Facing the Hard Truth: Evidence from Climate Change Ignorance*

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Abstract

In 2024, only 59% of Americans believed in human-caused climate change. This paper argues that motivated reasoning aimed at protecting self-image explains persistent climate-change ignorance. Using a difference-in-differences design we show that the share of believers in climate change increases more in U.S. counties experiencing coal miner layoffs relative to other coal-mining counties. A triple-differences analysis comparing layoffs in coal mining and manufacturing confirms that fossil-fuel employment sustains climate change ignorance. This effect remains unchanged even after controlling for the content of print media, suggesting that the supply side of the information environment plays a limited role. Finally, we find no comparable shifts in beliefs on unrelated policy issues, suggesting that changes in climate views reflect specific self-image dynamics rather than broader opinion shifts.

JEL Codes: Q54, D72, D83 **Kewords**: climate-change beliefs, motivated reasoning, fossil-fuel employment.

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1 Introduction

Skepticism about climate change despite a strong scientific consensus remains high in the US. In 2024, only 59% of adults reported believing that global warming is primarily caused by human activity. This widespread skepticism—especially in the U.S., the world's second-largest CO2 emitter—highlights the difficulty of building public consensus on climate issues. Yet, such consensus is essential for the stronger and faster global action needed to mitigate climate change; therefore, understanding the roots of climate skepticism is crucial.

Climate-change skepticism has long been attributed to "supply-side" factors, such as the influence of industrial lobbies on public discourse (Gelbspan, 1997; Stone, 2011) or the media's pursuit of balanced coverage (Shapiro, 2016). More recently, the increasing salience of climate-related weather events has shifted attention toward demand-side explanations, including the public's inability to understand scientific evidence and properly assess risk (Sunstein, 2007). Yet the importance of this mechanism is called into question by the weak correlation between scientific literacy and climate change ignorance (Kahan et al., 2012). In light of this, motivated reasoning has been proposed as a key factor shaping climate change beliefs (Epley and Gilovich, 2016; Kahan et al., 2011). Put simply, individuals may calibrate the extent of their belief in climate change according to how well such beliefs serve their interests (Golman et al., 2017).[1] However, existing evidence on motivated reasoning in the context of climate change is largely confined to laboratory or correlational studies. Moreover, this literature focuses primarily on confirmation bias and gives relatively little attention to why belief differences arise in the first place. This paper advances the field by offering new insights into why and how motivated reasoning shapes climate-belief formation, and by providing distinctive evidence from a high-stakes, real-world setting.

The central idea of the paper is that financial dependence on the fossil-fuel industry makes it difficult to believe in climate change while maintaining a positive self-image.[2]

We test this hypothesis in the context of coal mining in the US. We exploit mass layoffs in

[1]A definition of motivated reasoning is that people "reason their way to conclusions they favor, with their preferences influencing the way evidence is gathered, arguments are processed, and memories of past experience are recalled" (Epley and Gilovich, 2016).

[2]We formalize this intuition in a simple model of belief manipulation, which is presented in Appendix section B.

the industry to estimate how employment in the fossil-fuel sector sustains inaccurate beliefs about climate change. Using a difference-in-differences design, we compare how climate-change beliefs—obtained from the Cooperative Election Studies—evolved between 2012 and 2022 in *coal-mining counties* that experienced mass layoffs relative to those that did not.[3] We find that in 2012, right before a drastic down-sizing of the industry began, respondents from layoff and non-layoff counties held similar climate beliefs, but by 2022 the fraction of believers in climate change had been growing by 10 p.p. more in layoff versus non-layoff counties.[4] An event study graph (see Figure 1) shows that the different trajectory of climate beliefs is specific to the post-layoff period, strongly suggesting that layoff decisions are not related to local trends in climate beliefs. We interpret this result as evidence that layoffs, by weakening dependence on the fossil fuel industry, allow people to form climate beliefs more aligned with the scientific consensus.[5]

Mass layoffs, however, represent a bundle of different treatments: they not only reduce dependence on a given industry but may also impose large negative income shocks. These negative income shocks may influence climate beliefs through alternative channels as well. To account for alternative channels, we use a triple-differences design that compares layoffs in the coal mining sector with similar events in 4-digit manufacturing industries. These results show that the impact of layoffs on climate beliefs is unique to the coal mining industry suggesting that our interpretation is correct.

To disentangle the effect of potential changes in the information environment, we also examine the role of print media in shaping or transmitting the impact of layoffs on beliefs. We exploit variation in the alignment between county boundaries and newspaper audiences, which should generate differences in how local newspapers adjust their coverage in response to layoffs (Snyder Jr

[3]We define *coal-mining counties* as those where at least 300 people ($\approx$ 1.2% of the population on average) are employed in a coal mine as of 2012. In Appendix Section D.3 we show that our main result is robust to varying this threshold from 250 to 600, at increments of 10. Although coal mining in general employs only a small fraction of people in any U.S. county, a larger share of the county population arguably has economic stakes in the industry, through family linkages with coal-mine employees (Rud et al., 2024) and economic spillovers (Black et al., 2005). Moreover, employment in the coal industry likely shapes attitudes toward climate change at community level, through shared economic identities (Dewitte, 2024) and desire to conform to one's relevant cultural group (Kahan et al., 2012).

[4]In 2012 individuals in coal-mining counties were also 6 p.p. (s.e.=0.016) less likely to report believing in climate change than comparable individuals in otherwise similar counties across the U.S. The estimate, available upon request, is based on a regression that controls for individual and county-level characteristics as listed in Table 1.

[5]Notably, we find no evidence of selective migration from layoff-affected counties: estimates of the impacts of layoffs on key demographic characteristics are small and statistically insignificant.

and Strömberg, 2010). We construct a measure of exposure to layoffs for the newspapers serving each county, based on their readership composition, and use it as a proxy for readers' exposure to layoff-induced changes in media content. Controlling for this proxy, we find no evidence that the supply side contributes to climate change ignorance.

Finally, we examine whether changes in climate beliefs are part of a broader shift in political preferences. Estimating the effects of layoffs on political affiliation and support for reproductive rights and gun control, we find no evidence that changes in climate-change beliefs occur as part of a broader shift in political attitudes.

Our paper contributes to a growing literature on the drivers of climate apathy. Prior work highlighted the relevance of lobby groups (Gelbspan, 1997; Stone, 2011), media (Shapiro, 2016), partisan politics (Tesler, 2018), salience (Gagliarducci et al., 2019) and, especially related to our paper, motivated reasoning (Kahan et al., 2011; Sunstein et al., 2016; Hu, 2023). Our contribution to this literature is twofold. First, we investigate *why* people engage in motivated reasoning when forming beliefs about climate change, providing empirical evidence consistent with self-image concerns being important. In this respect, the paper closest to ours is Kahan et al. (2011), which proposes cultural cognition as a root cause of motivated reasoning around climate change.[6] Second, and specifically as compared to Kahan et al. (2011), we draw evidence from a high-stakes real-world context rather than from laboratory experiments or survey-based correlations.[7] In contemporaneous work, Dewitte (2024) and Toews and Suvorov (2025) document widespread climate skepticism in fossil-fuel communities. Dewitte (2024) emphasizes historically constructed economic identities: communities with long histories of oil and gas extraction develop persistent attachments to the industry, shaping climate attitudes. Exploiting cross-sectional variation in the historical presence of extraction, the paper shows that these identities have long-lasting effects on climate beliefs. Our

[6]The cultural cognition thesis is that individuals tend to "fit their perceptions of risk and related factual beliefs" (Kahan et al., 2011) to the moral evaluations that they share with the individuals with whom they have close ties (Kahan et al., 2012).

