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Jobs for a just transition: Evidence on coal job preferences from India☆

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ABSTRACT

As the global economy transitions to greater reliance on renewable energy, it is crucial that this be a *Just Transition* in which new jobs are created to offset reduced opportunities in fossil fuels. This is critical to mitigate political opposition to the renewable energy transition. We use a survey experiment in Jharkhand, one of India's largest coal-producing states, to identify the characteristics that make alternative jobs attractive compared to coal jobs. We provide evidence of a *coal penalty*: respondents were 36.2 percentage points [95% CI: 33.1–39.5] less likely to choose coal jobs than alternatives. Additionally, respondents were much more likely to select high-paying jobs, while distance was not a strong deterrent to job selection. The findings indicate that coal jobs are unpopular on the margin, and suggest the viability of policies such as jobs training programs and relocation assistance that allow workers to take advantage of higher-skilled, higher-paid livelihoods.

1. Introduction

According to the Intergovernmental Panel on Climate Change, limiting global temperature rise to 1.5 °C as targeted by the Paris Agreement will require that coal's share in total primary energy supply decline 83% by 2050, accompanied by 40% and 66% reductions for natural gas and oil (IPCC, 2018). Fortunately, the global economy is in the midst of an energy transition. Over the next several decades, consumers will increasingly rely on renewable sources of energy such as wind and solar rather than on fossil fuels (United Nations, 2011; UNEP, 2011; Aklin and Urpelainen, 2018). Beyond mitigating climate change, this transition will carry a number of benefits, including the potential to reduce air pollution and create new jobs in renewable energy industries (Ghose and Majee, 2007; Akella, Saini, and M.P.Sharma, 2009; Zhang et al., 2012; Kalkuhl et al., 2019).

At the same time, this transition will ultimately limit the potential for employment opportunities in fossil fuel-dependent industries. This poses problems for efforts to expand the use of renewables and mitigate climate change, as it carries the potential to generate a politically fraught trade-off between job creation and livelihoods, on the one hand, and the pursuit of clean energy, on the other (Kalkuhl et al., 2019; Patterson et al., 2018). Around 12 million workers are employed in the fossil fuel industries worldwide (UNEP, 2011), including 7 million workers in the coal industry (Pai et al., 2020a,b), and estimates suggest that 6 million of these jobs could be lost by 2030 (ILO, 2018). The costs of the energy transition will thus fall disproportionately on those who could have otherwise been employed in fossil fuel industries and their communities, who are likely to organize to protect their interests (Olson, 1965). Research on environmental politics has long demonstrated the political sensitivity of environmental policy's concentrated costs, suggesting the need for policies to offset these costs (Barrett, 2003; Bechtel and Scheve, 2013; Meckling et al., 2017; Bechtel et al., 2019; Mildenberger, 2020).

To reduce opposition to the transition to clean energy and mitigate its negative impacts, a number of scholars have called for ensuring that it is a *Just Transition* (Evans and Phelan, 2016; Healy and Barry, 2017; Cha, 2017; Heffron and McCauley, 2018; McCauley and Heffron, 2018). Here, we define a Just Transition as a shift away from fossil fuels that includes steps to dampen its negative consequences for those employed in affected industries. A core part of a Just Transition will be ensuring that those currently dependent on jobs in fossil fuel industries, or who might have otherwise been able to work in those industries, are able to find other livelihoods. Such an effort is aligned with multiple Sustainable Development Goals (SDG), including providing decent work for all

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(SDG 8) and combating climate change (SDG 13) (Bleischwitz et al., 2018).

But what are attractive employment alternatives? And how attractive are coal jobs in comparison? These are essential questions for policymakers who wish to know how intractable opposition to the transition is likely to be and who hope to craft policies to smooth the transition for workers and mitigate this opposition. In this article, we study these questions using a conjoint survey experiment that identifies the characteristics that make coal mining jobs more or less attractive in the state of Jharkhand, India. Coal is a major source of revenue and economic output in Jharkhand with India's state-owned coal company Coal India Limited (CIL) and its subsidiaries directly employing about 90,000 workers in Jharkhand, in addition to tens of thousands of workers employed as contractors (Central Coalfields Limited, 2018; Bharat Coking Coal Limited, 2019; Central Mine Planning and Design Institute Limited, 2019).

In our conjoint experiment, based on a representative sample of the rural population in Jharkhand ($N = 1,440$), respondents were asked to choose between two jobs, one of which was always a coal miner, whose characteristics were randomized. Because our results contain a representative statewide sample, we can get a sense of how rural households overall – as well as coal-reliant households – view coal employment. This gives insight into both how attractive entering the coal industry is and how public opinion views the coal industry. The former is important because the renewable energy transition will influence employment not only through its effect on currently employed workers but also through its effect on workers who might otherwise be employed in fossil fuels in the future, while the latter is interesting in its own right because public opinion could influence policymakers' willingness to embrace the renewable energy transition.

Our results provide evidence of a *coal penalty* in job preferences. In total, respondents only chose the coal mining job 31.8% [95% CI: 30.2–33.5%] of the time. Respondents unfamiliar with the coal industry – those who were far from a coal mine, did not work in the coal industry, and did not know anyone in the coal industry – were particularly unlikely to select the coal miner job. Similarly, we show that this coal penalty existed even when the coal job was quite well-paying and close to respondents homes. Finally, we show that even among workers already employed in the coal industry, the choice between the coal mining job and the alternative job was evenly split.

1.1. Novelty and scholarly contributions

This article makes a number of new contributions to scholarship. First, whereas scholarly work on the Just Transition to date has focused more on normative and legal issues surrounding a Just Transition (Evans and Phelan, 2016; Heffron and McCauley, 2018; Patterson et al., 2018), on the supply side of determining which jobs could be created (Newell and Mulvaney, 2013; Miller et al., 2013; Healy and Barry, 2017; Kalkuhl et al., 2019; Pai et al., 2020a,b), and on the broader institutional factors that shape adaptations to economic transitions (Esping-Andersen, 1990; Rodrik, 1998; Hall and Soskice, 2001), our findings shed light onto how communities view alternatives to working in coal mining and what a Just Transition should entail. In doing so, our findings speak to the importance of a bottom-up approach in which job preferences are elicited from the public rather than assumed by analysts or policymakers. In this way, our findings contribute to the broader literature on public preferences over energy and environmental policy, which to date has largely focused on public views on energy policies rather than their willingness to take jobs in versus outside of fossil fuel industries (Keohane, 1998; Attari et al., 2010; Rabe, 2018; Mildenberger, 2020).

