies with at the time. This is usually presented as a binary (two parties), ternary (two parties or neither), or seven point scale choice. Political affiliation is a large determinant of voting outcomes; in general, an individual is likely to vote for the party they identify with (Campbell et al, 1980; Bartlet, 2000; Green & Baltes, 2017). This relationship is not perfect; individuals can and do vote against the party they identify with. Particularly strong or weak candidates or prominent issues such as recessions or security issues will favour different parties from one election to another (Berrebi & Klor, 2008; Montalvo, 2011; Catellani & Alberici, 2012; Wright, 2012). Of course, a large number of voters do not identity strongly with either party, these are the swing voters often targeted by campaigns in each election (Mayer, 2007). The relationship between climate change beliefs and political affiliation is well established in the literature (Hamilton, 2008; McCright, 2010; McCright & Dunlap, 2011; Poortinga, 2011; Hornsey et al, 2016). Across nations, those who identify with conservative parties are more likely to be sceptical of or deny climate change statements while those who identify with liberal parties are more likely to believe them. This effect is stronger in the US than other countries (Zeigler, 2017). In a 2016 meta-analysis of the research on determinants of climate change beliefs, the authors describe political affiliation as "the largest demographic correlate of climate change beliefs" (Hornsey et al, 2016). Given these findings, we might expect an increase in scepticism to correspond with an increase in vote share for conservative parties. For the US, this would imply an increase in support for the Republican party. Though the evidence for the relationship between political affiliation and climate scepticism is strong, the research is largely correlational (Fielding & Hornsey, 2016; Hornsey et al, 2016). Therefore, the effects of climate change beliefs on electoral outcomes is difficult to forecast.

In the 2016 elections the Democratic and Republican parties took differing stances on anthropogenic climate change. The Republican party platform states that climate change is "far from the nation's most pressing national security issue" and describes the Intergovernmental Panel on Climate Change as a "political mechanism, not an unbiased scientific institution" (Republican Party Platform, 2016). In contrast, the Democratic party platform has a policy section dedicated to climate and the energy transition and describes climate change as an "urgent threat" (Democratic Party Platform, 2016). Though each party's stance on climate change is clear, the impact this had on the election is not.

The importance of climate change beliefs in election outcomes is not clear, despite the strong evidence of the relationship with political affiliation and the clear positions of the major parties. General support for climate action is strongly correlated with political affiliation (Hornsey et al 2016). The support for particular policies is generally much weaker and not as clearly divided by political affiliation (Hornsey et al 2016). In the past, climate change has been viewed as a low priority for voters, with party positions on economic and social concerns surpassing environmental concerns (Leiserowitz, 2019; Pew Research Centre, 2020). However, the importance of climate change has been increasing in recent elections (Leiserowitz, 2019; Pew Research Centre, 2020).

2.2 Purpose and Contribution

Taking all of the findings in the literature into account, we cannot at present make accurate predictions of the electoral effects of either coal mine closures or climate change beliefs. The difference in climate scepticism observed by Campa and Szucs and the correlation between political affiliation and climate beliefs would imply an increase in Republican party vote share. However, the importance of climate beliefs in electoral outcomes is not clear and may be surpassed by economic concerns. As previous literature indicates unemployment favours the Democrats at the polls. So, the greater importance of economic concerns over climate issues for voters would imply an increased vote share for the Democratic party. For coal mine closures specifically, the outcomes are complicated by changes in climate beliefs, the effects of unemployment and the direct appeal of the Republican party to their communities. Given the need to reduce coal employment to meet climate goals, understanding the particular outcomes of coal mining communities will be essential to avoid strong public backlash that could disrupt efforts to reduce emissions. Evidence is needed to guide policy during the economic transition away from fossil fuels and ensure that the costs and benefits are justly distributed. This paper aims to contribute towards this evidence. This paper has two main purposes:

1) Motivated by the findings of Campa and Szucs and the relationship between climate scepticism and political affiliation, the first purpose is to test if coal mine layoffs are associated with is an increase in Republican Party vote share in the same time period and counties analysed by Campa and Szucs.
2) To expand the above investigation of the relationship between coal mining layoffs and Republican Party vote share to Presidential elections and a wider time frame.

The first purpose will indirectly contribute to the literature on climate change beliefs and political outcomes. Though the correlational relationship between climate beliefs and political affiliation is well established, how these change over time and their impact on election outcomes is unclear.

This paper contributes to the work on the relationship between unemployment and political outcomes. In particular, this paper provides quantitative evidence for the outcomes of mining and in particular coal mining layoffs.

3 Theoretical Framework

3.1 Theoretical Model

Given the above findings in the literature I propose the following theoretical model inform the empirical strategy that follows. First, Republican vote share is given by:

$$y_{jt} = \frac{\sum_i v_{ijt}}{\sum_i t_{ijt}}$$

Where y_{jt} it is the Republican party vote share in county *j* at an election at time *t,* v_{ijt} is a binary variable taking the value 1 if individual i votes Republican and 0 otherwise in an election at time *t*, and t_{ijt} is a binary variable taking the value 0 or 1 representing individual i's decision to vote in the election at time t. As it is impossible to not vote and also vote Republican, if t_{ijt} is 0 then v_{ijt} is 0 and hence y_{jt} is between 0 and 1. If no individuals turn out to vote then y_{jt} is defined to be 0.

The decision to vote Republican or not is in part a function of political affiliation (Campbell et al, 1980; Green & Baltes, 2017; Bartlet, 2000) and employment shocks (Wright, 2012). That is:

$$v_{ijt} = f_i(s_{jt}, a_{ijt})$$

Where s_{jt} is a dummy variable representing an employment shock to the mining sector between *t-1* and *t.* and a_{ijt} is individual i's political affiliation at time *t.* In this simple model a_{ijt} can take two values, one for Republican and zero for non-Republican. Though other factors can affect the voting decision, I assume that all else being equal individuals will vote for the party they identify with. The literature broadly indicates that an employment shock will cause increased vote share for the Democrat party (Wright, 2012) and so v_{ijt} is decreasing in s_{jt}, that is an employment shock will reduce the Republican vote share.

Define b_{ijt} to be individual i's beliefs about climate change at time *t.* To simplify this, b_{ijt} is 0 if individual *i* does not believe in a particular climate change statement or 1 if they do. From the literature on determinants of climate scepticism, a decrease in belief in climate change corresponds to an increase in affiliation with the Republican party. So, define:

$$a_{ijt} = g_i(b_{ijt})$$

This function may be heterogenous across the population. I assume that a_{ijt} is decreasing in b_{ijt}. That is, if an individual changes from believing to not believing a climate change statement, then their political affiliation either remains the same or becomes Republican. I assume that an increasing belief in climate change will not result in an increase in political affiliation with the Republican party.

The results of Campa and Szucs show that climate beliefs are dependent on mining employment shocks. These beliefs are affected differentially depending on whether the county is a coal or metal mining county. Define:

$$b_{ijt} = h_i(s_{jt}, c_{jt})$$

Where s_{jt} is defined above and c_{jt} is a dummy variable taking the value 1 if county j is a coal mining county and 0 if it is a metal mining county.

By substitution we have:

$$y_{jt} = \frac{\sum_i f(s_{jt}, g_i(h_i(s_{jt}, c_{jt})))}{\sum_i t_{ijt}}$$

This can be simplified to a function R dependent on s_{jt} and c_{jt}:

$$y_{jt} = \frac{R(s_{jt}\, , c_{jt})}{\sum_i t_{ijt}}$$

The literature on the effect of unemployment on voter turnout is mixed; some results suggest shocks supress the turnout, others that difficult economic conditions motivate higher turnout (Rosenstone, 1982; Burden & Wichowsky, 2014). There is no evidence to suggest that employment shocks affect Republican and Democrat voter turnout differently, so changes in voter turnout should not affect party voter share.

With the above county level function established, we can then see how this would be empirically tested with four groups of observations split over two categories: counties that have and have not experienced a layoff and metal or coal mining counties. Using metal mining counties, we can remove the change in vote share caused by mining layoffs in general. This allows the effect that is specific to coal mines to isolated. This model is highly simplified and does not incorporate variables other than layoffs and mining classification. Of course, other factors such as national economic trends and characteristics of candidates will also affect vote share outcomes, therefore the empirical strategy employed will have to account for this.

4 Methods

4.1 Data Description

In this section I describe the data used for the empirical analysis. The dependent variable of interest for this paper is Republican party vote share. To test if there is a correlation between climate change beliefs and Republican vote share, I use House of Representatives elections in 2014 and 2018. To test the effect of mining layoffs more generally, I use results of Presidential elections from 2000 to 2016.

Elections for the House of Representatives take place in November in even numbered years. Each seat represents a congressional district within a State and appointment to a seat us by plurality. Every state has at least one Congressional district, with the number assigned by population observed in the US Census every ten years. Districts do not necessarily match county boundaries; some counties are entirely contained in one district, while others will be divided over two or more. House elections in 2014 and 2018 were chosen to match the time period analysed by Campa and Szucs.

Turnout for House Elections is generally much lower during midterms that fall between presidential elections. Midterm turnout is typically 20% lower than during presidential election years, though 2018 recorded the highest midterm turnout in a century. Therefore, changes in political affiliation caused by climate change beliefs may not translate to changes in house vote share, as only the most politically dedicated and thus strongest aligned to their political party turnout to vote. Further, the sample size of counties used for their analysis may be too small to detect changes in Republican vote share associated with coal mine closures. For this reason, results of presidential elections were chosen to test the electoral effects of coal mine closures more generally.

To measure the dependent variable, I used two datasets. For voting outcomes in House elections, I used data on county level outcomes from Dave Leip's Election Atlas which covers House elections every two years from 1994 to 2018. This dataset is construct by aggregating county level data from state and sub-state government agencies. For outcomes in Presidential Elections I used data from MIT Elections Data and Science Lab. The dataset "County Presidential Election Returns 2000-16" is a freely available dataset. Both datasets include total votes cast and votes cast for each major party by county for each election. Using the votes cast for the Republican party and total votes cast we produce the Republican party vote share for each county and election.

The main independent variable requires data on mining employment by county over time. To measure mining employment, I used data from the Mine Safety and Health Administration (MSHA). MSHA is a under the US Department of Labor. They provided data on mining employment in all American mines from 1990 to the end of 2017. Annual mining employment is recorded as the mean of quarterly employment figures at each mine. The dataset includes the county each mine is located in. Using this, aggregate county employment figures can be produced for each county and year, up to and including 2017. MSHA separately records data on metal and coal mining employment, allowing the two datasets to be merged to produce separate annual employment figures for coal and metal mining in each county.

Using FIPS codes, which uniquely identify US counties, election outcomes data can be matched to mining employment. All counties match with the exception of the Alaskan boroughs. In the elections outcomes datasets Alaskan counties are sorted into municipal districts. In the MSHA data, Alaskan mines are recorded by counties (named boroughs in Alaska). Unfortunately, these geographical units cannot be made to correspond. Some counties spread over multiple municipal districts while some are contained, along with other counties, inside a single district. There is no rigorous method to say how many people voted in each county, let alone which party. As such there is no accurate way to match political outcomes to Alaskan counties and they have been excluded from the analysis.