[7]Hu (2023) also studies motivated reasoning around a real-world shock, namely forest fires; our novelty vis-a-vis hers and similar papers, beside the investigation of the mechanism, is that we study how motivated reasoning leads to divergence in initially similar beliefs when these are exposed to differential shocks; this is opposed to documenting growing polarization among groups exposed to the same shock (Sunstein et al., 2016; Hu, 2023). Non-trivially, our focus is more informative of how different beliefs about scientific consensus arise from the start, before they polarize further, another feature that we share with Kahan et al. (2011).

paper differs in two key respects. First, we exploit within-community variation from coal-industry labor-market shocks to study how climate beliefs evolve as fossil-fuel dependence declines. Second, whereas Dewitte (2024) focuses on persistent community identities, we emphasize individual self-image concerns tied to financial reliance on polluting industries. In our setting, layoffs weaken incentives to maintain a positive self-image associated with fossil-fuel work, allowing beliefs to move closer to the scientific consensus.

We also build on prior work on self-image concerns as key drivers of motivated reasoning. While engaging with seminal theoretical work (Köszegi, 2006; Bénabou and Tirole, 2011), our contribution is especially relevant to the related empirical literature. Laboratory experiments show that individuals manipulate their believes to maintain a positive view about their intelligence and beauty (Eil and Rao, 2011; Zimmermann, 2020; Möbius et al., 2022; Drobner and Goerg, 2024), although this result is not uniform across settings (Drobner, 2022).[8]

Our paper also relates to a third literature on meaningful work, which argues that for many people, work is more than just a way to earn a living—it is a source of meaning.[9] Specifically, our results are in line with the suggestion that an organization's "mission" affects the perceived meaningfulness of the jobs that it offers (Cassar and Meier, 2018; Kosfeld et al., 2017).[10] We complement this line of work by suggesting that individuals might "cope" with low meaningfulness of jobs in polluting sectors with belief manipulation on climate change.

2 Data and Descriptive Statistics

Data. In this paper we combine several different datasets. Our measure of individual-level climate change beliefs is drawn from the Cooperative Election Study (CES), which asked respondents about their attitudes toward climate change in the 2006, 2007, 2009, 2010, 2011, 2012, and 2022 waves using the following question:

[8] Drobner (2022) shows that subjects are over-optimistic in updating their beliefs following ego-relevant information only when they expect no resolution of uncertainty.

[9] Cassar and Meier (2018) and Nikolova and Cnossen (2020) review this literature, born in the fields of human resources, management and psychological organization, from an economics perspective.

[10] Landini et al. (2025) theorize that *social esteem* is a component of jobs' perceived meaningfulness, and greener jobs deliver higher social esteem. Also, an organization's mission to improve job quality aligns with the idea that corporate social responsibility (CSR) helps motivate employees. (Kitzmueller and Shimshack, 2012).

From what you know about global climate change or global warming, which one of the following statements comes closest to your opinion?

1. *Global climate change has been established as a serious problem, and immediate action is necessary.*
2. *There is enough evidence that climate change is taking place and some action should be taken.*
3. *We don't know enough about global climate change, and more research is necessary before we take any actions.*
4. *Concern about global climate change is exaggerated. No action is necessary.*
5. *Global climate change is not occurring; this is not a real issue."*

We classify respondents as believing in climate change if they chose answers 1 or 2.[11]

From the CES, we also obtain individual-level demographics—age, gender, race, education, employment status, and household income—as well as political preferences, including party affiliation and attitudes toward reproductive rights and gun control.

We detect mass layoffs in the mining industry using employment data from the U.S. Mine Safety and Health Administration (MSHA) for the period of 1990-2020. As shown in Figure A1, coal mining employment declined sharply in the 1990s, stabilized in the 2000s, and fell steeply again between 2012 and 2016.[12] We focus on the 2012–2020 period, when the mining sector contracted significantly and data on climate beliefs was available. Overall, we identify 84 counties with more than 300 mining jobs in 2012. We define mass layoffs if a county lost 50% of its mining employment between 2012 and 2020, and find that, out of 84 counties, 48 underwent a mass layoff during this period. [13]

[11]In 2006, 2007 and 2009 the question allows only answers 1 to 4. Given that we classify answers 1 and 2 as "believing", the absence of option number 5 in these earlier waves is arguably not consequential, as presumably respondents who would have chosen 5 choose answer number 4 instead.

[12]Analysis of factors contributing to the decline of coal in the US over the last decade point to the crucial role of raising mining costs, increasingly stringent environmental regulation and declining prices of gas and renewable-energy sources (https://www.eia.gov/todayinenergy/detail.php?id=64924), as well as increased labor productivity (Kolstad, 2017)

[13]Figure A3 in the appendix presents a map of coal mining counties, distinguishing between those that experienced layoffs and those that did not.

We obtain data on employment in the manufacturing sector—for the same 2012-2020 period—from the US Bureau of Labor Statistics and data on basic demographics of US counties from the US Census Bureau.[14] Consistent with our definition of coal-mining counties, we identify manufacturing counties as those in which at least 300 individuals are employed in the same four-digit manufacturing industry.

To analyze changes in the information environment, we use county-level data on print media circulation for 2014, sourced from the Alliance for Audited Media (AAM).

Descriptive statistics. In 2012, the baseline year for our empirical analysis, survey respondents from layoff and non-layoff counties are similar along a few dimensions such as age, gender, education, ideological leaning and, most importantly, climate beliefs (see Table 1, Panel A).[15] However, respondents from non-layoff counties are significantly more likely to identify as black, and also tend to have higher incomes and lower unemployment rates. The differences in economic fundamentals largely mirror those in county-level data and are likely to reflect the fact that layoff counties are more rural and in general smaller (see Table 1, Panel B). The size of employment in coal-mining in the baseline year is also largely similar in layoff and non-layoff counties (see Figure A2).

Although our empirical strategy accounts for time-invariant differences between layoff and non-layoff counties, the comparisons in Table 1 suggest controlling for a few time-varying variables that could evolve differently between layoff and non-layoff counties, as well as some demographic-specific shocks. The addition of controls also serves the purpose of correcting for sampling variability.

3 Empirical Strategy

Difference in differences estimates. Our core empirical strategy is a difference-in-differences (DiD) approach that compares changes in climate change beliefs across counties affected by mass

[14]Data from the US Bureau of Labor Statistics report county-level employment by industry and year. The information is missing when aggregate statistics could reveal establishment-specific information, e.g. if industry employment is concentrated in one establishment. We consider only counties for which information is available in both years of interest, namely 2012 and 2020; while narrowing the sample of manufacturing counties that we can identify, this restriction should otherwise not affect our estimates.

[15]We report summary statistics for survey respondents with non-missing answer to the climate beliefs question in 2012, and for whom information on demographics is available.

Table 1: Balance of layoff and non-layoff coal-mining counties in 2012

	Non-layoff	Layoff	Diff	p-value
	Panel A. Individual-level, CES data			
Believe	0.52	0.49	0.02	0.55
	(0.03)	(0.03)	(0.04)	
Age	50.86	50.42	0.44	0.72
	(0.85)	(0.87)	(1.23)	
Female	0.56	0.59	-0.03	0.44
	(0.03)	(0.03)	(0.04)	
Educ. (years)	14.04	13.96	0.08	0.63
	(0.11)	(0.12)	(0.16)	
Unemployed	0.06	0.11	-0.04	0.05
	(0.01)	(0.02)	(0.02)	
Employed	0.45	0.38	0.07	0.07
	(0.03)	(0.03)	(0.04)	
Student	0.04	0.03	0.01	0.61
	(0.01)	(0.01)	(0.02)	
Household income	55,000	48,276	6,724	0.06
	(2,328)	(2,840)	(3,637)	
Black	0.14	0.05	0.09	0.00
	(0.02)	(0.01)	(0.02)	
Hispanic	0.03	0.02	0.01	0.27
	(0.01)	(0.01)	(0.01)	
Republican	0.26	0.24	0.02	0.61
	(0.02)	(0.02)	(0.03)	
N	359	293	652	
	Panel B. County-level, Census data			
Population	81,143	44,560	36,583	0.08
	(23,014)	(6,055)	(20,398)	
Younger than 5	0.06	0.06	0.00	0.21
	(0.00)	(0.00)	(0.00)	
Older than 65	0.15	0.15	-0.00	0.79
	(0.01)	(0.00)	(0.01)	
Median age	40.20	40.68	-0.49	0.61
	(0.85)	(0.53)	(0.95)	
Female	0.50	0.50	-0.00	0.36
	(0.00)	(0.00)	(0.00)	
High school or more	0.84	0.80	0.04	0.05
	(0.01)	(0.01)	(0.02)	
Bachelor or more	0.16	0.15	0.01	0.63
	(0.01)	(0.01)	(0.02)	
Black	0.05	0.03	0.02	0.17
	(0.02)	(0.01)	(0.02)	
Hispanic	0.05	0.02	0.03	0.01
	(0.01)	(0.00)	(0.01)	
Median household income	45,660	38,980	6,679	0.01
	(2,064)	(1,287)	(2,309)	
Mean household income	57,510	51,515	5,994	0.02
	(2,054)	(1,424)	(2,417)	
Urban	0.47	0.30	0.16	0.00
	(0.05)	(0.03)	(0.06)	
Unemployment rate	7.35	9.19	-1.84	0.00
	(0.34)	(0.37)	(0.53)	
N	31	45	76	