Second, while scholarly work on the Just Transition has mainly focused on North America, Australia and Europe, the role of the energy transition in shaping employment in economies in the Global South has received less attention (Pai et al., 2020b). This article thus joins recent work by Pai and coauthors in drawing attention to the issues surrounding the political economy of a transition away from coal in the Global South (Pai et al., 2020a,b). Notably, whereas Pai and coauthors stress the importance of creating new jobs *in communities affected by the transition*, our own findings suggest an important role for mobility, as workers appear fairly willing to find jobs outside their immediate areas (Pai et al., 2020a,b). This is likely to be especially important for workers in coal communities, where the coal industry is often the dominant local employer and landowner, and alternative job opportunities are limited (Lahiri-Dutt et al., 2012; Lahiri-Dutt, 2016; Reddy and Mishra, 2016; Banerjee and Ranjan, 2019).

Third, our findings have implications for understanding migration and employment preferences and for the scholarship on the determinants of migration, including within India. A substantial body of literature has studied whether workers who migrate tend to be more or less socioeconomically disadvantaged than those who remain in place, as well as whether poorer areas feature more out-migration, on average. The findings in this literature are mixed, with some studies suggesting that migrants may be of equal if not higher wealth, education, and caste as non-migrants (de Haan, 1997, 2011; Dubey et al., 2006; Kundu and Sarangi, 2007; Kundu and Saraswati, 2012) and others finding the opposite (Deshingkar and Start, 2003; Deshingkar, 2006). This in part reflects socioeconomic conditions' countervailing effects as both a "push" and a "pull" factor; migrants tend to flow toward areas where jobs and opportunities are more plentiful (Harris and Todaro, 1970; Deshingkar and Start, 2003; Deshingkar, 2006; Hunt, 2006), but a lack of wealth, education, and social capital can likewise constrain migrants' ability to move and take advantage of these opportunities (Kothari, 2002; de Haan, 2002; Calvó-Armengol and Jackson, 2004; Dustmann et al., 2011; Bryan et al., 2014). Yet it also partly reflects methodological limitations, as the existing literature tends to compare the characteristics of migrants and non-migrants in destination areas, which makes comparisons of migrants to non-migrants in source areas – and thus understanding who migrates and who does not – difficult (Deshingkar, 2006; Dubey et al., 2006; de Haan, 2011; Kundu and Saraswati, 2012). This article contributes to this literature and avoids these methodological hurdles by directly probing workers' actual job preferences and their willingness to take jobs that are relatively far from their homes. In doing so, our findings point to policies that could allow workers to actually realize these preferences. The results suggest that workers care more about pay than distance, and may be willing to move to find higher-paying jobs. Some rural workers may, however, be hindered from doing so by a combination of lack of resources needed to move, a lack of knowledge about alternative, higher-paying jobs particularly in urban areas, and limited human capital (Dubey et al., 2006; Hunt, 2006; de Haan, 2011; Kundu and Saraswati, 2012; Choudhury and Khanna, 2012). Thus, for workers who may be unable to access higher-skilled, higher-paid jobs in areas further from their homes due to financial, informational, or human capital constraints, programs such as job retraining or relocation support may be important elements of a Just Transition.

2. Job preferences and a just energy transition

In recent years, scholars, policymakers, and activists have paid increasing attention to the prospects for and consequences of a transition from fossil fuels to renewable energy sources – particularly wind and solar (Aklin and Urpelainen, 2018; Dubash, Swain, and Bhatia, 2019). Many observers argue that the rise of renewables is likely to negatively impact employment in fossil fuel industries like coal and oil, while reducing the revenue available to governments that rely on fossil fuel extraction (Evans and Phelan, 2016). This recognition has informed debate about what policy responses are required to ensure that there is a Just Transition that mitigates harm to those dependent upon fossil fuel industries for their livelihoods (Heffron and McCauley, 2018; World Bank, 2018; Pai and Carr-Wilson, 2018). To this end, many observers propose using government policy to cushion the transition's effects through job creation via investment in other industries, jobs retraining, and social safety nets (Healy and Barry, 2017; Miller et al., 2013; Newell and Mulvaney, 2013; Swilling et al., 2015; Pollin and Callaci, 2019).

To date, however, there has been little research on how households and communities actually think about alternative job options. This is an especially important gap since, as Healy and Barry point out in their call for more research on the Just Transition: "Job creation is clearly a poor proxy for a just transition – what matters more is the kinds of jobs, how secure they are, how long they last" (Healy and Barry, 2017, p. 455). Indeed, knowing workers' preferences can inform policies designed to help workers actually realize their preferences, such as job training programs.

We study this question in the context of Jharkhand, India. Home to about 26% of India's coal reserves and 18% of its production, Jharkhand relies on coal production for about 7% of its state budget, and Coal India and its subsidiaries employ about 90,000 people in the state, most of whom are highly concentrated in a few major coal-producing districts (Tongia and Gross, 2019; Central Coalfields Limited, 2018; Bharat Coking Coal Limited, 2019; Central Mine Planning and Design Institute Limited, 2019; Indian Bureau of Mines, 2019; Government of India, 2019). In many communities, the mining company owns a large portion of the land, which limits residents' ability to find alternative sources of employment such as farming (Lahiri-Dutt et al., 2012; Lahiri-Dutt, 2016; Reddy and Mishra, 2016; Banerjee and Ranjan, 2019). A recent study in the coal-dependent district of Ramgarh found that 27% of households directly depended on coal for their income, while 77% reported that coal impacted their incomes at least indirectly (Bhushan et al., 2020, 84–87). Indeed, among the coal workers in our survey – 40 respondents, 12 of whom worked directly for Coal India – 86% of them said it would be difficult for them to find comparably-paid jobs in the area.

Specifically, we are interested in which job characteristics are the most salient drivers of people's preference for coal mining jobs versus other jobs. We study this question using a forced-choice, conjoint survey experiment in which respondents are presented with two jobs, one of which is always a coal miner, whose other characteristics are randomized. We use these experiments to test several hypotheses about respondents' job preferences, with a focus on understanding both: (1) how attractive respondents view jobs in coal mining, with all else being equal; and (2) which factors shape respondents' relative preferences for coal mining jobs versus alternative jobs.

