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Summary

We study how occupation-related material interest affects environmental voting. Specifically, material interest hinges on the greenness vs. brownness of individual occupational profiles. That is, on the extent to which individuals are expected to benefit vs. lose in a greener economy. We employ individual-level data from 14 western European countries, over 2010-2019. To measure the greenness and brownness of occupational profiles, for each individual we compute predicted greenness and brownness scores based on the predicted probabilities to be employed in each possible occupation. These probabilities are combined with occupation-specific greenness and brownness scores. Individuals characterized by higher predicted brownness are less likely to vote for Green parties and for parties with a more environmentalist agenda, while the opposite holds for individuals characterized by higher predicted greenness. Voting preferences of brown profiles tend to converge towards those of greener profiles in regions that are better placed to gain from the green transition.

Keywords: green voting, material interests, green jobs, brown jobs, labour market effects of the green transition

JEL Classification: D72, Q52, P16

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Green Collars at the Voting Booth: Material Interest and Environmental Voting*

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Abstract

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1 Introduction

Protecting the environment and fighting climate change are key challenges for policy makers worldwide. In democracies, effective climate action requires political support for parties proposing environmentalist platforms. It is then crucial to understand the determinants of environmental voting. In this respect, a growing stream of studies is providing evidence on the role of individual demographic and cultural characteristics (e.g., Drews and van den Bergh, 2016), personal experiences of extreme events (e.g., Hazlett and Mildenberger, 2020), and on the impact of green policies (e.g., Stokes, 2016). In this paper, we focus on the role of individual material interest in the labor market, as related to occupational profiles. Specifically, in our analysis material interest hinges on the extent to which individual occupational profiles are expected to benefit vs. lose as the transition towards a greener economy unfolds. The underlying intuition is that the green transition generates distributional consequences in the labor market, with winners and losers, at least in relative terms. We study to what extent these distributional consequences shape voting behavior.

The labor market consequences of the green transition have become increasingly politically salient in Western democracies in recent years. This is not surprising, given the pervasive influence of green policies on the labor market, and the great deal of public funding and regulation involved by the green transition (e.g., IMF, 2022; OECD, 2023). For instance, US President Donald Trump repeatedly claimed that job security for people at risk of losing their jobs due to environmental policies, as per the so-called "job killing argument", was one of the top priorities for his administration, unlike climate change. Labor market concerns related to the green transition have also featured prominently as campaign issues in recent European elections, for instance in Germany, the Netherlands, and the UK.[1] These issues have also been central in the 2024 EU Parliament elections, which witnessed a significant setback for Green parties.[2] In parallel, responding to growing criticism from

[1] See, for instance, "How climate policies are becoming focus for far-right attacks in Germany" in The Guardian; "Nitrogen wars: the Dutch farmers' revolt that turned a nation upside-down" in the The Guardian; "What Starmer's clean energy strategy means for investors" in the Financial Times.

[2] See, for instance, "Europe's green backlash" in the Financial Times.

public opinion and political leaders, the President of the EU Commission, Ursula von der Leyen, scaled back some ambitious Green Deal proposals in a successful bid to secure a second term in office.

Several studies, as reviewed by Bosetti et al. (2025), are starting to provide evidence of a "green backlash" against climate policies that generate high and unevenly distributed costs. This entails reduced support for parties proposing more environmentalist platforms, and rising support for environmental-skeptic parties, especially of the populist right. In this paper, we study to what extent voter support for parties proposing environmentalist platforms is related to their occupational profile, which determines how likely they are to benefit from the green transition, as opposed to be penalized by it. More specifically, we investigate how economic material interest, as inferred from the greenness and brownness of occupational profiles, affects support for Green parties and for parties with relatively pro-environment policy platforms.