layoffs to those that were not. We estimate the following specification:

$$y_i = \alpha + \beta^{DiD}\text{Layoff}_{c(i)} \times \text{Post}_{t(i)} + \gamma' X_i + \gamma_{c(i)} + \delta_{t(i)} + u_i, \tag{1}$$

where y_i is one if individual i believes in climate change, $\text{Layoff}_{c(i)}$ is one if individual i resides in county c that experienced a mass layoff between 2012 and 2022, and $\text{Post}_{t(i)}$ is an indicator for year 2022. In the baseline specification we include county ($\alpha_{c(i)}$) and year ($\delta_{t(i)}$) fixed effects, and a vector of individual-level controls (X_i).

The specification in Equation (1) relies on the parallel trends assumption—that, absent mass layoffs, counties experiencing layoffs and those that did not would have followed similar trends in climate change beliefs over the 2012–2022 period. We evaluate this assumption using an event-study specification that examines whether layoff and non-layoff counties exhibited similar trends prior to 2012. To do so, we incorporate earlier waves of the CES, extending back to 2006, the first year in which climate change beliefs were surveyed.

Triple differences estimates. Our preferred interpretation of β^{DiD} is that it reflects mining communities' efforts to preserve a positive self-image and downplay perceptions of being harmful to society. However, layoff is a bundle of different treatments, of which separation from the fossil-fuel sector is only one component. Indeed, mass layoffs often impose a severe negative income shock and trigger profound transformations in many dimensions of the community's life. To separate our preferred channel, we use layoffs in similar industries as benchmarks by estimating the following triple-differences (TD) specification:

$$y_i = \alpha + \beta^{TD}\text{Layoff}_{c(i)} \times \text{Post}_{t(i)} \times \text{Coal}_{c(i)} + \lambda\text{Layoff}_{c(i)} \times \text{Post}_{t(i)} + \gamma' X_i + \alpha_{c(i)} + \delta_{t(i)} + u_i, \tag{2}$$

where $\text{Coal}_{c(i)}$ is an indicator for county c being a coal mining county. This specification relaxes the parallel trends assumption underlying our baseline DiD model and examines whether the observed divergence in climate change belief trends between layoff and no-layoff counties is unique to the coal mining sector. We estimate Equation (2) using four-digit manufacturing industries as benchmarks for coal mining. These industries—while also polluting—are less directly linked to climate-change-causing emissions, allowing us to isolate the specific impact on climate-change beliefs of phasing out from the most CO2 intense economic activities. We consider manufacturing attractive because of its high comparability to coal mining in terms of labor-force characteristics, and because it has also been exposed to spatially concentrated labor-demand shocks over the last decade.

In the data, we identify 750 manufacturing counties, of which 178 were exposed to mass layoffs between 2012 and 2020.[16] Although manufacturing counties tend to be more populous and more urban than coal-mining counties (see Table C6), the large number of manufacturing counties allows us to reweigh the benchmark group using propensity score reweighting. This approach enables us to construct a counterfactual set of 658 counties, out of which 118 exposed to layoffs, that closely resembles coal-mining counties in terms of population size and urban share.[17,18]

Role of the supply side. We interpret the effect of layoffs as operating primarily through the demand side of the information market—specifically, through the motivated cognition of residents in coal-mining communities. At the same time, the supply side of the information environment, often shaped by local elites, may also play an important role.

To account for this alternative channel, we examine the role of print media in transmitting the effects of layoffs on climate-change beliefs. We focus on print media because it is the only form of mass media capable of tailoring messages to small geographic areas, such as individual counties. To generate variation in climate change-related news exposure within our treatment and control groups, we exploit the imperfect overlap between counties and the audiences of print

[16] 11 coal counties are also manufacturing counties, but since they do not experience manufacturing layoffs we attribute them to the coal sample. We exclude from the triple differences analysis one coal county that is affected by a manufacturing layoff.

[17] Figure C2 plots the distributions of population and urban population share for coal-mining counties, manufacturing counties, and the reweighted manufacturing sample. Table C7 further documents broad similarities between coal-mining counties and the reweighted sample of manufacturing counties.

[18] We count one layoff in 98 out of 118 manufacturing counties, 2 layoffs in 14, 3 in 4 and 4 in 2. We verify that none of the layoffs is in the oil and gas sector, confirming our intuition that the belief response to large employment losses in oil and gas cannot be estimated under the period of study. We also note that working in the gas extraction industry has ambiguous implications for beliefs formation, given that natural gas tends to be perceived as a transition energy source.

newspapers. Our identification strategy builds on the idea that two counties experiencing similarly severe mining layoff shocks may nevertheless be exposed to different newspaper content, simply because their residents read newspapers with a different share of readers from layoff counties. We used data from the Alliance for Audited Media on county-level readership of print newspapers from 2014 to construct a measure of the layoff county audience share of newspapers read in each coal mining county.

$$\text{LC news audience}_c = \sum_j S_{cj} \times LS_j,$$

where S_{cj} denotes newspaper j's audience share in county c, and LS_j is the share of newspaper j's readers residing in layoff counties.

To shut down the news media channel, we estimate difference-in-differences specifications analogous to Equation (1), augmenting them with an interaction between layoff-county newspaper audience and an indicator for the post-layoff period. This interaction captures the effect of layoffs operating through media content, while the Layoff $\times$ Post interaction isolates the effect of layoffs on climate change beliefs holding news coverage constant.

4 Results

4.1 Cross-sectional estimates

To set the ground for our empirical analysis, in Table C1 we show estimates from two cross-sectional regressions, respectively in 2012 and 2022, of climate change beliefs on an indicator for whether the county experienced a mass layoff between 2012 and 2020, and a list of individual-level characteristics. Importantly for our identification strategy, in the baseline year, 2012, the coefficient on the layoff indicator is small and statistically insignificant, confirming that respondents in layoff counties held similar climate-change beliefs as those in non-layoff counties prior to the mass layoffs. A gap emerges between layoff and non-layoff counties in 2022, with respondents in layoff counties being 6 percentage points more likely to believe in climate change.

Among the control variables, self-reported Republican affiliation stands out as a strong correlate of climate beliefs: in 2012, Republicans were 22 p.p. less likely to believe in climate change than Democrats, Independents, or unaffiliated individuals; by 2022, this gap widens to 44 p.p. Years of education, identifying as a woman, and identifying as Black are all associated with a higher likelihood of believing in climate change, although the latter is economically and statistically significant only in 2012.[19]

4.2 Difference-in-differences results

Our main results are summarized in Table 2, where we report estimates from our main difference-in-differences specification, as outlined in Equation (1).