2.1. Job characteristics: coal vs. non-coal

First, we assess respondents' baseline preferences toward taking coal mining jobs. Here, there are two potential competing expectations. On the one hand, one might expect respondents to have favorable views of working in the coal industry because of the material benefits that the industry often brings to its employees. Formal, salaried jobs in the coal industry are often relatively well-paid, while coal companies frequently provide local communities around mines with benefits such as schools and infrastructure for water and electricity. On the other hand, however, respondents may have negative views of the coal industry owing to the health risks that come with working as a coal miner. Moreover, because coal tends to be concentrated geographically in Jharkhand, most people are likely to be relatively far away from coal-producing areas and may lack familiarity with the industry. Our preliminary fieldwork suggested that most people outside the immediate proximity of coal mines have very little familiarity with coal mining and the coal industry, and to the extent that they know anything about working in the coal industry it is likely to be the risks to health and safety that come with it.

Hypothesis 1a. Respondents' are on average more likely to choose coal mining jobs.

Hypothesis 1b. Respondents' are on average less likely to choose coal mining jobs.

2.2. Job characteristics: income, distance, and safety

Furthermore, we explore the relative weight of several other characteristics on respondents' job preferences. The first two of these relate to the relative income each job provides. We expect that, on the margin, respondents are more likely to choose jobs that pay more and provide more months of employment in the year (cf. Harris and Todaro, 1970; Hunt, 2006). We also explore the degree to which respondents' job preferences depend on the job's distance from their homes and on the job's safety. Specifically, we would expect respondents to be more likely to choose jobs that are closer to them (cf. Dubey et al., 2006; Hunt, 2006; de Haan, 2011; Kundu and Saraswati, 2012; Choudhury and Khanna, 2012). Finally, we expect that respondents will be more likely to choose jobs that are safe for their health.

Hypothesis 2. Respondents are more likely to choose jobs that provide more income per week.

Hypothesis 3. Respondents are more likely to choose jobs that provide more months of employment per year.

Hypothesis 4. Respondents are more likely to choose jobs that are closer to their homes.

Hypothesis 5. Respondents are more likely to choose jobs that are safe for their health.

Ultimately, this article is most interested in understanding perceptions of coal jobs. As a result, to explore the conditions under which coal jobs are more or less attractive, in additional sets of analyses we include interactions between our treatment conditions in order to assess how sensitive respondents' preferences for – or aversion to – the coal mining job are to the job's characteristics. We might expect, for example, that respondents' willingness to select the coal job will be higher when it offers more pay. This approach allows us to identify whether there are thresholds beyond which coal jobs becomes more or less attractive in comparison to alternative job presented in each scenario (described in more detail in Section 3).

2.3. Respondent characteristics

Additionally, as described in our pre-analysis plan, we explore potential, theoretically-motivated heterogeneous treatment effects.[1] First, we expect that respondents who are closer to and more familiar with the coal industry will be more favorably disposed to taking a coal mining job. In particular, we test whether respondents' preferences for coal mining jobs depend on: (1) their distance from the nearest coal mine; and (2) whether they know others who are employed in the coal industry. Respondents might be reluctant to choose jobs that they have little information about (Munshi, 2003; Calvó-Armengol and Jackson, 2004), and people close to the coal industry would have a comparatively clearer idea of how profitable and safe working in that industry is. Respondents who know others in the coal industry are in what Gelman and Margalit call the "penumbra" of the coal industry, which they define as "the set of individuals who are personally familiar with people in that group" (Gelman and Margalit, 2021, p. 1). Gelman and Margalit find that people in the penumbra of a variety of social groups have distinctive political attitudes toward members of that group (Gelman and Margalit, 2021).

Hypothesis 6. Households closer to a coal mine are more likely to choose jobs in the coal industry.

Hypothesis 7. Households who know others that work in the coal

[1] The pre-analysis plan with power analysis was registered on the Evidence in Governance and Politics (EGAP) registry on July 23, 2019. The registration ID is 20190723AA. The pre-analysis plan with power analysis can be accessed here: http://egap.org/registration/5933.

industry are more likely to choose jobs in the coal industry.

We also explore whether households' job preferences are conditioned by their level of education and household expenditures. We might expect, for example, that more educated households and those with greater household expenditures may be more sensitive to changes in the amount of income provided by the jobs in each scenario. More educated respondents likely have more attractive outside options for work, and thus would be unwilling to take a lower-paying job. While the presence of outside options is not a built-in feature of the experimental design, we nevertheless expect respondents to judge the options they are presented with in light of their own circumstances and preconceptions, even if only implicitly. Respondents from households with greater expenditures, in turn, should be less willing to tolerate a lower income, as doing so may not allow them to sustain the level of expenditure that allows them to enjoy their current standard of living. By a similar logic, respondents with more education should be less willing to take a job that is further from their home, owing to their more attractive outside options. However, respondents from households with more expenditures may be willing to take a more distant job, especially if doing so means being able to maintain their households' standard of living.

3. Research design

To test these expectations and explore respondents' relative preferences for coal mining jobs, we conducted a conjoint survey experiment during the summer of 2019 in Jharkhand, India.[2] In the conjoint experiment, we presented respondents with four pairs of two jobs whose characteristics were randomly selected – but one of which was always a coal miner – and asked respondents to choose which job they would prefer. Our sample consists of 1,440 rural households from 144 villages across all 24 districts of the state. Our unit of analysis is the respondent-scenario-job, and with four scenarios per respondent and two jobs per scenario, our total sample size is 11,520. The advantage of a conjoint experiment is that it allows us to compare how important each dimension is, and whether there are non-linear or threshold effects. Moreover, we can separate out the characteristics of each job in order to assess whether there is any *unique* appeal of coal jobs, distinct from the benefits that come with them. Some studies, for example, find evidence that part of the appeal of coal jobs is the identity attached to them (Bell and York, 2010; Carley et al., 2018; Lewin, 2019).

3.1. Survey

The study occurred in the state of Jharkhand, India. Jharkhand is among the poorest states in the country, has among the lowest levels and reliability of electricity connections, and is a major source of the country's coal production. The state possess 26% of India's coal reserves and relies on coal production for about 7% of its budget, and the state-owned Coal India Limited (CIL) directly employs about 90,000 people in the state (Central Coalfields Limited, 2018; Bharat Coking Coal Limited, 2019; Central Mine Planning and Design Institute Limited, 2019; Government of India, 2019; Tongia and Gross, 2019). About 40,000 thousand CIL workers are employed through subsidiary Central Coalfields Limited, while around 45,000 are employed through subsidiary Bharat Coking Coal Limited and a few thousand are employed through the Central Mine Planning and Design Institute (Central Coalfields Limited, 2018; Bharat Coking Coal Limited, 2019; Central Mine Planning and Design Institute Limited, 2019).