For the presidential analysis, several control variables were used. The motivation for their inclusion is discussed below. Estimates of total population and ethnic minority population are obtained from the US Census Bureau. Estimates of the percentage of a county's population holding a bachelor's degree or higher are obtained from the census, with adjusted estimates for 2014-2018 produced by the US Department of Agriculture Economic Research Service (USDA ERS) as part of the Atlas of Rural and Small-Town America. These estimates are produced using use census data and American Community Survey data. County level estimates of educational attainment are not produced for each year, values are known for 2000 and 2010 from the census and 2014-18 by the USDA ERS. Population density was calculated using total population data and land area data obtained from the Census Bureau. Annual total work force and unemployment rates by county and year are obtained from Local Area Unemployment Survey (LAUS) from the Bureau Labour Statistics. Finally, data on annual county natural gas production for 2000 to 2012 is obtained from the USDA ERS.

4.2 Model Specification

To estimate the electoral effects of layoff shocks on coal mining counties, I must define what changes in employment constitute a layoff and how counties are classified as coal or metal mining. A layoff in the mining sector of a county is defined as a 30% reduction in total mining employment between the two time periods. This level was chosen for two reasons. First, reductions must be large enough to constitute a shock and have an impact on the local county. On the other hand, if too large a level is selected then this would reduce the treatment group size and the statistical power of the analysis. There is no standard guidance for this in the literature. Second, 30% reduction follows the methodology of Campa and Szucs and so must be used to test if Republican vote share correlates with the differences in climate change beliefs. As the reduction level is essentially arbitrary, I have included sensitivity analysis in the results.

A county is defined as being a coal or metal mining county in time period *t* if there are at least 300 mining jobs in time period *t-1*. If a county has fewer than 300 jobs in both metal and coal mining, then it is excluded from the analysis. Similarly, as I wish to investigate the particular effect of being a coal mining community, counties that had more than 300 jobs in both metal and coal mining are excluded from the analysis. Therefore, all counties included are exclusively either coal or metal mining counties. For the first analysis of the House of Representatives elections, counties are categorised as coal mining counties if there were at least 300 coal mining jobs in 2014. Similarly, for metal mining counties. For the presidential elections, a county and year observation is classified as a coal or metal mining county if there were at least 300 jobs in coal or metal mining during the year of the previous election. For example, if a county had at least 300 jobs in metal mining in 2004 then the observation for 2008 for the county will be classified as a metal mining county. It is possible and expected that a county's mining employment will drop below 300. If this is the case, the observation is removed in the following election cycle. To continue the above example, if a county had 350 metal mining jobs in 2004 and 250 in 2008, the observations for 2008 would be classified as a metal mining county and the observation for 2012 would be dropped from the analysis.

The decision to use 300 jobs as the threshold for mining classification was chosen for two reasons. First, intuitively there must be a sufficiently large number of mining jobs for citizens of a county to affected by a shock. With low levels of mining employment, it is unlikely that the reductions will have a county wide impact on voting decisions. However, for larger numbers of jobs the local economy and community identity is associated with mining. A challenge to could result in a change to voting decisions even from citizens that are not employed in the mines. The number that is required for this is not defined by the literature. Similar to reduction levels, if too large a number of mining jobs is used then sample size is reduced and statistical power is lost. Second, I again follow the methodology of Campa and Szucs. As 300 jobs is essentially arbitrary, I have included sensitivity analysis in the results. A continuous measure could be used instead.

4.2.1 Model for House of Representatives Elections

The theoretical models outlined above informs the empirical strategy directly. First, the results from Campa and Szucs show a difference between climate change beliefs in coal counties due to coal mining layoffs and the literature on climate change beliefs indicates that there will be a corresponding difference in political affiliation and therefore electoral outcomes. There are a variety of national trends that an impact the House midterm elections which must be accounted for. If coal counties historically follow parallel trends for election outcomes, then a difference in difference strategy can be employed to remove the effect of unobserved variables and national trends. I first estimate:

$$Repub. Vote\ Share_{it} = \beta_0 + \beta_1 * After_{it} + \beta_2 * Layoff_i + \beta_3 * After_{it} * Layoff_i + \epsilon_{it} \qquad (1)$$

where i is a county and an election year; $After_{it}$ is a dummy variable taking value 1 for observations in the second time period (2018) and 0 for observations in the first time period (2014); $Layoff_i$ is a dummy variable taking value 1 in both time periods if the county experiences a 30% or higher reduction in mining employment between 2014 and 2018. I will refer to counties taking value 1 for $Layoff_i$ as treatment and counties taking value 0 as control. The coefficient of interest is the interaction term β_3.

In the theoretical model above, vote shares are affected by mining shocks both directly and via climate change beliefs. Therefore, estimation (1) may not capture changes in Republican vote share caused by coal layoffs. The literature finds that unemployment favours Democratic candidates; therefore, changes in Republican vote share due to climate change beliefs may be mitigated by increased Democratic vote share due to unemployment. To isolate the effect of climate change beliefs, I employ a triple difference estimation using metal mining counties. The difference in Republican vote share between treatment and control counties will capture the effect of mining layoffs on vote share. The particular effect of coal mining layoffs can then be isolated. This assumes that layoffs in metal mining counties do not affect climate beliefs, which the results in table 2 supports. I estimate using the following:

$$Republican\ Vote\ Share_{it} =$$

$$\beta_0 + \beta_1 * After_{it} + \beta_2 * Layoff_i + \beta_3 * Coal_{\ i} + \beta_4 * After_{it} * Layoff_i +$$

$$\beta_5 * After_{it} * Coal_{\ i} + \beta_6 * Layoff_i * Coal_{\ it} + \beta_7 \ * After_{it} * Layoff_i * Coal_{\ i} + \ \epsilon_{it} \quad \mathbf{(2)}$$

Where i represents a county and election year, and $After_{it}$ is defined as before. The model introduces the dummy variable $Coal_{\ i}$ which takes the value 1 for coal mining counties and 0 for metal mining counties. The variable $Layoff_i$ is generalised to include both metal and coal mining shocks. Our coefficient of interest is the triple interaction term β_7.

I estimated equations (1) for all counties with at least 300 coal mining jobs and fewer than 300 metal mining jobs. This is to remove counties where workers can transfer from coal to metal mining. Equation (1) was also estimated for the subset of counties which had a Democratic and Republican candidate contest the elections in both 2014 and 2018. If an election is contested in one time period but not the other, the difference in Republican vote share would clearly be driven by this. For counties with uncontested elections in both time periods it would not be possible to detect political affects of mine closures as there would be only one candidate to vote for. There were eight metal or coal counties with uncontested elections in one period and three with uncontested elections in both periods. I estimated model (2) over all metal and coal mining counties with at least 300 mining jobs in either coal or metal mining in 2014. Lastly, I estimate model (2) for the subset of counties with contested elections in both time periods.

4.2.2 Model for Presidential Elections

For the second purpose of this paper, to empirically establish the effect of coal mine layoffs on Republican votes share more generally, I use the results of presidential elections from 2000 to 2016. This window was chosen for two reasons. First, the effect of coal mine closures on political outcomes is not understood. Investigating the general historic election outcomes of coal mine closures will add evidence for understanding potential future layoffs. Second, though the literature does not indicate that there should be particular differences for the coal mining sector, the alignment of the Republican party with fossil fuel workers and the rise of climate change as a political issue may lead to increased Republican vote share. By using results over a longer time frame, recent elections can be compared to past elections to establish if these recent campaign trends translate into electoral outcomes. Further, Presidential elections have a larger turnout than House elections and so may better capture changes caused by mining job losses.

Using data over a wider time frame poses new challenges. Treatments will now be occurring in different time periods. Each election has its own national trends and each county has their long running association with a particular party. In order to generalise the difference in difference estimation above and to accommodate for this I use year and county fixed effects strategy. Over a sixteen-year period larger changes in demographics are also possible and must be controlled for. Therefore, I estimate the following model:

$$Republican\,Vote\,Share_{it} =$$

$$\alpha_t + \beta_1 Layoff_{it} * Coal_i + \beta_2 Layoff_{it} + Controls + \mu_i + \varepsilon_{it} \qquad \textbf{(3)}$$

where *i* represents a county and *t* an election year. Republican votes share is the percentage of votes casts for the Republican party in election year t. I include α_t for time fixed effects to account for election wide trends in Republican support, such as the strength of a particular candidate, and nationwide economic conditions. County fixed effects are captured by μ_i which accounts for time invariant support for the Republican party in each county. The inclusion of county fixed effects means that $Coal\ _i$ cannot be included in order to avoid collinearity. I estimate these models both with and without demographic controls. From the literature higher levels of ethnic minority population, higher educational attainment and higher population density are associated with increased support for Democrats (Mckee, 2008; Pew Research Centre, 2018; Gimpel et al, 2020;). I have included control variables for population density, the percent of the population that identifies as Black or Hispanic and the percent of the population over 25 years of age with a bachelor's degree or higher.

Local unemployment rate is included in some specifications as a control variable. This is possibly a bad control, as coal layoffs and local unemployment could be causally related to each other. Coal mine layoffs could cause local economic contractions if sufficiently large, or local contracts could cause layoffs. I chose to include the specifications with local unemployment to test the potential relationship.

4.3 Hypothesis

Given the strong relationship between climate scepticism and political affiliation my first hypothesis is that Republican vote share will be higher in coal mine counties due to the difference in climate scepticism observed by Campa and Szucs.

The second purpose of this paper is to establish if coal mine closures affect electoral outcomes. Given the literature we would broadly expect layoffs to reduce Republican votes share. The above theoretical model motivated by the findings of Campa and Szucs and the relationship between climate scepticism and would imply that coal mine closures increase Republican vote share. However, climate change was not an important electoral or political affiliation until more recently. So, the theoretical model may not apply to the full time period. Therefore, I hypothesis that any differential effect of layoffs on election outcomes between coal and metal mining counties will be observed in more recent elections.

5 Results

5.1 Results from House of Representatives Elections

First, I present the descriptive statistics and results of the difference in difference and triple difference regressions for the House elections between 2014 and 2018.

5.1.1 Descriptive Statistics

Table 1 shows the number of coal and mining counties in treatment and control groups and the number of counties with contested elections in both timer periods. Treatment groups are those that experienced a 30% or larger reduction in mining employment between 2014 and 2018. Counties are classified as either coal or metal mining counties if they had at least 300 jobs in their respective mining sector in 2014. One county had over 300 jobs in both coal and metal mining and is excluded from the analysis. A county is classified as having contested elections if there was a Democratic and Republican candidate for the district in both 2014 and 2018. Overall the sample of counties is smaller than Campa and Szucs as Alaskan boroughs could not be included. In total there are 164 counties in the sample, giving 328 observations. The distribution of contested elections appears to be fairly even. The number of metal counties in the treatment group is low and much smaller than the number of treatment coal mining counties.