Table 2: Believes in climate change

	(1)	(2)	(3)	(4)	(5)
Layoff X After	0.10*	0.13**	0.09	0.10+	0.09
	(0.05)	(0.05)	(0.07)	(0.05)	(0.06)
Observations	1547	1547	1547	1547	1547
Adjusted R^2	0.139	0.139	0.137	0.138	0.139
Mean(y)	0.52	0.52	0.52	0.52	0.52
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes
State X Year FE	No	Yes	No	No	No
Individual-level controls	Yes	Yes	Yes	Yes	Yes
County-level controls	No	No	Yes	No	No
Individual-characteristics shocks	No	No	No	Yes	No
County-characteristics shocks	No	No	No	No	Yes
N. Counties	84	84	84	84	84

Note: Mean(y) baseline prob. of believing in climate change. Individual-level controls include age, age squared, female, years of education, dummies for being unemployed, employed or a student, household income, dummies for identifying as Black or Hispanic, and a dummy for identifying as Republican. County-level controls include log population, share of individuals under 5, share over 65, median age, share of women, share with high-school education, share with bachelor degree, share of black, share of hispanic, median income, mean income, share of urban population and unemployment rate. SE clustered by county in parenthesis. **1%, *5%, + 10%.

Column 1 includes only county and year fixed effects. Because layoff counties are disproportionately concentrated in Appalachia, Column 2 replaces year fixed effects with state-by-year fixed

[19] We include all the demographics reported in Table C1 as controls in every regression throughout the paper.

effects to account for state-specific flexible trends. In the next columns we account for observable and potentially unobservable time-varying differences between layoff and non-layoff counties. As shown in Table 1, layoff counties tend to be smaller, more rural, poorer and racially less diverse than non-layoff counties. While these characteristics do not appear to evolve differently post layoffs (see Section D.2), we nevertheless show that our main estimate is unaffected by accounting for county-level controls, although the standard error increases moderately (Column 3). Moreover, to address potential differential trends arising from baseline unbalances, Column 5 and Column 6 control respectively for unobservable shocks specific to individual and county-level demographic characteristics.[20]

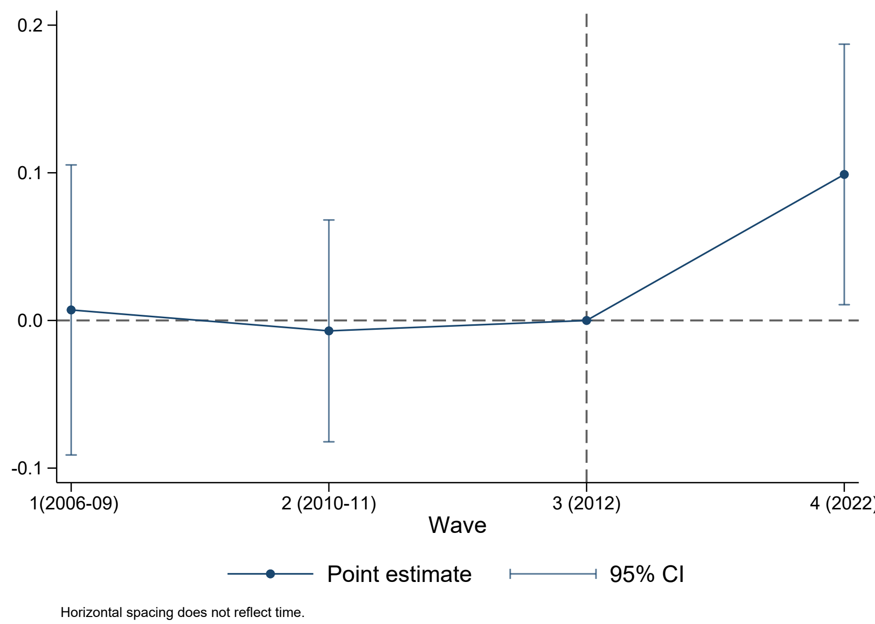
These specifications find that in layoff counties the share of respondents reporting to believe in climate change increased between 9 to 13 percentage points more than in non-layoff counties. We interpret this result as evidence that reduced dependence on the fossil fuel industry in layoff counties enables people to adopt beliefs more aligned with the scientific consensus. Although coal mining accounts for only a small fraction of total employment during our period of study—even in coal-mining counties—these communities often display an attachment to the industry that goes beyond direct or indirect employment relationships. Previous work attributes this attachment, which is central to many communities' identity, to the historical economic benefits generated by the fossil-fuel industry, including contributions to public finances and sponsorship of local events (Dewitte, 2024). In addition, perceptions of the industry's positive local impact have been reinforced by corporate narratives portraying coal as the backbone of the local economy, even as its economic importance declines (Bell and York, 2010). In Appendix Section B we conceptualize self-image concerns primarily in relation to an individual's job. However, one can naturally interpret these concerns—and the resulting evolution of climate beliefs—as reflecting financial reliance on the fossil-fuel economy more broadly, including at the household, family, and community levels.

[20]We consider all the variables that appear to differ significantly between layoff and non-layoff counties in 2012 (see Table 1), and we interact them with an indicator for post-layoff.

4.2.1 Robustness

Event study. We present results of the event study in Figure 1. The figure shows that differences between layoff and non-layoff counties were small and statistically insignificant in all waves from 2006 to 2012[21], consistent with the parallel trends assumption.

Figure 1: Event study



Notes: Points report event-study coefficients from regression of beliefs on layoff indicator interacted with dummies for each wave relative to the omitted year 2012, controlling for individual characteristics and period fixed effects. We collapse waves between 2006-2009 and 2010-2011 to make sample size comparable. Bars show 95% confidence intervals based on county-clustered standard errors.

Selective migration. A key concern regarding our preferred interpretation of the above results is that layoffs may induce selective out-migration of climate skeptics. In this case, layoffs would only alter the composition of survey respondents, without necessarily affecting the beliefs of any individual.

Although we lack direct data on inter-county migration, we assess the potential for selective migration by examining differences in trends in key respondent and county demographics between

[21] We collapse waves between 2006-2009 and 2010-2011 because the number of observations were smaller in those waves.

layoff and non-layoff counties. We do so by estimating a specification analogous to our main DiD model (equation 1), using the individual and county characteristics presented in Table 1 as the dependent variable.[22] The results, reported in Tables C2 and C3, broadly reveal no statistically detectable differences in changes in the demographic composition of survey respondents and in local characteristics across the two groups of counties: out of 10 individual-level and 13 county-level characteristics, only one turns out significant at 5% and one at 10%. Taken together, these findings suggest that the estimated effects of layoffs on climate change beliefs are unlikely to be driven by differential migration patterns.

Alternative cutoffs to identify coal mining counties. The choice of a 300-worker cutoff to define coal-mining counties reflects a trade-off between two competing objectives: retaining a sufficiently large sample of counties for statistical analysis, and identifying places where coal mining accounts for a meaningful number of jobs and, more broadly, anchors local community identity. Under this criterion, we identify 84 coal-mining counties in 2012.

Figure C1 reports estimates of the difference-in-differences coefficients under alternative definitions of a coal-mining county, where the employment threshold is varied from 250 to 600 in increments of 10. As the cutoff increases, the number of coal-mining counties declines. For example, a cutoff of 250 yields 94 counties—compared to 84 under a cutoff of 300. Raising the threshold to 320 reduces this number to 78, and at the highest cutoff of 600, only 51 counties qualify. Despite these changes in sample composition, the estimated coefficient is remarkably stable across thresholds. If anything, the point estimate increases slightly as the cutoff rises, although we do not detect any statistically significant differences across coefficients.

Treatment intensity results. We define a mass layoff as a county losing at least 50% of its mining employment between 2012 and 2020. To ensure that our results are not an artifact of this particular threshold, we re-estimate our main specification using a continuous measure of treatment, defined as the share of mining jobs lost in each county over this period.[23] The results, reported in Table C4, corroborate our main finding: greater employment losses in the mining sector increase the share of

[22] To be conservative, we employ a specification which controls only for county and year-fixed effects.

[23] Four counties increased their coal-mine employment during this period.

respondents reporting belief in climate change.