To select our sample, we selected six villages from all 24 districts in the state, for a total of 144 villages. The location of selected villages in Jharkhand is shown in Supplementary Fig. S1. Within each village, we randomly selected ten households, for a total sample size of 1,440 households. The selection of the villages was based on a stratified random sample in which we stratified each district's villages by their distance to the nearest coal mine.[3]

In sum, we sampled villages (and households) based on the following procedure:

1. Step 1: by district (24 districts): rank villages by distance to the closest coal mine.
2. Step 2: by district: divide these villages in three groups of equal population. So we have 3*24 = 72 groups.
3. Step 3: by group (72 groups): randomize the order of villages.
4. Step 4: compute the cumulative share of the population of each village as a share of the group (not the district)
5. Step 5: randomly generate 2 + 4 numbers (2 will be used to select villages, and 2 will be used to select backup villages)
6. Step 6: select 2 villages based on the bracket in which the two numbers selected in #5 fall. Also select backup villages. In total: 2*72 = 144 villages are selected.

3.2. Treatment variables

Our treatments consist of five dimensions in the conjoint survey experiment whose contents were randomly selected.[4] The first is the income each job provides. The format of the conjoint experiment can be found in Fig. 1. Each job can pay between 3,000 and 10,000 rupees per week, in increments of 1,000. Second is the number of months each job would employ the respondent for, which can range between 6 and 12 (in increments of 1). Third is the distance of each job from the respondent's home, which can take values of 1 km, 5 km, 10 km, 15 km, 20 km, and 50 km. Fourth, one of our primes specifies whether the job is either bad or safe for respondents' health. Finally, the type of job portrayed in each scenario is randomized, though one of the two jobs is always in coal mining. The other job can be either a solar energy worker, a street vendor, or a farmer.

3.3. Outcome variable

Our outcome of interest is a binary variable which captures whether a particular job was chosen in a given pair of scenarios. In our surveys, we include a conjoint experiment in which respondents are presented with two hypothetical jobs – one of which is always a coal mining job (though whether it is Job A or Job B is randomly assigned), the other of which is either a job as a farmer, solar energy worker, or street vendor. The conjoint experiment is conducted four times per respondent, such that all respondents compare four pairs of jobs, for a total of 1,440*4*2 = 11,520 observations (1,440 respondents, with four scenarios, each of which has two jobs).

3.4. Statistical methods

The model specification we use is specified as follows:

$$\begin{aligned}\text{JobChoice}_{i,j,k} = {} & \overrightarrow{\beta}_1\mathbf{Pay}_{i,j,k} + \overrightarrow{\beta}_2\mathbf{Distance}_{i,j,k} + \beta_3\text{Safety}_{i,j,k} \\ & + \overrightarrow{\beta}_4\mathbf{EmploymentPeriod}_{i,j,k} + \overrightarrow{\beta}_5\mathbf{JobType}_{i,j,k} + \gamma\mathbf{X}_i + \varepsilon_{i,j,k}\end{aligned}$$

where i indexes respondents, j indexes scenarios, and k indexes jobs. *JobChoice* is a dummy variable which captures whether a respondent chose a particular job. **Pay** is a vector of options for how much each job pays, where the amount of pay in each scenario varies between 3,000

[2] Institutional Review Board (IRB) approval was obtained on July 11, 2019. The IRB number is HIRB00009517. The field study was conducted in July and August of 2019, while the pilot was conducted in January 2019.

[3] Data on coal mine locations obtained from the U.S. Geological Survey, and are based on the centroids of coal mines. See https://pubs.usgs.gov/of/2011/1296/(accessed June 12, 2019).

[4] Balance tests can be found in Supplementary Table S3.

I will now present you two possible jobs, and I want to hear which you would prefer:

Job A	Job B
It is a job as a [coal miner, farmer, solar energy worker, street vendor]	It is a job as a [coal miner, farmer, solar energy worker, street vendor]
Pays [3000, 4000, 5000, 6000, 7000, 8000, 9000, 10000] rupees per week	Pays [3000, 4000, 5000, 6000, 7000, 8000, 9000, 10000] rupees per week
Is located [1, 5, 10, 15, 20, 50] kilometers away from your home	Is located [1, 5, 10, 15, 20, 50] kilometers away from your home
Is [bad, safe] for your health	Is [bad, safe] for your health
Will employ you [6 months per year, 7 months per year, 8 months per year, 9 months per year, 10 months per year, 11 months per year, the entire year]	Will employ you [6 months per year, 7 months per year, 8 months per year, 9 months per year, 10 months per year, 11 months per year, the entire year]

131. Which of the two jobs would you prefer?

Job A Job B

132. How strongly do you feel about your choice?

1 Not strongly 2 Somewhat strongly 3 Very strongly

Fig. 1. Illustration of the conjoint survey experiment. Values in brackets are randomized, with equal probability of occurring. One of the two jobs was always a coal miner job; if A was not selected as a coal miner, B would automatically be a coal miner. The experiment was repeated four times per respondent.

and 10,000 rupees per week, in increments of 1,000. **Distance** is a vector of options for how far each job is from the respondent's home, where the distance in each scenario can be 1, 5, 10, 15, 20, or 50 km. *Safety* is a dummy variable capturing whether a given job is safe for respondent's health, which in the survey was measuring by indicating that the job is either "bad" or "safe" for the respondent's health. **EmploymentPeriod** is a vector of options for how many months of employment would be offered by each job, which varies between 6 and 12 in each scenario. **JobType** is a vector of dummy variables for what type of work each job entailed, and can be either coal-miner, farmer, street vendor, or solar energy worker. Given our interest in the Just Transition, one of the two jobs (at random) always included coal mining. $\mathbf{X}_i$ is a vector of respondent-level control variables, and $\varepsilon_{i,j,k}$ is a stochastic error term. Standard errors are clustered at the individual level, as responses to the scenarios could possibly be correlated within individuals – though this does not seem very likely, that scenario characteristics are randomized.