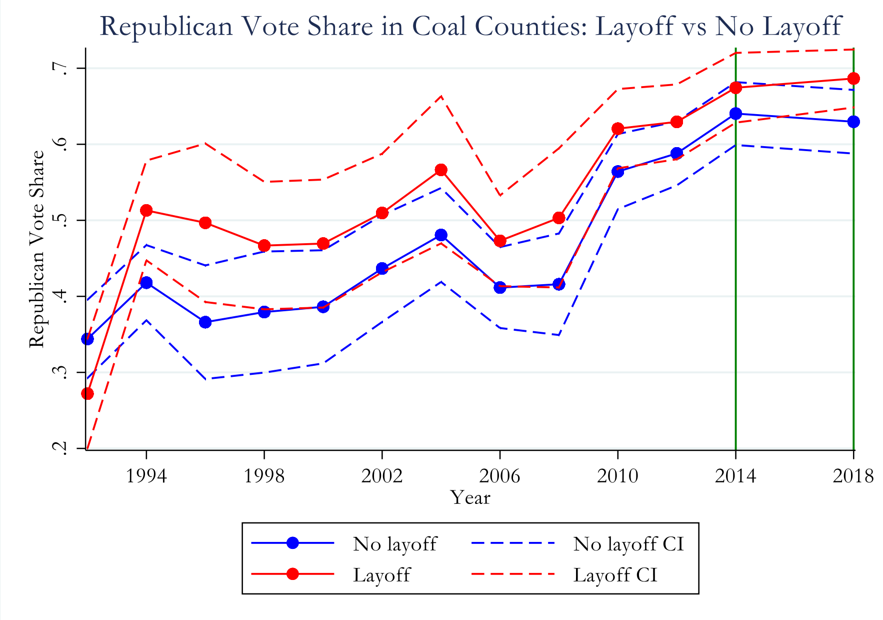
Table 1: Treatment and Control Groups for Coal and Metal Counties

	Coal		Metal	
	All	Contested	All	Contested
Layoff	33	31	10	9
No Layoff	48	45	73	68
Total	81	76	83	77

Notes: Coal counties are all US counties with more than 300 coal mining jobs and fewer than 300 metal mining jobs in 2014. Metal mining counties are all US counties with more than 300 metal mining jobs and fewer than 300 coal mining jobs. Layoff is the number of counties that had a reduction of 30% in mining employment between 2014 and 2018. All other reductions or increases are included under No Layoff. A county is considered a Contested county if there was both a Democratic and Republican candidate in the 2014 and 2018 House of Representative elections for the District or Districts representing the county.

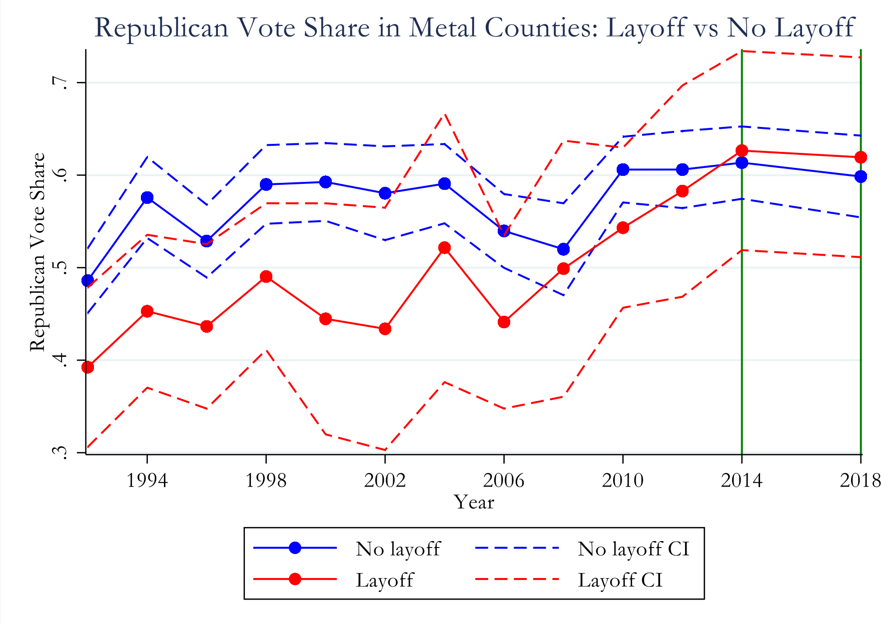
Figure 1 shows the trend graph for Republican vote share in House elections from 1992 to 2014. Visually both treatment and control counties follow similar trends up to and including 2014. Treatment counties have a consistently higher Republican vote share. It is also interesting to note that Republican vote share was historically lower with a recent rise in 2014. Figure 2 shows the same outcomes for metal mines over the same period. The number of observations in the treatment group is much smaller, leading to the wider confidence margins. The two groups of counties do not follow trends as closely as the coal mining counties.

Figure 1.



Notes: The figure plots the mean vote share for the Republican party in coal mining counties from House of Representatives elections. It compares the counties that had a 30% or large reduction in mining employment between 2014 and 2018 (the red line) to counties that did not (the blue line). Confidence intervals are displayed in corresponding line colours.

Figure 2.



Notes: The figure plots the mean vote share for the Republican party in metal mining counties from House of Representatives elections. It compares the counties that had a 30% or large reduction in mining employment between 2014 and 2018 (the red line) to counties that did not (the blue line). Confidence intervals are displayed in corresponding line colours.

Table 2 shows the balance table for treatment and control counties in 2014. Mean Republican vote share in the House election is 3.4% higher in counties that experience a shock. From the Figure 1 we saw that historically the treatment coal counties have had higher Republican vote share. Mean total coal mining employment is slightly lower in treatment counties, though this is not statistically significant. There is a large difference in both total population and density. This difference is caused by a few counties with very large populations; the difference between median population is 4%. Both counties have similarly low percentage of ethnic minority voters.

Table 2: 2014 Balance Table

	(1) No Layoff	(2) Layoff	(1) vs (2)
Republican Vote Share	64.0	67.4	-3.4
	(2.1)	(2.3)	(3.2)
Mining Employment	833	753	110
	(119)	(86)	(160)
Population	66,112	45,754	20,358
	(15,559)	(7,192)	(19,720)
Population Density	87.7	76.5	11.2
	(16.9)	(9.5)	(21.9)
Black & Hispanic Population (%)	7.0	6.1	0.9
	(1.2)	(1.3)	(1.8)
Count	48	33	81

Notes: The table displays the mean and standard errors for the dependent variable, independent variable and demographics in 2014 Column 1 is for all coal counties that did not have reduction of 30% or larger in mining employment between 2014 and 2018. Column 2 is the all coal counties that had such a reduction and column 3 is the difference between the two groups. Republican Vote Share is the percentage of total votes cast for the Republican party, Mining Employment is the total number of coal mining jobs, Population Density is total population over land area and Black & Hispanic Population (%) the percentage of the population identifying as Black or Hispanic. Standard errors are displayed in parenthesis.

Table 3 shows the balance table for the same counties in 2018. Mean Republican vote share has decreased in control counties and increased in treatment counties. This leads to a difference of means of 5.7%, an increase of 2.3%. Important demographics such as total population, voting population, and ethnic minority population have not changed significantly. Education level could be included in the tables 2 and 3 as the estimations of educational attainment at a county level produced by the various US agencies have not been updated from 2014 and 2018. Therefore, we cannot observe if there has been a change in education level. The treatment and control groups are balanced for Republican vote share, voter turn and percentage of Black and Hispanic voters. The large imbalance is caused by a few very populous mining counties, median population is not significantly different

Table 3: 2018 Balance Table

	(1) No Layoff	(2) Layoff	(1) vs (2)
Republican Vote Share (%)	63.0	68.7	-5.7
	(2.1)	(2.3)	(3.0)
Mining Employment	738	341	397
	(96)	(48)	(123)
Population	65,887	45,457	20,430)
	(15,543)	(7,206)	(19,705)
Population Density	87.2	75.9	11.3
	(16.8)	(9.5)	(21.8)
Black & Hispanic Population (%)	7.5	6.3	1.2
	(1.2)	(1.3)	(1.8)
Count	48	33	81

Notes: The table displays the mean and standard errors for the dependent variable, independent variable and demographics in 2018 Column 1 is for all coal counties that did not have reduction of 30% or larger in mining employment between 2014 and 2018. Column 2 is the all coal counties that had such a reduction and column 3 is the difference between the two groups. Republican Vote Share is the percentage of total votes cast for the Republican party, Mining Employment is the total number of coal mining jobs, Population Density is total population over land area and Black & Hispanic Population (%) the percentage of the population identifying as Black or Hispanic. Standard errors are displayed in parenthesis.

5.1.2 Estimation Results

Table 4 presents the estimates for the effect of coal mining layoffs on Republican votes share and turnout. For each outcome, I estimated equation (1) with all coal mining counties (1) and over only counties with elections which were contested by a Democrat and Republican candidate in both time periods (2). Robust standard errors are displayed in parentheses.

Table 4: Republican Vote Share and Coal Layoffs

	(1)	(2)
After*Layoff	0.0229	0.0220
	(0.0427)	(0.0439)
After	-0.00267	-0.00153
	(0.00752)	(0.00767)
Layoff	0.0340	0.0357
	(0.0315)	(0.0319)
Constant	6.028	3.717
	(15.16)	(15.47)
Observations	162	152
R-squared	0.028	0.030

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table reports the regression for equation (1) for Republican vote share in by county in US House of Representatives elections in 2014 and 2018. Observations are of outcomes in 2014 and 2018 for counties with more than 300 coal mining jobs and fewer than 300 metal mining jobs in 2014. Republican vote share is the dependent variable in both columns and is a continuous variable from 0 to 1. After is a dummy variable taking the value 1 if the observation is in 2018 and 0 otherwise. Layoff is a dummy variable taking the value1 if the county had a 30% or higher reduction in coal mining employment between 2014 and 2018. After*Layoff is the interaction term of the two. Robust standard errors are reported in parenthesis.

For both specifications, the estimated coefficient of the interaction term is not statistically significant, and I fail to reject the null hypothesis. For specification (1) this is 0.0229, predicting a 2.2% higher mean county Republican vote share in House elections following a layoff compared to unaffected counties. For the sub-set of counties with contested elections in both years, this is reduced to 0.022. The other coefficients are not of interest to this test, though all are also not statistically significant. The results indicate that a 30% reduction in coal mining employment does not have a detectable effect on House elections. The results are also not significant for other definitions of Layoff and Coal variables (see appendix). Taken together, this indicates that coal mining layoffs do not have an effect on Republican vote share. As seen in table 1, there was a significant difference in climate scepticism between the two groups of counties. The above results do not find a corresponding change in electoral outcomes. It is possible that any increase in Republican vote share due to changes in climate scepticism is offset by an increase Democratic vote share due to unemployment and so we must look at the results of the triple difference estimate using metal mining counties.

Table 5 presents the estimates of equation (2). Specification (1) includes all mining counties in the sample and specification (2) is restricted to counties where the House election were contested in both 2014 and 2018. Robust standard errors are displayed in parenthesis

The coefficients of the interaction term After*Coal*Layoff are not statistically significant for all counties and contested counties and for both Republican vote share and voter turnout. In both cases I fail to reject the null hypothesis. The direction of the coefficient for the triple interaction term is positive, though again the standard errors are large. The estimates of the second specification predict that Republican vote share will be 5.7% more in coal counties that experience a layoff compared to unaffected coal counties. For coal and metal counties that both experiences a layoff, the estimates predict Republican vote share will be 10.4% higher in coal counties.

Table 5: Republican Vote Share and Mining Layoffs

	(1)	(2)
After*Layoff*Coal	0.0151	0.0125
	(0.0912)	(0.0748)
After*Layoff	0.00779	0.00954
	(0.0806)	(0.0605)
Layoff*Coal	0.0210	0.0602
	(0.0646)	(0.0530)
After*Coal	0.00429	0.0112
	(0.0427)	(0.0411)
After	-0.00375	-0.00434
	(0.00757)	(0.00685)
Layoff	0.0130	-0.0245
	(0.0564)	(0.0423)
Coal	0.0269	0.0205
	(0.0291)	(0.0277)
Constant	8.162	9.343
	(15.26)	(13.80)
Observations	328	306
R-squared	0.031	0.041

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table reports the estimates of equation (2) for Republican vote share in by county in US House of Representatives elections in 2014 and 2018. Observations are of outcomes in 2014 and 2018 for counties with more than mining jobs in 2014. Republican vote share is the dependent variable in both columns and is a continuous variable from 0 to 1. After is a dummy variable taking the value 1 if the observation is in 2018 and 0 otherwise. Layoff is a dummy variable taking the value1 if the county had a 30% or higher reduction in mining employment between 2014 and 2018. Coal is a dummy variable taking the value 1 if a county has more than 300 coal mining jobs and 0 if a county has more than 300 metal mining jobs. Other terms are interactions of the three dummy variables. Robust standard errors are reported in parenthesis.