Balanced panel of counties. There are 84 counties where coal mining employment surpasses 300 in 2012, and we have survey responses from each of them in either 2012 or 2022. Specifically, 76 counties have survey data in 2012, 80 counties in 2022, and 72 counties have observations in both years. In our baseline specifications, we use the full available sample. However, in Table C5, we re-estimate our main specification using only the balanced panel of counties and obtain similar results.

4.3 Triple-differences results

Layoffs in coal mining reduce communities' dependence on the fossil fuel industry, but the loss of well-paid jobs also generates a negative income shock that may affect mining communities through multiple channels. To account for other potential channels, we examine whether the effect of layoffs on climate change beliefs is unique to coal mining or whether similar patterns emerge following the destruction of comparable jobs in other industries. More specifically, we employ a triple differences design as outlined in Equation (2).

Results are reported in Table 3. The coefficient on *Layoff* $\times$ *After* captures the weighted average effect—weighted to represent the average effect in a county comparable to mining counties in population and urban share—of layoffs on climate change beliefs in four-digit manufacturing industries, while the triple interaction *Layoff* $\times$ *After* $\times$ *Coal* measures the additional impact of layoffs in coal-mining communities.

The specifications shown across columns mirror those in Table 2, accounting for a number of observed differences and unobserved shocks.

Across all specifications, we find small and statistically insignificant layoff effects in manufacturing counties. In coal counties instead, layoffs increase the share of individuals believing in climate change by 7 to 11 p.p., an estimate that is statistically significant across all specifications. These patterns indicate that the impact of layoffs on climate-change beliefs is concentrated in coal mining, strengthening our interpretation that reduced dependence on the fossil fuel industry plays a central role in motivated reasoning and climate apathy.

Table 3: Believes in climate change: Impact of coal-mining layoffs relative to manufacturing layoffs.

	(1)	(2)	(3)	(4)	(5)
Layoff X After X Coal	0.08*	0.11*	0.08*	0.07*	0.08*
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
Layoff X After	0.02	0.02	0.02	0.02	0.02
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Observations	41529	41529	41415	41529	41312
Adjusted R^2	0.207	0.209	0.208	0.208	0.207
Mean(y)	0.51	0.51	0.51	0.51	0.51
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes
State X Year FE	No	Yes	No	No	No
Individual-level controls	Yes	Yes	Yes	Yes	Yes
County-level controls	No	No	Yes	No	No
Individual-characteristics shocks	No	No	No	Yes	No
County-characteristics shocks	No	No	No	No	Yes
N. Counties	741	741	741	741	741

Note: Mean(y) baseline prob. of believing in climate change. Sample is made of survey respondents from counties that, according to our taxonomy, are classified as either coal or manufacturing counties. We construct weights as the ratio of the predicted odds of being a coal county to the sample odds, where predicted probabilities are obtained from a first-stage model including population and urban share, and we apply the weights to all the regressions. SE clustered by county in parenthesis. See Table 2 for list of controls. **1%, *5% + 10%.

4.4 Role of print media

In this subsection, we focus on specifications designed to disentangle the effects of layoffs operating through the demand and supply sides of the information environment. Specifically, we control for a proxy for print-media content when estimating the impact of layoffs on climate-change beliefs.

Results are reported in Table 4 and mirror the specifications in Table 2. Even after controlling for the layoff-county share of newspapers' audience, residents of layoff counties increased their climate change beliefs by 11 to 15 percentage points more relative to residents of non-layoff counties. If anything, reading newspapers that have relatively more incentives to alter their content post layoffs has a negative effect on beliefs, although the result is not robust across specifications.[24]

[24] The negative coefficient could reflect an effort of local elites to portray layoffs as caused by climate policy; another hypothesis is that the elite tries to preserve the community attachment to the coal industry as its weight in the local economy declines (Bell and York, 2010). Investigating the robustness and implications of this coefficient is beyond the scope of this paper.

Table 4: Believes in climate change: The role of print media

	(1)	(2)	(3)	(4)	(5)
Layoff X After	0.11*	0.15**	0.14*	0.11*	0.14**
	(0.05)	(0.04)	(0.07)	(0.05)	(0.05)
Local newspapers layoff-county readership X After	-0.01	-0.04	-0.20**	0.01	-0.11+
	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
Observations	1518	1518	1518	1518	1518
Adjusted R^2	0.138	0.137	0.138	0.137	0.141
Mean(y)	0.52	0.52	0.52	0.56	0.56
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes
State X Year Shocks	No	Yes	No	No	No
Individual-level controls	Yes	Yes	Yes	Yes	Yes
County-level controls	No	No	Yes	No	No
Demographic-specific shocks	No	No	Yes	Yes	No
N. Counties	81	81	81	81	81

Note: Mean(y) baseline prob. of believing in climate change. *Local newspapers layoff-county readership* is a measure of the layoff-counties audience share of newspapers read in the county; interacted with the indicator for post layoff, it is intended to proxy for changes in the information environment as newspapers that serve communities affected by layoffs might alter their coverage of climate change and related issues following the layoffs. See Table 2 for list of controls. SE clustered by county in parenthesis.**1%, *5% + 10%

4.5 Results on political preferences

An alternative interpretation of the effect of layoffs on climate change beliefs is that it is not driven by self-image concerns but reflects a broader shift in political identity. Changes in a community's industrial composition may shape individuals' party affiliations, and, ultimately, a broad set of their political preferences and beliefs. Specifically, the decline of coal mining may shift a county's population away from the Republican Party, leading to policy preferences more common among Democrats and independents.

We investigate this hypothesis in Table 5, which applies the specifications in Table 2 to alternative outcomes: party affiliation, support for the access to abortion and support for gun control. We do not find evidence of a broader shift in political preferences: layoffs seem to have no detectable effect on Republican affiliation or support for two salient partisan issues—abortion choice and gun control.[25]

[25] See Section C in the Appendix for the full text of the questions in the CES survey that we use to construct the variables *Identifying as Republican*, *Pro choice* and *More gun control*.

Table 5: Broader ideological shift

	(1)	(2)	(3)	(4)	(5)
Dep. var:			Panel A. Identifying as republican		
Layoff X After	0.06	-0.02	0.08	0.05	0.00
	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)
Observations	1547	1547	1547	1547	1547
Adjusted R^2	0.075	0.082	0.082	0.077	0.078
Mean(y)	0.26	0.26	0.26	0.26	0.26
Dep. var:			Panel B. Pro choice		
Layoff X After	0.03	0.05	-0.04	0.03	0.03
	(0.05)	(0.06)	(0.06)	(0.05)	(0.06)
Observations	1545	1545	1545	1545	1545
Adjusted R^2	0.169	0.165	0.168	0.179	0.168
Mean(y)	0.37	0.37	0.37	0.37	0.37
Dep. var:			Panel C. More gun control		
Layoff X After	0.02	0.05	0.02	0.01	0.06
	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)
Observations	1545	1545	1545	1545	1545
Adjusted R^2	0.197	0.201	0.194	0.196	0.197
Mean(y)	0.39	0.39	0.39	0.39	0.39
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes
State X Year FE	No	Yes	No	No	No
Individual-level controls	Yes	Yes	Yes	Yes	Yes
County-level controls	No	No	Yes	No	No
Individual-characteristics shocks	No	No	No	Yes	No
County-characteristics shocks	No	No	No	No	Yes
N. Counties	84	84	84	84	84

Note: Mean(y) baseline prob. of Dep. Variable. See Appendix section C for a complete description of the dependent variables. See Table 2 for list of controls. SE clustered by county in parenthesis. **1%, *5%, + 10%.

5 Conclusion

This paper examines why some individuals resist evidence on climate change while others update their beliefs. We argue that self-image concerns play a central role: financial dependence on a polluting industry makes it harder to accept the reality of climate change without cognitive dissonance. Building on this intuition, we develop a simple model of belief manipulation and test its implications in the context of U.S. coal mining. Using a difference-in-differences design, we show that climate change beliefs increase more in counties that experienced mass layoffs of coal miners than in otherwise similar coal-mining counties. A triple-differences design, which benchmarks these results against layoffs in manufacturing, confirms that the effect is unique to coal mining.