4. Results

The main results are shown in Fig. 2, which shows how the predicted probability that a respondent would choose a particular job changed based on that job's characteristics. Estimates are based on a logistic regression model with standard errors clustered by respondent. The results are robust to including a variety of control variables, including respondent age, gender, caste, and household size and expenditures, though these control variables are unnecessary due to the treatment conditions being randomized.[5]

Several baseline findings emerge from the results. First and most notably, the results provide evidence of a *coal penalty*. Compared to the other options – solar energy worker, street vendor, and farmer – respondents were more than thirty percentage points less likely to select the coal miner option, on average selecting it only 31.8% [95% CI: 30.2–33.5%] of the time. Second, respondents were more likely to choose a job that paid more in a fairly linear fashion; jobs offering the maximum 10,000 INR/week were 18.6% [15.2–22.0] more likely to be chosen than those offering the 3000 INR/week minimum. Third, for each additional month of employment that a job offered, respondents were on average 2.2 percentage points more likely to select that job; compared to jobs that offered six months of employment, jobs that offered a full year were 13.4% [10.1–16.7] more likely to be chosen. Fourth, being told that a job was safe for their health increased the probability of respondents choosing it by 14.2 percentage points [12.3–16.1] compared to when they were told that a job was bad for their health. Finally, the distance of the job from the respondent's home had a weakly negative effect on the probability of that job being selected. Respondents were only 6.9% [4.0–10.0] less likely to select a job that was 20 km from their home than one 1 km away. The distance at which a job became considerably less attractive was at 50 km, which made respondents 12.7 points [9.7–15.6] less likely to select it.

In Fig. 3 we further explore how the magnitude of the coal penalty varies by the other characteristics of the job, namely distance and pay. Fig. 3a-b shows that even when the coal job was 1 km away, respondents only selected it with a predicted probability of 38.0% [95% CI: 34.5–41.3] compared to 72.2% [69.2–75.3] for non-coal jobs, while when the coal job paid 10,000 INR/week respondents only selected it with a predicted probability of 42.1% [38.2–46.0], compared to 76.5% [73.3–79.8] for non-coal jobs. Most strikingly, respondents showed a greater propensity to select non-coal jobs that paid 3000 INR/week or were 50 km away than coal jobs that paid 10,000 INR/week or were 1 km away.

4.1. Heterogeneous treatment effects

Next, we test for heterogeneous treatment effects using Bayesian Additive Regression Trees (BART), a nonparametric regression approach that allows us to interact our independent variables with a variety of moderator variables (Chipman2010; James et al., 2021). BART uses a sum-of-trees model with m trees, and uses the treatment variable and moderator variables to split the sample into subgroups. The comparison of the predicted values of the dependent variable in these subgroups are averaged and compared across treatment and control groups at each level of the moderator variable in order to estimate conditional average treatment effects. In effect, BART fits the data to a model, and then uses simulations to predict counterfactual outcomes for each observation being treated and untreated. It then produces a series of estimated treatment effects, which are estimated as the difference between the

[5] A regression table can be found in Supplementary Table S2.

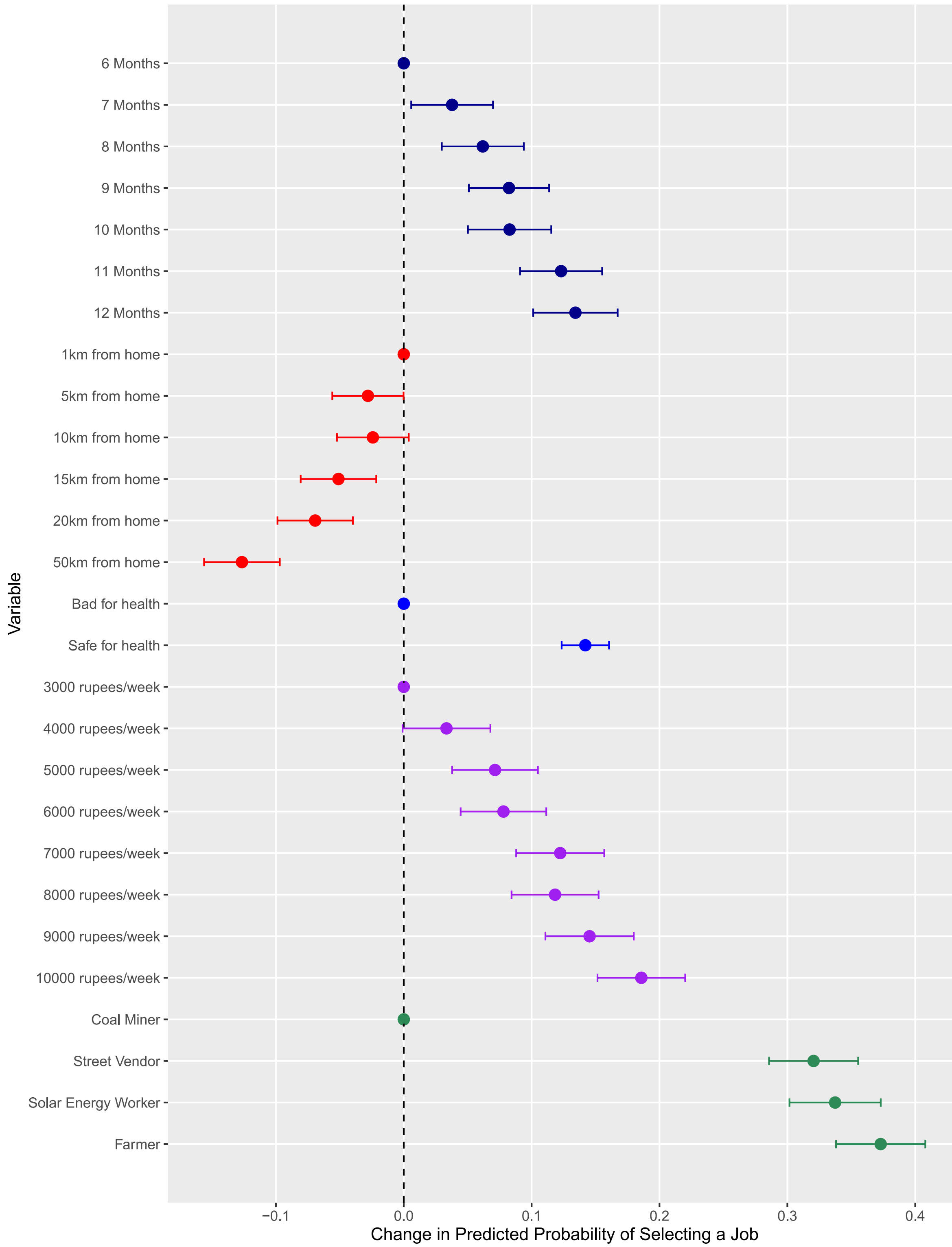
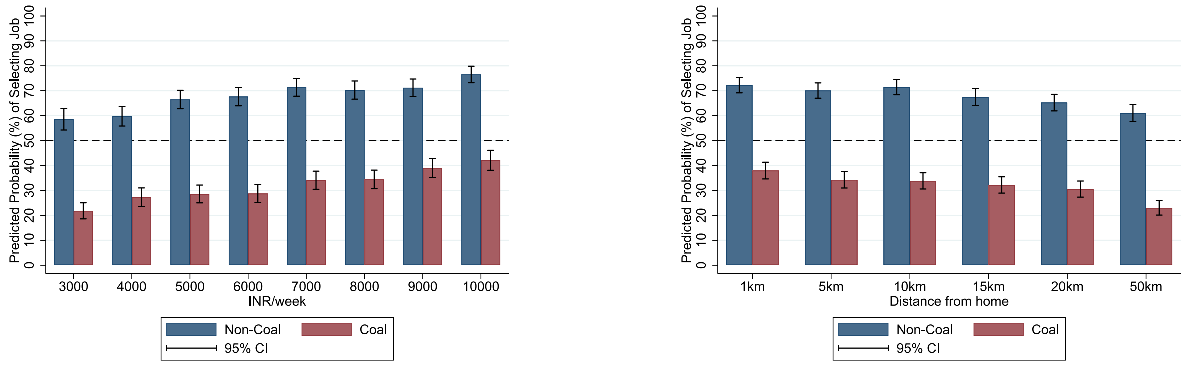