5.2 Results from Presidential Elections

5.2.1 Descriptive Statistics

Table 6 displays summary statistics for the observations for the analysis of the presidential elections. An observation is one county in one election year. A county is included if there were more than 300 mining jobs in the previous time period. Alaskan counties are not included as before. Eureka county Nevada is also excluded for the exceptional fact that there are more mining jobs than residents in the county. This highlights an issue that will be discussed in the limitations section. Table 6 displays means and standard deviations for the dependent and independent variables. An observation is included under the layoff column if there was a 30% reduction between that observation and the last time period. Prev. Mining Employment displays the total number of mining jobs during the year of the previous election. For all other variables the means displayed are for the time period of the observation. Population and population density may jump out as being particularly different, these are largely drive by a few very populous counties such as Miami Dade, Florida. The relationship between population density, ethnic minority population and education level with party voting is well established, and so the table shows the need for their inclusion as control variables in the estimation as large changes are possible over the time period under examination. Full summary statistics with quartiles are included in the appendix.

Table 6: Summary Statistics

	Coal		Metal	
	No Layoff	Layoff	No Layoff	Layoff
Observations	278	103	415	52
Repub. Vote Share (%)	59.1	65.23	55.47	52.83
	(12.72)	(14.23)	(13.66)	(13.8)
Prev. Mining Employment	950	956	770	679
	(853)	(770)	(660)	(760)
Mining Employment	980	453	739	353
	(847)	(360)	(627)	(498)
Population	54,610	55,196	457,929	601,558
	(81,884)	(93,223)	(1,200,343)	(1,612,162)
Population Density	72.49	84.33	270.27	378.82
	(75.79)	(88.87)	(628.92)	(869)
Black & Hispanic Population (%)	6.76	5.81	22.77	18.74
	(7.8)	(8.44)	(19.7)	(17.79)
Bachelors or Higher (%)	14.51	14.37	20.46	21.63
	(7.73)	(7.88)	(8.92)	(10.37)

Notes: The table displays the means and standard deviations of the dependent variable, independent variables and demographic controls of all observations. Statistics are disaggregated by treatment status and mining type. Prev. Mining Employment is the employment during the year of the previous election. All other variables are for the year of the observation. Standard deviations in parenthesis

5.2.2 Estimation Results

Table 7 shows the results from the estimation of equation (3) on the above observations. The table reports five specifications. The first is the simple model with no control variables. The second to fourth report the inclusion of each control variable and the fifth includes all demographic controls. Time and county fixed effects are included in all models and standard errors are cluster at the county level. There are 190 individual counties in the sample. When the model was estimated there were 49 observations which occurred at only one time period and so are dropped from the analysis. These are all observations in 2000 in which mining employment was above the 300 jobs level in 1996 but dropped below the required level for further election years. As the model estimates fixed effects, these observations are removed.

Table 7: Effect of Coal Mine Layoffs on Republican Vote Share

	(1)	(2)	(3)	(4)	(5)
Layoff*Coal	0.0966***	0.0911***	0.0862***	0.0801***	0.0723***
	(0.0154)	(0.0149)	(0.0150)	(0.0147)	(0.0146)
Layoff	-0.0292***	-0.0302***	-0.0310***	-0.0205**	-0.0245***
	(0.00801)	(0.00742)	(0.00932)	(0.00818)	(0.00917)
Population Density		-0.000917***			-0.000511***
		(0.000196)			(0.000143)
Ethnic Minority			-1.930***		-1.570***
			(0.299)		(0.300)
Bachelor's or Higher				-0.0119***	-0.00930***
				(0.00311)	(0.00283)
Constant	0.570***	0.742***	0.871***	0.783***	1.076***
	(0.00156)	(0.0366)	(0.0465)	(0.0554)	(0.0696)
Observations	799	799	799	799	799
R-squared	0.842	0.858	0.865	0.852	0.877

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the results five specifications of the fixed effects estimation with demographic controls. Observations comprise of all county/years with at least 300 mining jobs in the previous time period. The dependent variable in all specifications is Republican party vote share measured as continuous variable from 0 to 1. Coal is a dummy variable taking the value 1 if there were more than 300 jobs in coal mining. Layoff is a dummy variable taking the value 1 if the county had a 30% reduction in mining employment between the previous time period and the observation. Population density is given by total population over land area. Ethnic Minority is the percentage of the population identifying as Black or Hispanic. Bachelor's or Higher is the percent of the over 25 years old with a bachelor's degree or higher. Time and county fixed effects are included in all specifications. Standard errors are clustered at the county level and reported in parenthesis.

In all specifications the coefficient of the interaction term Layoff*Coal is statistically significant ($p<0.01$) and positive. The magnitude of the coefficient for the interaction term is reduced slightly with the inclusion of the controls but remains large. In all specifications the estimation of the Layoff dummy is significant ($p<0.01$) and the coefficient is negative. For specification (5), the results predict a layoff between elections is associated with a 2.45% decrease in Republican party vote share. This agrees with the general findings of the literature on unemployment and electoral outcomes. The results in specification (5) predict that a coal mining county which experiences a 30% reduction in coal mining employment before an election will have a 4.77% higher vote share for the Republican party than a coal or metal mining county that did not experience a lay off in the previous period. Comparing the coal and metal mining counties that both experience a 30% layoff in mining jobs, the results predict a higher Republican vote share in coal mining counties. This result was not predicted from the literature and indicates a differential response to layoff shocks between the two counties. All the control variables except for the percentage of jobs in the mining are statistically significant ($p<0.01$) and the direction of the coefficients match the predicted result in the literature.

Before examining potential explanations for the results, I estimated equation (3) with the inclusion of local unemployment rate as a control variable. This may be a potential bad control due to the causal relationship between local unemployment and mining layoffs. From the summary statistics we can see that mining employment makes up a significant part of the work force. In coal mining communities, a 30% reduction in mining employment would on average directly result in a 1.5% increase to the county unemployment rate. I have included estimations to examine their effect and discuss the results. Table 8 shows the estimates of equation (3) with the inclusion of local unemployment rate as a control variable both with and without demographic controls. The estimates for equation (3) with the demographic controls as before is included for direct comparison. Standard errors are cluster at the county level.

Table 8: Inclusion of Local Unemployment Rates

	(1)	(2)	(3)
Layoff*Coal	0.0897***	0.0677***	0.0723***
	(0.0149)	(0.0143)	(0.0146)
Layoff	-0.0315***	-0.0271***	-0.0245***
	(0.00799)	(0.00910)	(0.00917)
Local Unemployment Rate	0.00645**	0.00530**	
	(0.00274)	(0.00224)	
Population Density		-0.000503***	-0.000511***
		(0.000146)	(0.000143)
Ethnic Minority		-1.616***	-1.570***
		(0.309)	(0.300)
Bachelor's or Higher		-0.00837***	-0.00930***
		(0.00275)	(0.00283)
Constant	0.530***	1.032***	1.076***
	(0.0170)	(0.0657)	(0.0696)
Observations	799	799	799
R-squared	0.844	0.879	0.877

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table reports the results two specifications of the fixed effects estimation with demographic controls. The first column is the results of the simple fixed effects specification with local unemployment rate as a control variable. The second column extends this to include demographic variables. Observations comprise of all county/years with at least 300 mining jobs in the previous time period. The dependent variable in all specifications is Republican party vote share which is measured as continuous variable from 0 to 1. Local Unemployment Rate is a continuous variable from 0 to 1 representing the mean unemployment rate in the year of the observation. Time and county fixed effects are included in all specifications. Standard errors are clustered at the county level and reported in parenthesis.

In both specifications the interaction term remains statistically significant ($p<0.01$). The estimated coefficient for local unemployment is positive and statistically significant ($p<0.05$). In the second specification with all control variables, this would predict that an increase of the unemployment rate by 1% in the year of an election is associated with an increase in the Republican vote share by 0.5% As noted above, this is potentially a bad control and it is not clear how its inclusion adds to the analysis. First, the direction of the coefficient for the unemployment rate is positive, predicting an increase to Republican vote share which contradicts the evidences from the literature. Second, coefficient of the layoff dummy is negative. So, the results predict that a mining layoff is associated with an in increased vote share the Democrats but increased local unemployment results in an increased vote share for the Republicans. Given the mining jobs are a large part of the county work force this appears to be contradictory. The results likely reflect that the unemployment variable is removing some of the effect of both layoff dummy and the interaction term. I do not see that its inclusion adds to the analysis and so local unemployment been excluded in further specifications with mining layoff variables. To test the relationship between unemployment rates and Republican vote share directly I estimated the following:

$$Republican\,Vote\,Share_{it} = \alpha_t + \beta_1 Local\,Unemployment_{it} * Coal_i$$

$$+ \beta_2 Local\,Unemployment_{it} + Controls + \mu_i + \varepsilon_{it} \quad \textbf{(4)}$$

Where variables are defined as before and $Local\,Unemployment_{it}$ is the county unemployment rate measured as a continuous variable from 0 to 1. I estimated this model both with and without demographic controls as above. Table 9 displays the results. Year and county fixed effects are included in both models and standard errors are clustered at the county level.

The results from these estimations are similar to the estimation using layoff dummies. The interaction of Coal and local unemployment rate is positive and statistically significant ($p<0.01$). However, the coefficient for the local unemployment rate alone is not statistically significant in the specification with all controls. In both specifications, the coefficient for the interaction term is larger in magnitude than the coefficient for local unemployment rate alone, leading to a net increase of Republican vote share for coal mining counties due to a 1% increase in unemployment. For coal mining counties the estimates predict that a 1% increase in the local unemployment rate in the year of an election is associated with an increase in Republican vote share of 1.89% of the vote. For metal mining counties, this is 0.003% decrease. The differential response to unemployment is very similar to the differential response to mining layoffs. As there is no motivation to expect

Table 9: Local Unemployment Rates & Republican Vote Share

	(1)	(2)
Local Rate*Coal	0.0305***	0.0220***
	(0.00337)	(0.00320)
Local Rate	-0.00542**	-0.00310
	(0.00219)	(0.00219)
Population Density		-0.000479***
		(0.000138)
Ethnic Minority		-1.373***
		(0.276)
Bachelor's or Higher		-0.00706***
		(0.00253)
Constant	0.517***	0.956***
	(0.0130)	(0.0646)
Observations	799	799
R-squared	0.862	0.886

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table displays the estimates of equation (4) with and without demographic controls. Observations comprise of all county/years with at least 300 mining jobs in the previous time period. The dependent variable in all specifications is Republican party vote share which is measured as continuous variable from 0 to 1. Local Unemployment Rate is a continuous variable from 0 to 1 representing the mean unemployment rate in the year of the observation. Local Rate*Coal is the interaction of these two variables. Time and county fixed effects are included in both specifications. Standard errors are clustered at the county level and reported in parenthesis.

unemployment generally to have differential responses and this paper is focused on the effects of mining layoffs, I have not included local unemployment in further specifications.