Specifications that control for print media content suggest that the supply side of the information environment plays a limited, if any, role in propagating the effects of layoffs on climate change beliefs. This evidence points to the importance of individual-level motivated reasoning.

Our findings suggest that employment in polluting industries sustains climate change ignorance by reinforcing incentives for motivated reasoning. At the same time, they indicate that economic shocks reducing such dependence can weaken this channel and bring beliefs closer to the scientific consensus. Importantly, we find no evidence that these changes reflect a broader realignment of political attitudes, underscoring that the effect is specific to climate change.

Taken together, our results highlight the importance of demand-side mechanisms in explaining persistent climate skepticism. Understanding these mechanisms is crucial for anticipating how the ongoing green transition may shape public opinion and, ultimately, political support for climate policy.

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Appendix

A Additional Figures

Figure A1: Coal mining employment over time

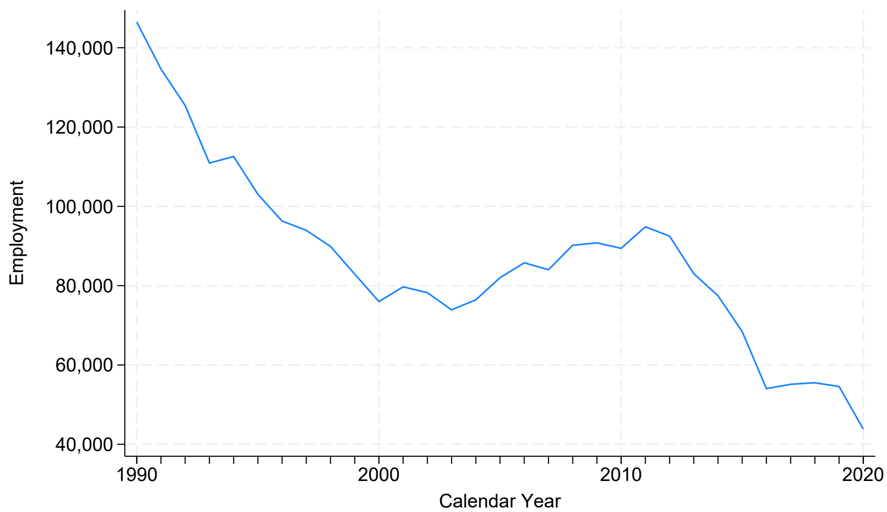


Figure A2: Average mining employment in layoff and non-layoff counties

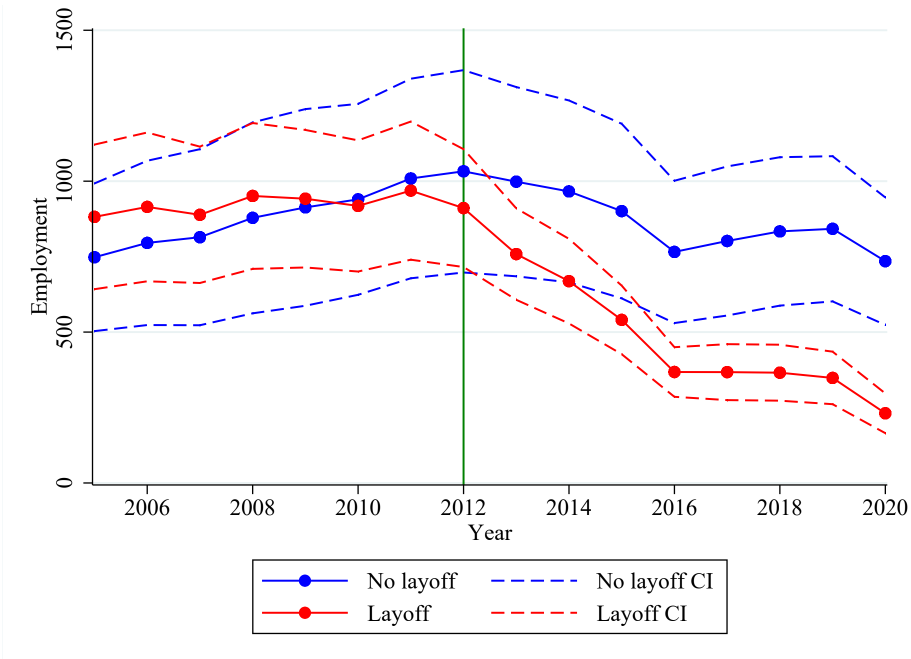
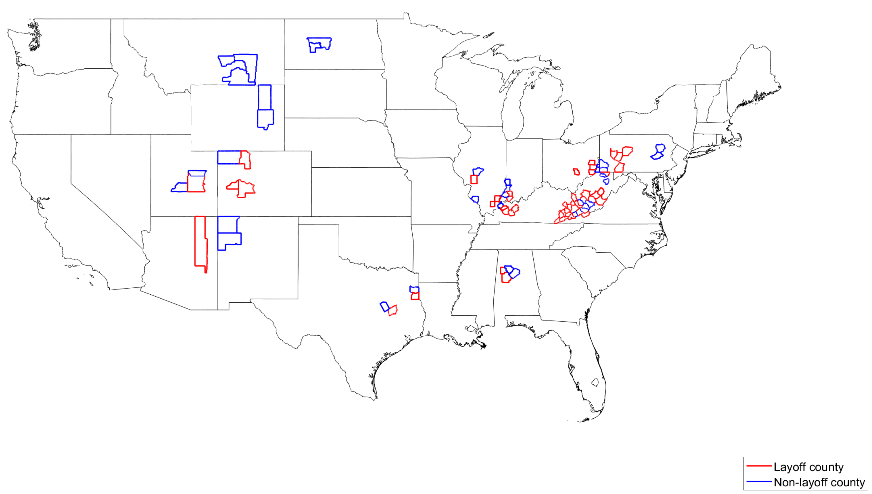


Figure A3: Map of coal mining counties



B Model of climate change denial

This is a model focusing on the demand for climate change denial.

An individual considers to work in polluting sector—e.g. mining—, which influences the person's moral integrity if on only if there is man made climate change $\theta \in \{0, 1\}$.

The utility of the person is

$$U = u(w - \theta) \cdot m + u(0) \cdot (1 - m), \tag{B1}$$

where $m \in \{0, 1\}$ is and indicator for working in mining, w is wage premium from mining—normalized to the outside option—, and $u(\cdot)$ is an increasing and concave function. The individual's "true" beliefs about climate change is $\mu(\theta = 1) = p$. He can manipulate his belief to $\hat{\mu}(\theta = 1) = \pi$ at a cost of

$$c(p, \pi) = \frac{1}{2} (p - \pi)^2 . \tag{B2}$$

Proposition 1. *Under these assumptions,*

- *If wage premium $w < \bar{w}$, then*
$$m = 0 \text{ and } p - \pi = 0$$
- *If wage premium $w \geq \bar{w}$, then*
$$m = 1 \text{ and } p - \pi = \min\{\Delta u(w), p\},$$
where $\Delta u(w) \equiv u(w) - u(w - 1)$ is a decreasing function of w, and $\bar{w}$ is a wage threshold.