Fig. 2. Change in predicted probability (with 95% confidence intervals) of selecting a job, given characteristics of the job.

treated and non-treated units, and estimates the conditional average treatment effect of the treatment variable at each level of the moderator variable. We use the default number of trees ($m = 200$) and priors on the trees and nodes ($k = 2$, $\nu = 3$, $\alpha = 0.95$, and $\beta = 2$) recommend by Chipman et al. (2010).[6]

The advantage of BART is that unlike with a standard interaction, we

[6] Our calculation are made using R's *dbarts* package. For more technical details on BART, please see Chipman et al. (2010), Green and Kern (2012, 496–500), and James et al. (2021).



(a) Job Pay (b) Job Distance

Fig. 3. Predicted probability of selecting the coal job vs. non-coal job (with 95% confidence interval) at given levels of how much the job paid (Subfigure A) or how far each job was from respondents' homes (Subfigure B), with other variables held at their means. The y-axis represents the predicted probability of choosing a job. Results obtained using an interaction between a binary job type indicator (coal/non-coal) and each job's distance. The dashed line indicates the baseline 50% probability of selecting a job.

do not have to make potentially untenable assumptions about the functional form of the relationship that come with using a model such as ordinary least squares or logistic regression, and for this reason the use of BART and other models that rely on regression trees has become increasingly popular in economics and political science (Green and Kern, 2012; Athey and Imbens, 2019; Mullainathan and Spiess, 2017; Grimmer et al., 2021). Using BART, we create dichotomous version of our treatment variables which capture observations in which the difference between the pair of scenarios is extreme – for example, scenarios in which a job is only 1 km away – and interact them with a number of respondent characteristics. In particular as described in Section 2.3, we use four respondent characteristics as moderators: (1) respondents' distance from the nearest coal mine; (2) a dummy variable indicating whether respondents know anyone in the coal industry; (3) household monthly expenditures (in rupees); and (4) respondent education, which can take five values: No formal schooling; Up to 5th

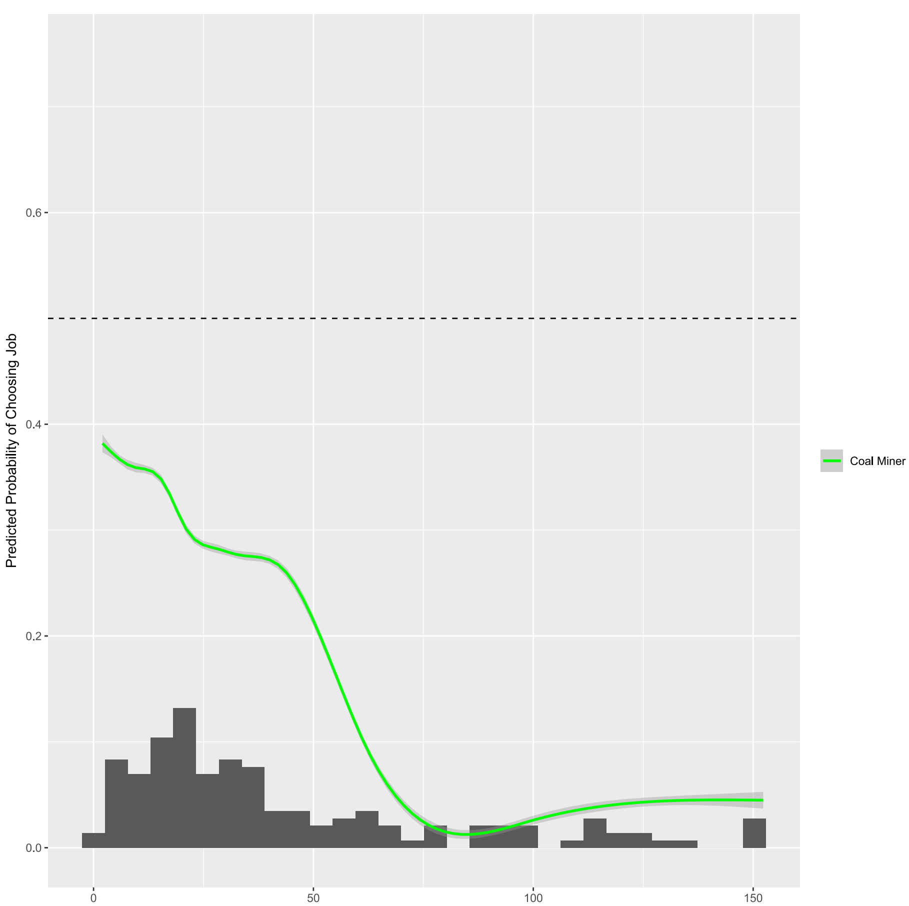


Fig. 4. Predicted probability of a coal job being chosen, given households' distance from the nearest coal mine. The y-axis represents the predicted probability of choosing a job obtained using Bayesian Additive Regression Trees, while the x-axis shows the distance from the nearest coal mine. The gray histogram shows the proportion of observations at each level of distance from nearest coal mine. The line is the smoothed, estimated conditional average treatment effect at each level of the variable on the x-axis, with a 95% confidence interval around that average treatment effect. The dashed line indicates the baseline 50% probability of selecting a job.