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The results of fixed effects regression are surprising and contradict the literature on unemployment. We would not expect climate change beliefs to be a factor in earlier elections. The direct support for coal miners from the Republican Party and their presidential candidates is a recent phenomenon. Therefore, the results may be driven by more recent elections. A potential test would be to repeat the difference in difference and triple difference strategy and estimate equations (1) and (2) on the results of the presidential election in 2012 and 2016. This would introduce more stringent identifying assumptions than the fixed effects model. Past Republican vote share trends are not as similar between treatment and control groups for the presidential elections as in the House elections. As the parallel trends assumption may not hold, I chose to estimate equation (3) over elections from 2000 to 2008 and 2012 to 2016 to examine the effect of recent elections. More than one time period is required in order to include county fixed effects and so 2016 cannot be analysed alone. Table 10 present the results from these estimations:

Table 10: Disaggregated Effect of Layoffs

	(1) 2012 - 2016	(2) 2000 - 2008
Layoff*Coal	0.0371**	-0.0119
	(0.0146)	(0.0122)
Layoff	0.00981	-0.00822
	(0.00862)	(0.00773)
Population Density	-0.00162***	-0.000121
	(0.000550)	(0.000181)
Ethnic Minority	-0.561	-0.926***
	(0.595)	(0.317)
Constant	0.925***	0.713***
	(0.109)	(0.0420)
Observations	280	473
R-squared	0.947	0.935

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table reports the results two specification of equation (3) with demographic controls. Column (1) reports the results from elections in 2012 and 2016. Column (2) reports the results from elections in 2000, 2004 and 2008. Observations comprise of all county/years with at least 300 mining jobs in the previous time period. The dependent variable in both specifications is Republican party vote share measured as continuous variable from 0 to 1. Population density is given by total population over land area. Ethnic Minority is the percentage of the population identifying as Black or Hispanic. Time and county fixed effects are included in all specifications. Standard errors are clustered at the county level and reported in parenthesis.

For observations for the 2012 and 2016 elections the estimation of interaction term coefficient is positive and statistically significant ($p<0.01$). For observations in 2000 to 2008 the estimate of the same coefficient is not significant and is negative. This indicates that the results from the time period are being driven by the more recent elections. In both specifications the estimate of the coefficient for the layoff dummy is not significant. Though the direction of this estmate is reversed in the 2012 to 2016 specification, the standard errors are large, and I do not think this should be interpreted as meaningful. The estimates of specification (1) predict that a coal mining county experiencing a 30% reduction in mining employment will have a 4.69% higher Republican vote share than an unaffected coal county and 3.71% higher Republican vote share than a metal mining county experiencing a layoff. Though the estimate of the interaction term is much smaller than specification using all time periods, the final predicted difference between treatment and control counties is similar. This is due to the positive estimate for the Layoff term. Overall, the findings indicate that a coal mining employment shock is associated with higher Republican vote share. This effect is not due to unemployment but is specific for coal mining counties.

Omitted variables are a challenge to the identifying assumptions of model (3). If there are events which both decrease coal mining employment, but not metal mining employment while increasing Republican vote share in treatment counties, this would produce the same results as above. The discovery of shale gas could be such a potential omitted variable. Results from Fedaseyeu *et al* show that at a county level the development of shale gas wells leads to higher Republican vote share in presidential elections (Fedaseyeu et al 2015). Such a shock could also reduce employment in coal mining, as coal is replaced by cheaper natural gas thus reducing demand. Taken together, this would both increase Republican vote share while inducing layoffs in coal mining. The same events would not reduce metal mining layoffs, though we would expect an increased Republican vote share. To test if shale gas extraction is a potential omitted variable, I used data on natural gas production by county from 2000 to 2012 gathered by the USDA ERS. I estimated the following model:

$$Republican\,Vote\,Share_{it} =$$

$$\alpha_t + \beta_1 Layoff_{it} * Coal_i + \beta_2 Layoff_{it} + \beta_3 Log(1 + Gas_{it}) + Controls + \mu_i + \varepsilon_{it} \quad \textbf{(5)}$$

Where Gas_{it} is the total annual withdrawal of natural gas in thousand cubic feet for county i at time t and all other variables are defined as before. The USDA ERS discontinued the county level dataset in 2012 and so I cannot estimate equation (5) on the outcomes of the 2016 elections. This reduced the observations to 643. The results from this estimation are shown in table 11, along with the estimation of (3) with all controls as before. Time and county fixed effects are included, and standard errors are clustered at the county level.

Table 11: Effect of Natural Gas Extraction

	(1)	(2)
Layoff*Coal	0.0244	0.0235
	(0.0175)	(0.0174)
Layoff	-0.0262***	-0.0257***
	(0.00907)	(0.00902)
Population Density	-0.000169	-0.000141
	(0.000144)	(0.000137)
Ethnic Minority	-1.272***	-1.271***
	(0.310)	(0.308)
Bachelors or Higher	-0.00971***	-0.0100***
	(0.00229)	(0.00230)
Log (1 + Gas)		0.00315*
		(0.00187)
Constant	0.960***	0.936***
	(0.0621)	(0.0620)
Observations	643	643
R-squared	0.909	0.909

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table displays the results estimates of equation (3) in column one and equation (5) in column two. Observations comprise of all county/years with at least 300 mining jobs in the previous time period. The dependent variable in both specifications is Republican party vote share in Presidential elections measured as continuous variable from 0 to 1. Equations were estimated over results from 2000 to 2012 elections. Log(1+Gas) is the logarithm of annual county natural gas production in thousand cubic feet plus one. Population density is given by total population over land area. Ethnic Minority is the percentage of the population identifying as Black or Hispanic. Time and county fixed effects are included in all specifications. Standard errors are clustered at the county level and reported in parenthesis.

In both models the coefficients of the interaction term Layoff*Coal are not statistically significant. The coefficient of the Layoff term is statistically significant and negative as predicted by the literature. For specification (2) above, the estimate of the coefficient of log of natural gas production is significant (p<0.1) and positive. This matches the findings of Fedaseyeu *et al.* The estimates predict that a 1% increase in natural gas production is associated with an increase in Republican vote share of 0.3%. The inclusion of Log (1 + Gas) does not alter the magnitudes of either of these estimates, though in both specifications the estimate is much lower than previous results. This is likely caused by the exclusion of 2016 election results from the observations and offers further evidence that the results are mostly driven by recent elections. Despite the null findings for the interaction term, the stability of the coefficients between the two specifications indicates that the wider positive results are not explained by shale gas extraction. If this were an omitted variable, we would expect a much larger reduction in the estimate of the interaction term after the inclusion natural gas production as a control.

There are limitations to drawing conclusion from these results. First, due to restrictions on data I have used natural gas production by county. This includes both traditional and unconventional natural gas extraction. Shale gas represents part, but not all of this total. Similarly, shale well also produce shale oil which is not included in the above figures. Second, the data does not extend beyond 2012. As the 2016 election is responsible for most of the results, ideally this would be tested with more recent data. An ideal test would be to use the number of shale wells as done by Fedaseyeu et al. I did not have access to this data at the time of writing. We cannot therefore rule out that shale gas extraction is an omitted variable in for the regression with later election results.

6 Discussion

Before interpreting the results in depth, I will evaluate some of the limitations of the data and empirical strategy employed. This will inform how the results should be interpreted.

For mining employment, at present we have data up to and including 2017 for all counties. However, elections took place in November 2018. It is possible that a county could experience a mining shock during the start of 2018 which would not be recorded in the data. This shock could have an effect on voting outcomes. For presidential elections analysis, the mining employment data includes 2016 and so this issue applies only to the results for the House election, which did not produce significant estimations. As future mining data is released, this could be addressed with future research.

The sample size of the difference in difference and triple difference models is small. In particular there are only 10 metal mining counties which experienced a layoff between 2014 and 2018. This means that noise in the data will make any underlying effect difficult to detect. This also highlights a problem with the parallel trends assumption for the House elections. Figure 2 shows that treatment and control coal counties followed very similar trends. However, this is not the same for metal mining counties. If treatment metal mining counties had different electoral trends to control counties, their use to remove the general effect of layoffs would be problematic Again, this may be due to the small sample size and large confidence intervals.

These two limitations raise an important question; given the similar empirical strategy and identical counties analysed, why did Campa and Szucs produce significant differences in climate change beliefs and the above results are insignificant for election outcomes. First, there is no prior data on county level climate change beliefs. Therefore, the parallel trends assumption cannot be examined directly. It is possible therefore, that the results are not due to changes layoffs but other factors causing different trends. For the House election results, treatment and control coal mining communities have close previous trends. It is possible that there is no change caused by layoffs in both election outcomes and climate change beliefs, with the latter significant findings come from differences in trends. Second, there is a huge number of additional factors that affect election outcomes. Across all US counties in 2018, the standard deviation for republican vote share in house elections is three times larger than county level belief that climate change is happening. Therefore, the difference in findings maybe due to the much larger variability of election outcomes compared to climate change beliefs. This reflects the fact that political affiliation and climate change beliefs are not perfectly correlated. Further, political affiliation and voting for the party you affiliate with in a particular election are not perfectly correlated.

An important assumption in both the difference in difference models and fixed effects models is the non-interference of treatment and control groups. There are several counties which border each other in the dataset, include those in different treatment groups. Individuals can and do work outside of their county of residence and the economic effect of unemployment is not restricted by county borders. If an individual or community living within control a county is exposed to a layoff over a nearby county border, this may impact their voting decision. However, the potential effect on voting behaviour would be registered in the control group rather than the treatment group. The inverse is also possible, with workers remaining employed over the border and unaffected by a mining shock in their county. A proposed solution for future research would be to investigate the effect shocks on a geographic area around the mine location. Unfortunately, the dataset from MSHA only provides accurate county locations.

The definitions of layoff shocks and the classification of counties as coal/metal mining was ultimately arbitrary. There is no standard measure for how to make this decision. The levels of mining jobs and reduction in employment were chosen to be sufficiently high to capture the effects of both. It is clear that for a county with five mining jobs, electoral outcomes are unlikely to be impact by changes in this level. Similarly, a 2% drop in mining jobs is unlikely to have any effect on electoral outcomes. At the other end, if the level chosen is too high there would be too few observations to achieve sufficient statistical power. To test if the results are simply due to the random levels chosen, I conducted sensitivity analysis included in the appendix. I estimated equations (1) to (3) with *Layoff* defined as either a 20%, 30%, 40% or 50% reduction in mining jobs. I estimated them again including observations of counties with at least 250, 300 and 350 jobs in either coal or metal mining, with Layoffs defined as a 30% reduction in employment. For equation (3) I estimated the differing levels on all county/election observations from 2000 to 2016 and from 2012 to 2016 separately as the most recent elections are driving the significant results.

Tables 12 and 13 include the results from the 2012-2016 estimates of equation (3). All other results are included in the appendix.

For the House elections, the results remain null at under all specifications (see appendix). For the presidential analysis the main results remain largely robust. The coefficient of the interaction term remains statistically significant, positive and larger than the coefficient for the Layoff dummy variable. This holds when layoffs are defined as 20, 30 or 50% reductions in mining employment and when the minimum number of mining jobs is defined as 250 or 350. Interestingly, the coefficient of the interaction term Layoff*Coal ceases to be significant for when layoffs are classified as a 40% or larger reduction in employment. The standard errors are not different between specifications and the null result is caused by a reduction in the magnitude of the coefficient. For larger levels of layoff this is reversed, and the magnitude of the coefficient is larger again. This could occur if the counties that experienced a coal layoff of 30 to 40% did not increase their Republican vote share as much as counties with higher and lower reductions in unemployment. I do not think this invalidates the results but shows the complex range of factors that affect election outcomes. This makes it all the more startling that the results remain so robust under different specifications.