Proof

The individual chooses whether to work in mining and how much to manipulate her beliefs about climate change to maximize expected utility (B1) minus the cost (B2),

$$\max_{\substack{m \in \{0,1\} \\ \pi \in [0,1]}} m \left[\pi u(w - 1) + (1 - \pi) u(w) - \frac{1}{2} (p - \pi)^2 \right] + (1 - m) u(0),$$

Assuming that she chooses mining ($m = 1$), the FOC is

$$-\Delta u(w) + p - \pi = 0,$$

where $\Delta u(w) \equiv u(w) - u(w - 1)$ is a decreasing function of w. Therefore the optimal belief manipulation is

$$p - \pi^* = \min\{\Delta u(w), p\} \tag{B3}$$

Denote the value conditional on $m = 1$ by

$$\begin{aligned} v(w,p) &\equiv \pi^* u(w-1) + (1-\pi^*)u(w) - \frac{1}{2}(p-\pi^*)^2 \\ &= \max\left\{u(w) - \Delta u(w)\left[p - \frac{1}{2}\Delta u(w)\right], u(w) - \frac{1}{2}p^2\right\} \end{aligned} \tag{B4}$$

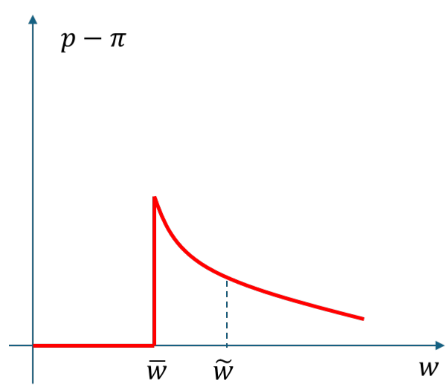
If $v(w,p) < u(0)$, then the person does not work in mining. In this case, he chooses $\pi^* = p$, since for $m = 0$ the person's utility (B1) does not depend on climate his change belief, so he has no incentive to manipulate it. It is easy to show that the value is increasing in the wage premium

$$\frac{dv(w,p)}{dw} = \frac{\partial u(w)}{\partial w} - p\frac{\partial \Delta u(w)}{\partial w} > 0.$$

Notice that for $w = 0$ and $p > 0$, the value $v(w,p)$ is smaller than $u(0)$, since $\Delta u(0) > 0$. As a result, there is a threshold $\bar{w}(p) > 0$, which solves $v(\bar{w},p) = u(0)$, and the person works in mining if and only if $w \geq \bar{w}(p)$. The threshold is increasing in the "true" climate change belief p.

The proposition is summarized by Figure B1. The solid red line depicts the optimal belief manipulation as a function of the wage premium. It shows that below the $\bar{w}$ threshold, individuals choose not to work in mining—or settle in a mining community where they indirectly benefit from mining. Above the $\bar{w}$ threshold, the manipulation is positive and decreasing in the wage premium. The logic of the result is that if mining pays a very small premium relative to alternatives, then belief manipulation making mining worthwhile is too costly, thus the person decides to choose another job or community. However, when the premium is sufficiently large he chooses mining, and since wage and moral integrity are substitutes, then the belief manipulation decreases in the wage premium.

Figure B1: Optimal belief manipulation



Welfare. As we have seen in Proposition 1 people jointly choose their employment action and their beliefs. The next proposition investigates the welfare consequences of these decisions.

Proposition 2. *Strategic belief manipulation about climate change reduces the threshold wage premium to work in mining. Formally, without manipulation the individual only works in mining if the wage premium is above* $\tilde{w}$ *which is larger than* $\bar{w}$.

Proof

Now let's assume the person can not manipulate his beliefs. Then his value from mining is

$$\tilde{v}(w,p) \equiv pu(w-1) + (1-p)u(w) = u(w) - p\Delta u(w) \tag{B5}$$

Notice that similarly to the value with belief manipulation $\tilde{v}(w,p)$ increases in w and $\tilde{v}(0,p) < u(0)$ for any $p > 0$. This yields a threshold wage $\tilde{w}(p)$ above which the person works as a miner. It is also easy to show that $\tilde{v}(w,p) > v(w,p)$ for all w and $p > 0$, therefore the new threshold $\tilde{w}(p)$ is larger than the original threshold $\bar{w}(p)$.

The figure shows that for wages below $\bar{w}$ the person does not work as a miner, while above manipulation is decreasing in the wage. For low wages $w \in [\bar{w}, \tilde{w}]$, she only takes the mining jobs because she manipulates her beliefs about climate change, therefore the decision on climate change has important consequences on individual action. Above $\tilde{w}$ belief manipulation does not change employment decisions just increases the person's utility.

Figure B1 illustrates the statement. As we have seen before, for wage premiums below $\bar{w}$ the individual chooses not to work in mining. However for wages $w \in [\bar{w}, \tilde{w}]$, he only takes the mining job because he manipulates his beliefs about climate change, therefore the choice of belief has important implications on individual action. Above $\tilde{w}$ belief manipulation does not change employment decisions just increases the person's utility. This implies that belief manipulation about climate change reduces wages and reduces the cost of labor in polluting sectors, potentially making more projects profitable.

C Survey questions

Below, we report the full text of the questions in the CES that we use to define the dependent variables in Table 5.

Identifying as Republican This variable takes value of 1 if the respondent answered *Republican* to the following question: *Generally speaking, do you think of yourself as a ...?*

Democrat
Independent
Republican
Other
Not sure

Pro choice In 2012, this variable takes value of one if the respondent answered *By law, a woman should always be able to obtain an abortion as a matter of personal choice* to the following question:

Which one of the opinions on this page best agrees with your view on abortion?
By law, abortion should never be permitted
The law should permit abortion only in case of rape, incest or when the womans life is in danger
The law should permit abortion for reasons other than rape, incest, or danger to the womans life, but only after the need for the abortion has been clearly established
By law, a woman should always be able to obtain an abortion as a matter of personal choice
Skipped

In 2022, this variable takes value of one if the respondent answered *Support* to the following question:

Abortion – Always allow a woman to obtain an abortion as a matter of choice:
Support
Oppose

More gun control In 2012, this variable takes value of one if the respondent answered *More Strict* to the following question:

In general, do you feel that the laws covering the sale of firearms should be...
More Strict
Less Strict
Kept As They Are
Skipped

In 2022, this variable takes value of one if the respondent answered *Support* to the following question:

Gun control – Ban assault rifles:
Support
Oppose

D Additional Evidence

D.1 Correlates of climate beliefs

Table C1: Believes in climate change: OLS

	(1) 2012	(2) 2022
Layoff	-0.03	0.06+
	(0.03)	(0.03)
Age sq.	0.01+	-0.01+
	(0.01)	(0.01)
age2	-0.00*	0.00
	(0.00)	(0.00)
Female	0.09*	0.04
	(0.04)	(0.03)
Educ. (years)	0.01	0.02*
	(0.01)	(0.01)
Unemployed	-0.07	0.07
	(0.07)	(0.06)
Employed	-0.05	-0.02
	(0.05)	(0.03)
Student	0.00	0.16
	(0.11)	(0.10)
Household income	-0.00	-0.00
	(0.00)	(0.00)
Black	0.09*	0.01
	(0.04)	(0.04)
Hispanic	0.11	-0.05
	(0.11)	(0.12)
Republican	-0.28**	-0.40**
	(0.04)	(0.04)
Observations	652	895
Adjusted R^2	0.079	0.167
Mean(y)	0.52	0.60
N. Counties	76	80

Note: Mean(y) prob. of believing in climate change in non-layoff counties. SE clustered by county in parenthesis. **1%, *5%.

D.2 Selective Migration

Table C2: Compositional change: Individual-level characteristics

	(1) Age	(2) Female	(3) Educ.	(4) Unempl.	(5) Empl.	(6) Student	(7) Household inc.	(8) Black	(9) Hispanic	(10) Rep.
Layoff X After	-0.16	-0.02	-0.16	-0.03	0.05	0.01	-2660.37	0.01	0.01	0.06
	(1.46)	(0.06)	(0.23)	(0.03)	(0.06)	(0.02)	(4370.27)	(0.03)	(0.02)	(0.07)
Observations	1547	1547	1547	1547	1547	1547	1547	1547	1547	1547
Adjusted R^2	0.018	0.003	0.070	0.023	0.023	0.018	0.042	0.218	0.011	0.034
Mean(y)	50.86	0.56	14.04	0.06	0.45	0.04	55000.00	0.14	0.03	0.26

Note: Mean(y) baseline mean dep. variable. SE clustered by county (83) in parenthesis. County and year FE included in all regressions. **1%, *5%, + 10%.