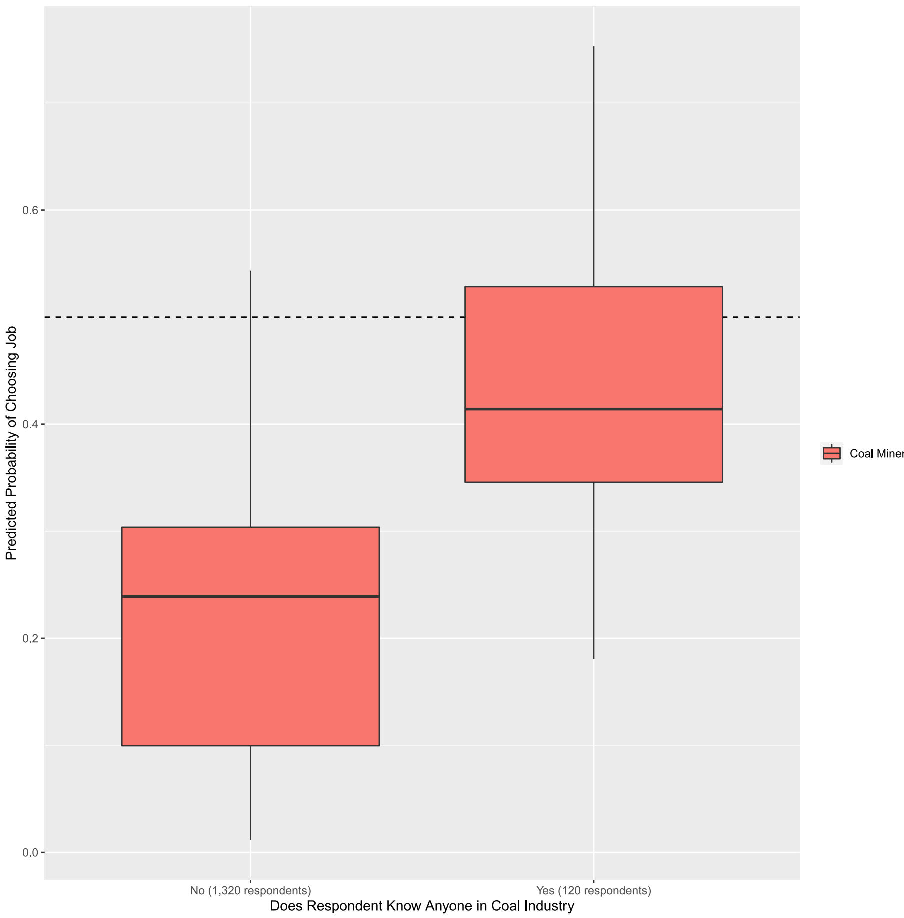


Fig. 5. Box-and-whisker plot showing the predicted probability of a coal job being chosen, based on whether households know anyone in the coal industry or not. The y-axis represents the predicted probability of choosing a job obtained using Bayesian Additive Regression Trees, while the x-axis indicates whether respondents knew anyone who worked in the coal industry. The line in the middle of each box-and-whisker plot is the median estimated treatment effect estimated by BART, and the edges of the box are the upper and lower quartiles of the estimated treatment effects. The dashed line indicates the baseline 50% probability of selecting a job.

standard; Up to 10th standard; 12th standard or diploma; Graduate or above.

The results are shown in Figs. 4,5. The line in Fig. 4 is the smoothed, estimated conditional average treatment effect at each level of the variable on the x-axis, with a 95% confidence interval around that average treatment effect indicating a 95% chance that the "actual" mean treatment effect at a given level of the moderator variable falls in that band. Since the moderator variables in Fig. 5 is binary, we use box-and-whisker plots, where the line in the middle is the median treatment effect, and the edges of the box are the upper and lower quartiles.

The results in Figs. 4 and 5 show that respondents' aversion to selecting the coal mining job was especially potent for respondents that were further away from a coal mine, with the probability of selecting the coal job dropping to nearly zero for respondents that were more than 50 km from a coal mine. Knowing someone who worked in the coal industry nearly doubled the probability of selecting the coal miner job. Notably, however, the probability remains below fifty percent even for respondents living a few kilometers from a coal mine and for those who knew others in the coal industry. The other moderator variables – respondent education and household expenditures – have no discernible effect on the magnitude of the coal penalty, or on the effects of the other treatment conditions.[7]

4.2. Further analysis

We extend the results in several ways. First, we compare the choices of respondents who actually worked in the coal industry to those who did not. The results shown in Fig. 6 show that coal workers were more likely to choose the coal mining job, but on average still only selected it just over fifty percent of the time; the median predicted probability of selecting the coal mining job calculated using BART is 60% for coal workers, and just under 35% for non-coal workers. Supplementary Fig. S6 shows that this result is almost identical for workers directly employed by Coal India.

Next, one might expect that a formal job working for CIL would be more attractive than an informal contracting job. Our survey included questions on how attractive working as a coal miner for CIL versus working as a contractor in a coal mine would be, and the results in Supplementary Fig. S9 suggest that this is the case. However, a large plurality of respondents said both jobs would not be attractive at all (49% and 55% for the CIL and contractor job, respectively, though 22% answered "Don't know."). Additionally, in Supplementary Figs. S7 and S8 we use responses to these questions to predict the choice of the coal mining job in the conjoint scenario. The results are substantively similar, and show a positive effect of the baseline attractiveness of coal mining on selection of the coal mining job in the conjoint experiment. But even among respondents that rated the jobs "very attractive," the median predicted probability of selecting the coal job was still below 60%.

Finally, in Supplementary Fig. S10, we further explore the causes of respondents' aversion to the coal mining job using the (pre-treatment) questions from our survey which asked respondents about their perceptions of the coal industry. The results suggest that respondents who selected the coal job more often were more positively predisposed toward the coal industry, being more likely to say that the coal industry helps the economy of Jharkhand, less likely to think that jobs with Coal

[7] Results are available in Supplementary Figs. S3 and S4.