Table 12: Sensitivity of Layoff Reduction Classification 2012-2016

	(1)	(2)	(3)	(4)
Layoff*Coal	0.0406**	0.0392***	0.0269	0.0458***
	(0.0163)	(0.0146)	(0.0162)	(0.0161)
Layoff	0.00199	0.00981	0.00645	-0.0212
	(0.0133)	(0.00861)	(0.0141)	(0.0149)
Density	-0.00167***	-0.00162***	-0.00175***	-0.00180***
	(0.000567)	(0.000550)	(0.000553)	(0.000553)
Ethnic Percent	-0.756	-0.545	-0.970	-1.116*
	(0.562)	(0.597)	(0.607)	(0.616)
Constant	0.956***	0.916***	1.006***	1.038***
	(0.107)	(0.107)	(0.107)	(0.110)
Observations	278	278	278	278
R-squared	0.947	0.948	0.944	0.943
Layoff Reduction	>20%	>30%	>40%	>50%

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the estimates of equation (3) over 4 specifications of Layoff variable. Column (1) reports estimates with layoff dummy defined as a 20% reduction between elections, (2) reports estimates with 30% reduction, (3) estimates with 40% reduction and (4) estimates with 50% reduction. Observations comprise of all county/years with at least 300 mining jobs in the previous time period. Observations are for 2012 and 2016 presidential elections. Time and county fixed effects are included in all specifications. Standard errors are clustered at the county level and reported in parenthesis.

Table 13: Sensitivity of Classification of Mining Counties

	(1)	(2)	(3)
Layoff*Coal	0.0495***	0.0371**	0.0347**
	(0.0141)	(0.0146)	(0.0151)
Layoff	-0.00384	0.00981	0.0130
	(0.0101)	(0.00862)	(0.00906)
Density	-0.00169***	-0.00162***	-0.00158***
	(0.000494)	(0.000550)	(0.000585)
Ethnic Percent	-0.469	-0.561	-0.556
	(0.536)	(0.595)	(0.606)
Constant	0.945***	0.925***	0.900***
	(0.104)	(0.109)	(0.106)
Observations	350	280	246
R-squared	0.956	0.947	0.944
Minimum Mining Jobs	250	300	350

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the estimates of equation (3) over differing classification of mining counties. Observations are included if they have at least 250 mining jobs in the first column, 300 mining jobs in the second column and 350 mining jobs in the final column. Layoff is a dummy variable taking the value 1 if an observation had a 30% reduction in mining employment between time periods. Observations are for 2012 and 2016 presidential elections. Time and county fixed effects are included in all specifications. Standard errors are clustered at the county level and reported in parenthesis.

There is a similar problem with the decision to define a layoff as binary variable rather than using a continuous measure of job losses. First, the model implies that the response of voters to a 30% reduction will be the same as to a 100% reduction. Intuitively we might expect a heterogenous response to layoffs, with higher reductions leading to greater Republican vote share. Therefore, a continuous variable may more accurately describe the underlying model. However, there are a variety of ways to measure a layoff and each has challenges. We could define the Layoff variable as the number of jobs lost, the percentage of total mining jobs lost, or the percent of the county work force laid off from mining. Each represents a potential measure of mining layoffs. The paper began as an investigation into the political outcomes of the difference in climate change beliefs observed by Campa and Szucs and the purpose was expanded to look at coal mining layoffs more generally upon discovering the lack of quantitative research. Therefore, the strategy was originally chosen to follow previous work. Other potential choices could have been made. As there are so many decisions, the risk of potential false positives from p-hacking and forking becomes much higher (Simmons et al, 2011; Gelman & Loken, 2013). There is no standardised method available in the literature and choices had to made. Therefore, to avoid false positives I have included results from models using the percentage loss of mining employment and the number of jobs lost a continuous treatment variable in the appendix. The general finding remains significant and under all definitions of job reductions with the exception of a categorical classification of at least 40% loss in jobs.

For the definition of a layoff in a county, I chose to use the reduction between elections. Another possible definition would be to examine the effect of large layoffs which are closer to elections. We might expect that more recent employment reductions would have larger effects on election outcomes compared to reductions taking place two or three years prior. In the strategy used above, A county experiencing a 30% reduction in the year after an election is treated equal to a county experiencing the same reduction in the year of all election. This analysis would require other potential definitions of layoffs in order to produce a large enough sample size, as 30% reduction in one year is less common than over four years. Such an analysis is a potential avenue for future work.

In light of these limitations, I can now examine the evidence for my hypotheses. First, we fail to reject the null hypothesis that the coefficient for the interaction term is zero in the difference in difference and triple difference analysis of the House elections. The results do not offer evidence that the observed difference in climate change beliefs has a corresponding difference in election outcomes. However, I would not interpret the results as providing evidence for the null hypothesis. The confidence intervals are too large to support a null effect. The low voter turnout in the House elections and small sample sizes make it difficult to detect any effect that climate change beliefs might have on elections. With additional elections, information on mining employment, and climate change beliefs surveys, future analysis can be conducted to further investigate the relationship.

For my second hypothesis, the results of the fixed effect estimation indicate that coal mine layoffs are associated with higher Republican vote share in proceeding elections. This effect is being driven by the 2016 election and is robust to different specifications off layoffs and mining counties. Elections outcomes are complex and depend on a huge number of factors, so there is a possibility of omitted variables. In particular, the effect of shale gas extraction on the 2016 elections is not established. Despite these concerns, the findings are important to understanding the political outcomes of coal mine closures.

The results indicate that there is a differential response to layoffs in coal mining counties compared to metal mining counties. However, I do not think the coefficients provide accurate predictions of the effect. First, there are too many choices in defining a layoff and no guidance on which is the most appropriate. It is not possible at present to say which most appropriately captures the underlying model. Second, election outcomes are influenced by such a wide range of variables at the individual, county, state and national level. If predicting election outcomes could be done accurately, the pundit industry should have a much greater success. Third, there is no previous work that suggests layoffs favour the Republicans, nor that there are differential responses to layoffs between different industries. However, in the context of the 2016 election campaign and the rising importance of climate change, the finds are not unexpected. The Republican platform made clear overtures to coal mining communities and their candidate made regular references to "bringing back" coal mining employment. Further, both the party and president expressed climate sceptical views (Republican Party Platform, 2016; Selby, 2019). Despite these problems, in under definition of reduction of mining employment, coal mining and metal mining counties responded differentially at the polls in the 2016 election. I argue that the results show a general differential response to layoffs rather than a prediction of the effect size. This finding has important implications for policy and future research.

First, the changes in election outcomes are caused by more than the effected miners voting Republican. Though I have highlighted that the exact coefficients should not be used for predictions, we can perform some calculations to show this. The mean reduction is in coal mining jobs is 522 and mean total votes cast in treatment counties is 22,800. The estimates from the specification with demographic controls for 2012 to 2016 elections imply 1069 citizens voting for the Republican party than if there had been fewer than 30% job losses. Therefore, the difference is caused by individuals other than miners changing their vote. We cannot expect that all laid off miners previously voted Democrat and so the effect on the community is even larger. These numbers are reasonable; we can imagine some members in the community would alter their vote due to a neighbour or friend losing their job.

The potential impact on elections is significant. Pennsylvania has a large population living in coal mining counties, is a swing state that has voted for the overall victor in 80% of presidential elections and carries a large number of electoral college votes. If all coal mining counties in Pennsylvania experienced a 30% reduction in mining employment between elections, the results of the fixed effects regression on 2012-2016 predict an increase of 1.05% for state-wide Republican vote share (presuming a turnout of 55%). This is larger than the margin that President Trump won Pennsylvania in 2016, when he was carried to the office by small marginal wins across a few key states. His later withdrawal of America from the Paris Agreement shows that the presidential office has very real effects on climate change policy. Of course, simultaneous layoffs across all counties in a state are not expected and as noted above we should not be confident in the exact value of the predicted coefficients. The above example does illustrate the possible ramifications that coal mining layoffs could have. The results from this paper show that past research on the effects of unemployment may not guide future outcomes. Given the potentially large impacts, further research is needed to confirm the results, uncover the causal relationship driving the findings, test the long- term outcomes from mining layoffs, and evaluate the extremality of the findings.

As the results are found in most recent elections, this paper cannot establish the long run impact of coal mine layoffs. It is not clear whether Republican vote share should return to previous levels or not in later elections. Mining identities are long lasting (Pini et al 2010) and so their loss may continue to impact later elections. Alternatively, there could be a ceiling for how much the local area will alter their political affiliation due to job losses in one particular sector. The results could be entirely down to the particular characters and platforms of the 2016 elections. Therefore, it is not clear if the observed effect on election outcomes will translate into an electoral backlash against policies to decommission mines. The results show a need for similar evaluations using further election results and investigate the long run effects of mine closures.

The above findings show a correlation between coal layoffs and Republican vote share but do not reveal the causal mechanism behind this. There are two potential pathways. First, coal mine closures result in increased climate scepticism directly, perhaps due to beliefs that climate policies are responsible for job losses. This in turn leads to increased voting for the Republican party due to their climate sceptical position and the association between climate beliefs and political affiliation. Should this be the case, then understanding the relationship between layoffs and climate beliefs is essential. The second pathway is via changes in political affiliation directly, with climate beliefs being altered to align with changing political identities. In this scenario, affected coal mining counties vote for the Republican party not due to climate beliefs but because they believe they will help their challenged community. How then can we explain the increased support from coal counties enduring a layoff compared to unaffected coal counties? The 2016 party platform makes several references to supporting coal as a source of energy and so employed coal communities are also offered political support. The differential response could be due to the specific focus on "bringing back" coal jobs, which may elicit a stronger electoral response from laid off communities. It is also possible that the results are combination of both causal mechanisms, with disgruntled coal mining communities becoming climate sceptical and economically challenged and looking for a party that supports both positions.

Each causal mechanism has differing implications. If climate change beliefs are the important cause, then we may expect a similar response from other emitting industries. A similar investigation could be conducted using oil and shale gas extraction, beef production, heavy manufacturing, or aviation. If the mechanism between layoffs in coal mining and the changes in climate beliefs can be established, then potential policy interventions can be produced. To avoid an electoral pushback, the causal chain can be broken before climate sceptical beliefs are formed. It may be too much to hope to change the beliefs of directly affected workers that have lost their profession; but limiting climate scepticism from affecting the wider community could ensure support for policy measures.

On the other hand, if the causal mechanism is direct affiliation with the Republican party, and not due to climate change beliefs then understanding the relationship behind the identification is important. The Republican party platform made clear statements to support coal mining communities. This takes the form of even directly pledging to bring jobs back. It is not surprising that this appealed to distressed coal communities. This raises important issues that cut to the heart of a just policy to transition the economy. The costs of decarbonising may not be distributed evenly. While costs will of course include the capital investment to enable the transition, for some people this will involve the loss of their livelihood. For many this can be a profession that generations of their family have performed, and which is deeply tied to their identity (Della Bosca & Gillespie, 2018). It is reasonable for such communities to support a party that offers a return to the status quo. For climate policy this is a challenging issue. A way must be found that both eliminates coal mining jobs while supporting these communities. Research must be conducted to understand what would be required to support coal mining communities through the transition. To advocate both eliminating someone's jobs and pledging to support them is a difficult message to sell. Potential avenues of future research include the mitigating affect of employment retraining and benefits.