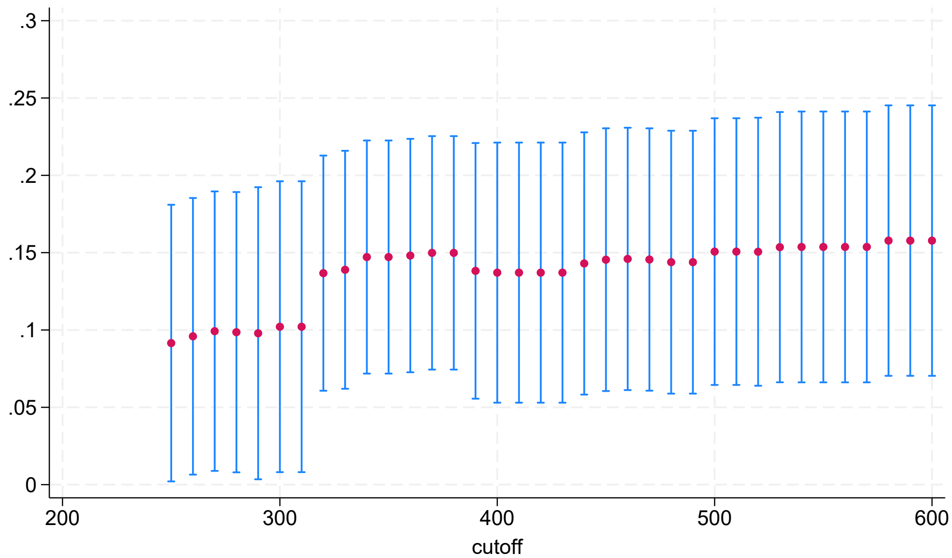
Table C3: Compositional change: County-level characteristics

	(1) Pop.	(2) Share below 5	(3) Share above 65	(4) Median age	(5) Share female	(6) Share high-school	(7) Share bachelor	(8) Share black	(9) Share hispanic	(10) Median inc.	(11) Mean inc.	(12) Share urban	(13) Unemp. rate
Layoff X After	-306.54	0.00	0.00	0.04	-0.00	0.01	-0.00	0.00	-0.01+	523.70	653.98	0.01	-1.32*
	(1833.75)	(0.00)	(0.01)	(0.44)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(2009.92)	(2675.60)	(0.03)	(0.61)
Obs.	156	156	156	156	156	156	156	156	156	156	156	156	156
Mean(y)	81143	0.06	0.15	40.20	0.50	0.84	0.16	0.05	0.05	45660	57510	0.47	7.35

Note: Mean(y) baseline mean dep. variable. SE clustered by county (83) in parenthesis. County and year FE included in all regressions. **1%, *5%, + 10%.

D.3 Alternative Employment Thresholds

Figure C1: Robustness to alternative definitions of coal-mining county, by employment cutoff.



Note: This Figure plots point estimates and 95% confidence intervals for Diff-in-Diff coefficients of the effect of mass layoffs of coal-miners on climate beliefs (namely β^{DiD} in Equation (1)). Each estimate corresponds to a different definition of coal-mining county, where we vary the employment cutoff in 2012 from 250 to 600, at increments of 10. For instance, a cutoff of 250 means that a coal-mining county is one where in 2012 at least 250 people were employed in a coal mine.

D.4 Layoff Intensity

Table C4: Believes in climate change, continuous layoff variable

	(1)	(2)	(3)	(4)	(5)
Layoff continuous	0.16*	0.21**	0.19+	0.15+	0.19*
	(0.07)	(0.08)	(0.11)	(0.08)	(0.08)
Observations	1547	1547	1547	1547	1547
Adjusted R^2	0.139	0.138	0.138	0.137	0.140
Mean(y)	0.52	0.52	0.52	0.52	0.52
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes
State X Year FE	No	Yes	No	No	No
Individual-level controls	Yes	Yes	Yes	Yes	Yes
County-level controls	No	No	Yes	No	No
Individual-characteristics shocks	No	No	No	Yes	No
County-characteristics shocks	No	No	No	No	Yes
N. Counties	84	84	84	84	84

Note: Mean(y) is the baseline probability of believing in climate change. Layoff continuous equals the negative of the 2012–2020 change in county coal employment; larger values indicate greater coal job losses. Standard errors clustered by county are in parentheses. **1%, *5%, + 10%.

D.5 Balanced panel

Table C5: Believes in climate change: Counties that are represented in both the 2012 and the 2022 surveys.

	(1)	(2)	(3)	(4)	(5)
Layoff X After	0.10*	0.13**	0.09	0.10*	0.09
	(0.05)	(0.05)	(0.07)	(0.05)	(0.06)
Observations	1520	1520	1520	1520	1520
Adjusted R^2	0.140	0.140	0.138	0.139	0.140
Mean(y)	0.52	0.52	0.52	0.52	0.52
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes
State X Year FE	No	Yes	No	No	No
Individual-level controls	Yes	Yes	Yes	Yes	Yes
County-level controls	No	No	Yes	No	No
Individual-characteristics shocks	No	No	No	Yes	No
County-characteristics shocks	No	No	No	No	Yes
N. Counties	72	72	72	72	72

Note: Mean(y) baseline prob. of believing in climate change. Sample is restricted to counties that have respondents both in 2012 and 2022. SE clustered by county in parenthesis. **1%, *5%, + 10%.

D.6 Comparison of coal-mining and manufacturing counties

Table C6: County-level characteristics in manufacturing and coal-mining counties in 2012.

	Manufacturing	Coal	Diff.	P-value
Population	316482.81	59482.08	257000.73	0.00
	(21453.00)	(10171.72)	(67506.14)	
Younger than 5	0.06	0.06	0.00	0.00
	(0.00)	(0.00)	(0.00)	
Older than 65	0.14	0.15	-0.02	0.00
	(0.00)	(0.00)	(0.00)	
Median age	38.04	40.49	-2.44	0.00
	(0.14)	(0.47)	(0.48)	
Female	0.51	0.50	0.01	0.00
	(0.00)	(0.00)	(0.00)	
High school or more	0.87	0.81	0.05	0.00
	(0.00)	(0.01)	(0.01)	
Bachelor or more	0.25	0.16	0.10	0.00
	(0.00)	(0.01)	(0.01)	
Black	0.10	0.04	0.06	0.00
	(0.00)	(0.01)	(0.01)	
Hispanic	0.10	0.03	0.07	0.00
	(0.00)	(0.01)	(0.01)	
Median household income	52509.31	41704.74	10804.58	0.00
	(473.79)	(1189.36)	(1536.05)	
Mean household income	68058.20	53960.53	14097.67	0.00
	(597.04)	(1228.12)	(1916.43)	
Urban	0.70	0.37	0.33	0.00
	(0.01)	(0.03)	(0.03)	
N	750	76	826	

Standard errors in parentheses.

Table C7: County-level characteristics in weighted sample of manufacturing counties and coal-mining counties in 2012.

	Manufacturing, weighted		Coal	
	Mean	SD	Mean	SD
Population	66599.92	(81172.53)	59482.08	(88674.98)
Younger than 5	0.06	(0.01)	0.06	(0.01)
Older than 65	0.16	(0.03)	0.15	(0.03)
Median age	40.11	(3.73)	40.49	(4.06)
Female	0.50	(0.01)	0.50	(0.01)
High school or more	0.84	(0.06)	0.81	(0.08)
Bachelor or more	0.18	(0.07)	0.16	(0.08)
Black	0.07	(0.11)	0.04	(0.07)
Hispanic	0.05	(0.08)	0.03	(0.04)
Median household income	45471.08	(9369.65)	41704.74	(10368.64)
Mean household income	57847.40	(10697.30)	53960.53	(10706.51)
Urban	0.39	(0.24)	0.37	(0.25)
Observations	658		76	

Figure C2: Distribution of population and urban share, by sample