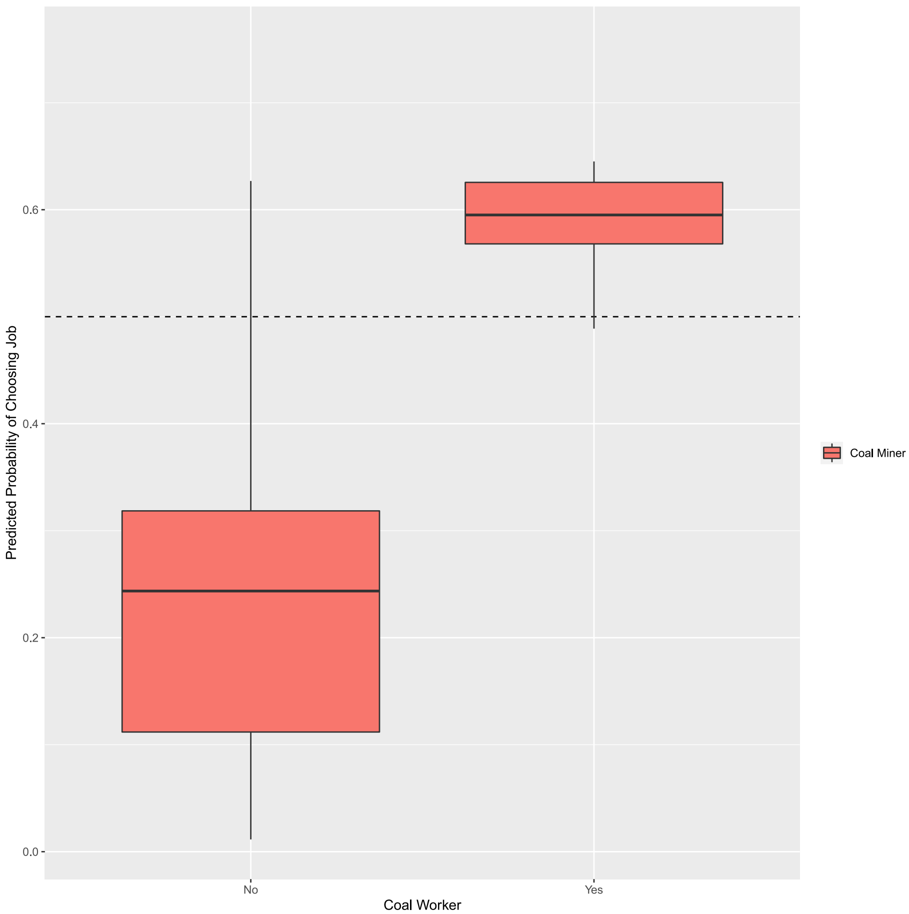


Fig. 6. Box-and-whisker plot showing the predicted probability of a coal job being chosen, based on whether respondents worked in the coal industry. The y-axis represents the predicted probability of choosing a job obtained using Bayesian Additive Regression Trees, while the x-axis indicates whether respondents worked in the coal industry. The line in the middle is the median estimated treatment effect estimated by BART, and the edges of the box are the upper and lower quartiles of the estimated treatment effects. The dashed line indicates the baseline 50% probability of selecting a job.

India were dangerous or demanding, and more likely to view jobs with Coal India as high-paying.

Taken together, our results suggest several key implications. First, the coal mining job was highly unattractive, especially for people unfamiliar with the coal industry. Notably, however, this coal penalty was independent of the coal job's characteristics. Indeed, more than ninety percent of respondents thought that coal miners made higher wages than they did in their own current jobs. What drove the magnitude of the coal penalty, then, was familiarity. Yet even respondents close to a coal mine were less likely to choose the coal mining job than the alternative job. Similarly, even among coal workers, there was no substantial coal "premium." Second, respondents appear willing to take jobs that are relatively far from their home. Both of these findings suggest room for optimism when it comes to the broader subject of Just Transition. Respondents exhibit a baseline aversion to selecting the coal job, even if they may have to travel some distance to work.

5. Conclusion and policy implications

In this study, we used a conjoint survey experiment in Jharkhand, India in order to identify the characteristics that make jobs appealing for a Just Transition. We presented evidence of a "coal penalty." Most respondents – and especially those further away from a coal mine – showed a strong aversion to choosing to work as a coal miner. Notably, this was in spite of the prevailing view among respondents that coal mining jobs were well-paid compared to their current wages. Additionally, respondents were more likely to choose jobs that paid better, were safe for their health, and were closer to their homes.

Taken together, the results suggest that people are quite willing to take alternatives to working in the coal industry. Politically, this suggests that popular opposition to the renewable energy transition is surmountable, and that the main obstacle to helping workers navigate the transition away from coal is not their willingness to take alternative jobs. Instead, our findings suggest two other obstacles. The first of these is ensuring that attractive alternative jobs are created. Doing so is easier said than done, of course, and the question of how to do so is beyond this study's scope. Among renewables, Pai and coauthors find that solar power carries far greater potential to generate new employment opportunities than wind. Even solar, however, will have difficulty meeting the full demand for jobs (Pai et al., 2020a,b). Thus, the full menu of alternative industries should be considered as potential sources of new employment for coal workers – not just the renewables industries. Moreover, our findings indicate that workers may be willing to take jobs that are further away but better-paying.

Second, given that our findings indicate that workers may be willing to take jobs that are further away but better-paying, another obstacle is ensuring that workers have access to the alternative livelihoods they desire, even if they are relatively further away. Fortunately, workers' willingness to travel suggests that jobs in more central, urban areas may be able to substitute for jobs in workers' immediate areas. In areas dominated by the coal industry, alternative employment opportunities are often not readily available, and those that are have often built up as a result of the coal industry's presence, and may be subject to decline as coal production does (Reddy and Mishra, 2016; Banerjee and Ranjan, 2019).[8] By contrast, the literature on economic development and urbanization has long argued that a diverse array of jobs tend to concentrate in more densely-populated urban areas (Krugman, 1991; Gallup et al., 1999; Fujita et al., 1999; Henderson, 2003; Quigley, 2008). Nevertheless, some workers may be held back from relocating jobs by insufficient funds to move or by a lack of human capital for – and knowledge of – higher-skilled jobs, which research suggests can hinder rural workers' ability to move (Choudhury and Khanna, 2012; Dubey et al., 2006; de Haan, 2011). In such cases, programs such as subsidizing workers' transportation and moving costs and offering training so that they can take advantage of higher-skilled opportunities in urban areas could go a long way in ensuring that workers have the skills and resources to switch jobs.

CRediT authorship contribution statement

Brian Blankenship: Writing – original draft, Writing – review & editing, Conceptualization, Methodology. **Michaël Aklin:** Writing – review & editing, Conceptualization, Methodology. **Johannes Urpelainen:** Supervision, Funding acquisition, Writing – review & editing, Conceptualization, Methodology. **Vagisha Nandan:** Conceptualization.

Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2022.112910.

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