Finally, it is not clear how these results generalise beyond the United States. This paper has focused only on US counties, where there were 65,000 jobs in 2017. Worldwide, there are 7.9 million jobs in coal mining (IBIS World, 2019). An understanding of the causal mechanism may offer more guidance for policy outside of the US. Similar effects may be expected elsewhere, though this will likely depend on the nuances of each country's party platforms. If the effect is due to direct affiliation with the Republican party due to their overt support, coal mine layoffs may translate into support for which ever local party is associated with the coal mining community. On the other hand, if the causal mechanism is via climate change beliefs, this would translate into support for climate sceptical parties. Future research could focus on a potential relationship between coal mining and layoffs in other countries.

7 Conclusion

This paper shows that mining communities respond differently at the polls after experiencing a layoff. Coal mining counties significantly increase their support for the Republican party following a layoff in the mining sector. This effect was not found among metal mining counties and was not predicted by the literature. The results show the same behaviour under a variety of definitions of job losses.

We require drastic changes to the global energy system and in turn job allocation in order to avoid the worst effects of climate change. This necessitates leaving some fossil fuel reserves untouched and reducing employment in fossil fuel extraction. The effects that this change will have on climate change beliefs, election outcomes and future policy is still unknown. The results of this paper provide evidence that the past research may not guide future outcomes. Understanding the effects and the causal relationship driving them will be important for implementing future climate change policy and avoiding electoral backlash that hampers future action to mitigate emissions. Transitioning the economy will require huge changes in the allocation of employment. There will be costs and benefits and these are not necessarily evenly distributed. It is reasonable for those absorbing the costs and not receiving the benefits to express their dissatisfaction with the changes.

Learning how to reduce this burden and support workers through the transition will be necessary to ensure climate targets are met.

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A Appendix

A.I Results from Campa and Szucs

Below are the results of the estimates of the effect of mining employment on climate change beliefs from Camp and Szucs. Each column represents a different question in the Yale climate survey. Happening is belief that climate change is happening. Human is belief that this is caused by human action.

Table 1: Difference in Difference Estimate from Campa and Szucs

	ΔHappening	ΔHuman	ΔWorried	ΔHarm US	ΔRegulate
	(1)	(2)	(3)	(4)	(5)
Layoff	-1.704***	-1.772**	-1.557**	-1.209	-1.464***
	(0.646)	(0.712)	(0.712)	(0.772)	(0.608)
Constant	4.554***	6.119***	5.063***	6.185***	.534*2**
	(0.602)	(0.574)	(0.675)	(0.675)	(0.553)
Observations	81	81	81	81	81

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the results of a first difference estimation on difference in count climate change beliefs. Each column reports the estimates with the corresponding change in mean county belief in each climate statement. Estimates are over all counties with at least 300 coal mining jobs and fewer than 300 metal mining jobs. Layoff is a dummy variable taking the value 1 if there was at least a 30% reduction in mining employment between 2014 and 2018. Standard errors are reported in parenthesis. This table displays Tables reproduced directly from data with permission from the authors.

Table 2: Climate Change Beliefs Triple Difference Estimates from Campa and Szucs

	ΔHappening	ΔHuman	ΔWorried	ΔHarm US	ΔRegulate
	(1)	(2)	(3)	(4)	(5)
Layoff*Coal	-3.370***	-3.211**	-3.136**	-1.886	-2.145**
	(1.252)	(1.229)	(1.334)	(1.314)	(0.852)
Layoff	1.666	1.438	1.578	0.677	0.681
	(1.009)	(0.913)	(1.041)	(0.981)	(0.580)
Coal	-0.763	-0.458	-0.748	-0.340	0.527
	(0.767)	(0.656)	(0.803)	(0.711)	(0.620)
Constant	4.554***	6.119***	5.063***	6.185***	.534*2**
	(0.602)	(0.574)	(0.675)	(0.675)	(0.553)
Observations	163	163	163	163	163

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table displays the results of a triple difference estimate on county climate change beliefs. Each column reports the estimates with the corresponding change in mean county belief in each climate statement. Estimates are over all counties with at least 300 mining jobs. Layoff is a dummy variable taking the value 1 if there was at least a 30% reduction in mining employment between 2014 and 2018. Coal is a dummy taking the value 1 if a county has at least 300 coal mining jobs and 0 otherwise. Standard errors are reported in parenthesis. This table displays Tables reproduced directly from data with permission from the authors.

A. II Sensitivity Analysis of House Election Results

Layoff Classification Sensitivity: Difference-in-Difference estimates over All House Elections

	(1)	(2)	(3)	(4)
After*Layoff	0.00557	0.0229	0.0124	0.0105
	(0.0427)	(0.0427)	(0.0440)	(0.0470)
After	-0.00116	-0.00267	-0.00142	-0.000899
	(0.00724)	(0.00752)	(0.00704)	(0.00639)
Layoff	-0.0261	0.0340	0.0285	0.0105
	(0.0306)	(0.0315)	(0.0325)	(0.0470)
Constant	2.996	6.028	3.497	2.457
	(14.59)	(15.16)	(14.19)	(12.88)
Observations	162	162	162	162
R-squared	0.007	0.028	0.015	0.016
Layoff Reduction	>20%	>30%	>40%	>50%

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table report the estimates of equation (1) under different specifications of Layoffs. Column (1) is for 20% reduction, column (2) 30% reduction, (3) 40% reduction and (4) 50% reduction. Robust standard errors are displayed in parenthesis.

Layoff Classification Sensitivity: Difference-in-Difference estimates over Contested House Elections

	(1)	(2)	(3)	(4)
After*Layoff	0.00941	0.0220	0.0120	0.00718
	(0.0440)	(0.0439)	(0.0455)	(0.0482)
After	-0.000648	-0.00153	-0.000313	0.000336
	(0.00767)	(0.00767)	(0.00718)	(0.00656)
Layoff	-0.0393	0.0357	0.0271	0.0392
	(0.0310)	(0.0319)	(0.0332)	(0.0368)
Constant	1.972	3.717	1.265	-0.0413
	(15.47)	(15.47)	(14.47)	(13.22)
Observations	152	152	152	152
R-squared	0.016	0.030	0.014	0.016
Layoff Reduction	>20%	>30%	>40%	>50%

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table report the estimates of equation (1) under different specifications of Layoffs over all counties with contested elections in both time periods. Column (1) is for 20% reduction, column (2) 30% reduction, (3) 40% reduction and (4) 50% reduction. Robust standard errors are displayed in parenthesis.

Layoff Classification Sensitivity: Triple Difference estimates over all House Elections

	(1)	(2)	(3)	(4)
After*Coal*Layoff	-0.000145	0.0151	-0.0266	-0.0284
	(0.0768)	(0.0912)	(0.0867)	(0.0882)
After*Layoff	0.00571	0.00779	0.0390	0.0390
	(0.0638)	(0.0806)	(0.0747)	(0.0747)
Coal*Layoff	-0.0392	0.0210	0.0264	0.0352
	(0.0533)	(0.0646)	(0.0644)	(0.0662)
After*Coal	0.0105	0.00429	0.0103	0.0123
	(0.0432)	(0.0427)	(0.0407)	(0.0389)
After	-0.00377	-0.00375	-0.00398	-0.00398
	(0.00802)	(0.00757)	(0.00733)	(0.00733)
Layoff	0.0131	0.0130	0.00204	0.00204
	(0.0437)	(0.0564)	(0.0556)	(0.0556)
Coal	0.0566*	0.0269	0.0294	0.0314
	(0.0294)	(0.0291)	(0.0279)	(0.0267)
Constant	8.208	8.162	8.636	8.636
	(16.16)	(15.26)	(14.78)	(14.78)
Observations	328	328	328	328
R-squared	0.024	0.031	0.027	0.027
Layoff Reduction	>20%	>30%	>40%	>50%

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table report the estimates of equation (2) under different specifications of Layoffs. Column (1) is for 20% reduction, column (2) 30% reduction, (3) 40% reduction and (4) 50% reduction. Robust standard errors are displayed in parenthesis.

Layoff Classification Sensitivity: Triple Difference estimates over Contested House Elections

	(1)	(2)	(3)	(4)
After*Coal*Layoff	0.00169	0.0125	-0.0294	-0.0342
	(0.0684)	(0.0748)	(0.0865)	(0.0880)
After*Layoff	0.00772	0.00954	0.0414	0.0414
	(0.0523)	(0.0605)	(0.0736)	(0.0736)
Coal*Layoff	-0.0300	0.0602	0.0162	0.0283
	(0.0470)	(0.0530)	(0.0641)	(0.0660)
After*Coal	0.0150	0.0112	0.0171	0.0197
	(0.0422)	(0.0411)	(0.0388)	(0.0370)
After	-0.00441	-0.00434	-0.00460	-0.00460
	(0.00725)	(0.00685)	(0.00652)	(0.00652)
Layoff	-0.00923	-0.0245	0.0110	0.0110
	(0.0354)	(0.0423)	(0.0549)	(0.0549)
Coal	0.0590**	0.0205	0.0292	0.0302
	(0.0287)	(0.0277)	(0.0262)	(0.0250)
Constant	9.487	9.343	9.861	9.861
	(14.62)	(13.80)	(13.14)	(13.14)
Observations	306	306	306	306
R-squared	0.034	0.041	0.035	0.036
Layoff Reduction	>20%	>30%	>40%	>50%

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table report the estimates of equation (2) under different specifications of Layoffs over all counties with contested elections in both time periods. Column (1) is for 20% reduction, column (2) 30% reduction, (3) 40% reduction and (4) 50% reduction. Robust standard errors are displayed in parenthesis.

Mining County Classification Sensitivity: Difference-in-Difference Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Layoff*After	0.0233	0.0226	0.0233	0.0226	0.0254	0.0229
	(0.0423)	(0.0435)	(0.0423)	(0.0435)	(0.0473)	(0.0483)
Layoff	0.0341	0.0356	0.0341	0.0356	0.0223	0.0300
	(0.0312)	(0.0316)	(0.0312)	(0.0316)	(0.0351)	(0.0352)
After	-0.0111	-0.00669	-0.0111	-0.00669	-0.00738	-0.00139
	(0.0295)	(0.0300)	(0.0295)	(0.0300)	(0.0321)	(0.0327)
Constant	0.640***	0.630***	0.640***	0.630***	0.637***	0.624***
	(0.0207)	(0.0206)	(0.0207)	(0.0206)	(0.0231)	(0.0228)
Observations	164	154	164	154	132	124
R-squared	0.028	0.030	0.028	0.030	0.018	0.026
Minimum Mining Jobs	250	250	300	300	350	350
Elections Contested	No	Yes	No	Yes	No	Yes

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the estimates of equation (1) with different classification of mining counties for all elections and contested elections. Robust standard errors are displayed in parenthesis.

Mining County Classification Sensitivity: Triple Difference Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
After*Coal*Layoff	0.0143	0.0116	0.0151	0.0125	0.0189	0.0213
	(0.0912)	(0.0747)	(0.0912)	(0.0748)	(0.106)	(0.0866)
Coal*Layoff	0.0167	0.0559	0.0210	0.0602	-0.0323	0.0274
	(0.0646)	(0.0530)	(0.0646)	(0.0530)	(0.0742)	(0.0604)
After*Coal	0.00501	0.0121	0.00429	0.0112	0.0125	0.0153
	(0.0426)	(0.0411)	(0.0427)	(0.0411)	(0.0453)	(0.0438)
Layoff*After	0.00779	0.00954	0.00779	0.00954	0.00643	0.00159
	(0.0806)	(0.0605)	(0.0806)	(0.0605)	(0.0947)	(0.0719)
After	-0.0150	-0.0173	-0.0150	-0.0173	-0.0199	-0.0167
	(0.0303)	(0.0274)	(0.0303)	(0.0274)	(0.0320)	(0.0292)
Layoff	0.0130	-0.0245	0.0130	-0.0245	0.0546	0.00261
	(0.0564)	(0.0424)	(0.0564)	(0.0423)	(0.0654)	(0.0491)
Coal	0.0311	0.0248	0.0269	0.0205	0.0413	0.0259
	(0.0292)	(0.0277)	(0.0291)	(0.0277)	(0.0317)	(0.0298)
Constant	0.614***	0.609***	0.614***	0.609***	0.596***	0.598***
	(0.0201)	(0.0180)	(0.0201)	(0.0180)	(0.0217)	(0.0193)
Observations	326	304	328	306	268	252
R-squared	0.032	0.042	0.031	0.041	0.046	0.043
Minimum Mining Jobs	250	250	300	300	350	350
All Elections Contested	No	Yes	No	Yes	No	Yes

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the estimates of equation (2) with different classification of mining counties for all elections and contested elections. Robust standard errors are displayed in parenthesis.

A. III Summary Statistics for Presidential Elections

Summary Statistics of Observations for Fixed Effects Estimations

	N	Mean	P1	P25	Median	P75	P99	S.D.
Repub. Vote Share								
Coal No Layoff	278	59.1	31.1	50.0	58.4	68.8	86.7	12.7
Coal Layoff	103	65.2	32.9	53.4	67.9	76.4	88.6	14.2
Metal No Layoff	415	55.4	25.2	45.4	55.3	65.3	83.4	13.6
Metal Layoff	52	52.8	17.7	45.2	54.6	62.1	82.9	13.8
Previous Mining Employment								
Coal No Layoff	278	950.8777	313	446	652.5	1078	4956	853.12
Coal Layoff	103	955.9126	313	493	727	1330	3096	635.3
Metal No Layoff	415	770.3952	303	365	513	916	3394	660.30
Metal Layoff	52	679	304	371	464	720	5448	760.73
Mining Employment								
Coal No Layoff	278	980.2194	236	453	696	1188	4436	847.16
Coal Layoff	103	453.1942	5	169	342	661	1476	360.87
Metal No Layoff	415	738.959	228	356	503	905	3128	627.41
Metal Layoff	52	353.1346	7	168.5	227.5	348.5	3394	498.22
Total Population								
Coal No Layoff	278	54610.3	8400	16322	29234.5	65275	656023	81884.26
Coal Layoff	103	55196.32	8820	16925	31215	56715	659095	93823.05
Metal No Layoff	415	457929	4340	18218	66539	297520	5373418	1200343
Metal Layoff	52	601557.9	4185	20634.5	90923	383341	9840025	1612162
Population Density								
Coal No Layoff	278	72.4	1.8	20.6	52.3	83.8	589.6	85.7
Coal Layoff	103	84.3	2.4	40.1	66.8	94.6	593.0	88.8
Metal No Layoff	415	270.2	1.0	19.2	64.6	235.6	2478.4	628.9
Metal Layoff	52	378.8	0.8	27.2	67.1	312.1	5498.2	869.0
Ethnic Minority								
Coal No Layoff	278	6.76	0.38	1.71	4.33	7.97	.43.12	7.79
Coal Layoff	103	5.80	0.31	1.28	3.14	6.37	44.12	8.43
Metal No Layoff	415	22.74	0.87	4.61	16.94	35.05	81.99	19.69
Metal Layoff	52	18.73	01.28	4.36	11.22	33.04	56.55	17.79
Bachelor's or Higher								
Coal No Layoff	278	14.5	5.6	9.8	12.3	16.4	43.6	7.7
Coal Layoff	103	14.3	6.3	10	12.3	15.5	50.4	7.8
Metal No Layoff	415	20.4	7.5	13.5	18.4	26.1	46.3	8.9
Metal Layoff	52	21.6	5.4	13.45	20.6	27.95	51.4	10.3

Notes: The table reports the summary statistics for dependent and independent variables and demographic controls. Previous Mining employment is the total employment in coal or metal mining in the previous time period.

A. IV Sensitivity Analysis for Presidential Elections Estimates

Layoff Classification Sensitivity: Fixed Effects Estimates – All Observations

	(1)	(2)	(3)	(4)
Layoff*Coal	0.0599***	0.0741***	0.0715***	0.110***
	(0.0123)	(0.0146)	(0.0184)	(0.0225)
Layoff	-0.0191***	-0.0247***	-0.0255**	-0.0492***
	(0.00678)	(0.00915)	(0.0120)	(0.0160)
Density	-0.000507***	-0.000519***	-0.000523***	-0.000504***
	(0.000145)	(0.000145)	(0.000142)	(0.000145)
Ethnic Minority	-1.644***	-1.555***	-1.575***	-1.553***
	(0.304)	(0.302)	(0.304)	(0.304)
Bachelors or Higher	-0.00943***	-0.00898***	-0.00956***	-0.00984***
	(0.00282)	(0.00284)	(0.00283)	(0.00286)
	(0.0703)	(0.0693)	(0.0702)	(0.0718)
Observations	794	794	794	794
R-squared	0.877	0.878	0.875	0.877
Layoff Reduction	>20%	>30%	>40%	>50%

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the estimates of equation (3) over 4 specifications of Layoff variable. Column (1) reports estimates with layoff dummy defined as a 20% reduction between elections, (2) reports estimates with 30% reduction, (3) estimates with 40% reduction and (4) estimates with 50% reduction. Observations comprise of all county/years with at least 300 mining jobs in the previous time period. Observations are for 2000 and 2016 presidential elections. The dependent variable in both specifications is Republican party vote share measured as continuous variable from 0 to 1. Population density is given by total population over land area. Ethnic Minority is the percentage of the population identifying as Black or Hispanic. Time and county fixed effects are included in all specifications. Standard errors are clustered at the county level and reported in parenthesis.

Mining County Classification Sensitivity: Fixed Effects Estimates – All Observations

VARIABLES	(1)	(2)	(3)
Layoff*Coal	0.0557***	0.0723***	0.0544***
	(0.0149)	(0.0146)	(0.0149)
Layoff	-0.0136	-0.0245***	-0.00836
	(0.0104)	(0.00917)	(0.00917)
Density	-0.000473***	-0.000511***	-0.000467***
	(0.000105)	(0.000143)	(0.000147)
Ethnic Minority	-1.362***	-1.570***	-1.728***
	(0.274)	(0.300)	(0.310)
Bachelor's or Higher	-0.00985***	-0.00930***	-0.0109***
	(0.00253)	(0.00283)	(0.00322)
Constant	1.060***	1.076***	1.119***
	(0.0656)	(0.0696)	(0.0753)
Observations	1,003	799	676
R-squared	0.883	0.877	0.869
Minimum Mining Jobs	250	300	350

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table reports the estimates of equation (3) over differing classification of mining counties. Observations are included if they have at least 250 mining jobs in the first column, 300 mining jobs in the second column and 350 mining jobs in the final column. Layoff is a dummy variable taking the value 1 if an observation had a 30% reduction in mining employment between time periods. Observations are for 2--- and 2016 presidential elections. The dependent variable in both specifications is Republican party vote share measured as continuous variable from 0 to 1. Population density is given by total population over land area. Ethnic Minority is the percentage of the population identifying as Black or Hispanic. Time and county fixed effects are included in all specifications. Standard errors are clustered at the county level and reported in parenthesis.

A. V Fixed Effects Estimates with Continuous Definition of Unemployment

To test the effect of the different definitions of unemployment on the results I estimated the following equation:

$$Republican\ Vote\ Share_{it} = \alpha_t +$$

$$\beta_1 \Delta Mining\ Employment_{it} * Coal_{it} + \beta_2 \Delta Mining\ Employment_{it} + Controls + \mu_i + \varepsilon_{it} \quad \textbf{(6)}$$

Where $\Delta Mining\ Employment_{it}$ is the percentage change in mining employment between *t* and *t-1*. This variable is a continuous measure from -1 to 1. The table below reports the results of the estimate of equation (6) over all observations from 2000 to 2016 and restrict to observations from 2012 to 2016. All specifications are with demographic controls and fixed effects. Standard errors are cluster at the county level.

Effect of Change in Mining Employment on Republican Vote Share		
	(1)	(2)
	2000-16	2012-16
ΔEmployment*Coal	-0.0543***	-0.0478*
	(0.0167)	(0.0248)
ΔEmployment	0.00884	-0.0181
	(0.0118)	(0.0206)
Density	-0.000505***	-0.00157***
	(0.000145)	(0.000588)
Ethnic Percent	-1.643***	-0.670
	(0.309)	(0.571)
Bachelor's or Higher	-0.0101***	-
	(0.00284)	
Constant	1.104***	0.939***
	(0.0711)	(0.107)
Observations	799	280
R-squared	0.874	0.948

*** p<0.01, ** p<0.05, * p<0.1

Notes: Year and county fixed effects included in both models. Standard errors clustered at county level and shown in parenthesis

The estimates of the interaction term between change in mining employment and the coal dummy are statistically significant and negative in both specifications ($p<0.1$). This matches the results from previous findings as a coal reduction in mining employment is associated with an increase in Republican vote share. For the 2012 to 2016 elections, the estimates predict that a 30% decrease in mining employment is associated with a 1.97% higher Republican vote share than an unaffected coal mining county. The estimates for a reduction over all mining, not specifically to coal, are not statistically significant. For the full time frame, mining employment reductions are associated with increased vote share for the Democrats generally, with coal mining specifically increasing their vote share for the Republican party. For the 2012 to 2016 election, reductions in general are associated with an increased vote share for the Republican party, though the increase for coal mining counties is even larger.

For a final alternative specification, I estimated the following equation:

$$Republican\ Vote\ Share_{it} = \alpha_t +$$

$$\beta_1 log(Jobs\ Lost_{it} + 1) * Coal_{it} + \beta_2 log(Jobs\ Lost_{it} + 1) + Controls + \mu_i + \varepsilon_{it} \quad \textbf{(7)}$$

Where $Jobs\ Lost_{it}$ is the number of jobs lost between *t* and *t-1*. Logs were chosen as the number of jobs lost were large. Therefore, all counties which had gained jobs took the value 0 for $Jobs\ Lost_{it}$. The table below reports the results of the estimate of equation (7) over all observations from 2000 to 2016 and restrict to observations from 2012 to 2016. All specifications are with demographic controls and fixed effects. Standard errors are cluster at the county level.

Effect of Mining Jobs on Republican Vote Share

VARIABLES	(1) 2000-2016	(2) 2012-2016
Lost Jobs*Coal	0.00602***	0.00695**
	(0.00204)	(0.00348)
Lost Jobs	-0.000719	0.00123
	(0.00126)	(0.00282)
Density	-0.000511***	-0.00163***
	(0.000146)	(0.000603)
Minority Percent	-1.640***	-0.737
	(0.313)	(0.578)
Bachelor's or Higher	-0.0104***	-
	(0.00286)	
Constant	1.104***	0.948***
	(0.0712)	(0.111)
Observations	799	280
R-squared	0.873	0.947

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Notes: Year and county fixed effects included in both models. Standard errors clustered at county level and shown in parenthesis

The results follow the other definitions of unemployment in mining. The estimates of the interaction term are statistically significant and positive over both sets of observations. ($p<0.05$). So the results indicate increased support for the Republican party following a job reductions in coal mining counties. The estimates for lost jobs generally are not significant, but the direction of the coefficients follow other definitions of layoffs.

Taken with the other findings, this adds further evidence that the results point to a differential response to job losses between coal and metal mining counties.