The analysis focuses on 14 western European countries, over the period 2010-2019. We employ individual-level data from the European Social Survey (ESS) containing information on voting behavior and occupational status. To characterize individual occupational profiles in relation to the green transition, we start from information on job characteristics sourced from the O*NET database (US Bureau of Labor Statistics). In particular, following the labor economics literature on the green transition (Vona et al., 2018; Vona, Marin and Consoli, 2019), we compute occupation-specific indicators of *greenness* and *brownness*. These are, respectively, measures of compatibility/complementarity and incompatibility/substitutability of each specific occupation with respect to the ecological transition, based on the task content of occupations. To give an idea, a worker employed in an occupation featuring a strong role of green tasks, such as performing building weatherization or designing wind farm collector systems, is more likely to benefit from the transition, while the opposite holds for a worker in an occupation where pollution-intensive activities are more prevalent. Importantly, the measures of greenness and brownness of occupations that we employ are complementary and not redundant: each occupation can be classified according to both a greenness and a brownness scale. In fact, the two measures capture different aspects of the labor market impact of the green transition (Vona et al., 2021), allowing to assess the role of material interest along two different, and complementary, dimensions.

Importantly, we reckon that the greenness and brownness of an individual occupational profile cannot be properly assessed by measuring the greenness and brownness of the current observed occupation of the individual, for several reasons. For instance, two individuals in the same occupation, which has a high level of brownness and is therefore penalized by the green transition, may differ in terms of age, gender, and skill profile. These characteristics influence their outside options in the labor market as the green transition unfolds and threatens their current job. In this respect, the greenness and brownness of the current occupation provide only a partial, and potentially noisy, proxy for the greenness and brownness of an individual occupational profile. An analysis based on the current occupation of individuals would also necessarily exclude unemployed workers, a very interesting segment of the electorate in this context. Moreover, there could be confounding factors related at the same time to both vote and current occupation, which could be problematic as we aim to study the effects of the greenness and brownness of occupational profiles on voting. For instance, relatively more environmentally-conscious individuals could be more likely to self-select into relatively greener (vs. browner) occupations, and by the same token they could be more likely to support more environmentalist parties.

To fully capture the greenness and brownness of individual occupational profiles, in a way that is not prone to endogeneity bias in vote regressions, for each individual we compute predicted greenness and brownness scores that do not rely on current occupation. These predicted scores are computed as a weighted average of all the occupation-specific greenness and brownness scores, where the weights are given by the individual-specific probabilities of employment in each possible occupation. In turn, these probabilities are predicted based on individual demographic characteristics: age, gender, education, and region of residence, leveraging pre-sample EU Labor Force Survey data from 2005-2006.

Our measures of predicted greenness and brownness assign higher scores to individuals who, based on their characteristics, are more likely to be employed in occupations characterized by higher greenness or brownness scores. In other words, they are counterfactual measures of material interest for individual respondents. They do not reflect the compatibility of a respondent's current occupation with the ecological transition. Rather, they capture the average compatibility of the occupations that individuals with the same characteristics, in the same regional labor market, would more likely be employed in.

This counterfactual methodological approach is inspired by a strategy originally proposed by Anelli, Colantone and Stanig (2021) for studying the political implications of robot adoption. This approach allows us to assess in a comprehensive way the positioning of individuals in the labor market, capturing the role of green-related job opportunities and outside options beyond the current occupation. It also allows us to assign predicted greenness and brownness scores to individuals who are currently unemployed, as we exploit information on individual demographic characteristics combined with labor market features of the region of residence. In so doing, we are capturing individual occupational profiles independently of the current occupational status. This is also a strategy to isolate plausibly exogenous variation in individual material interest, without hinging on the observed current occupation, which could be influenced by confounding factors in vote regressions.

We find that an increase in predicted brownness decreases the probability of voting for Green parties and for parties with a more environmentalist agenda, while the opposite holds for predicted greenness. The regressions include controls for age, gender and education, along with fixed effects for regions and elections (i.e., country-year pairs). The results hold across a wide range of robustness checks. These include controlling for the greenness and brownness of the current occupation, and for the current industry of employment. In line with the evidence on voting, we also document that individuals with higher greenness scores are significantly more supportive of higher taxes on fossil fuels and more generous subsidies for renewable energy. In contrast, individuals with higher brownness scores exhibit lower support for fossil fuel taxes.

To further characterize the implications of occupation-related material interest on voting, we assess the effects of predicted greenness and brownness on support for parties belonging to different party families. In the right camp, higher predicted brownness scores are related to higher support for radical-right parties and lower support for mainstream-right parties. In the left camp, they are related to less support for Green parties and more support for mainstream-left parties. Higher predicted greenness scores are related to lower support for both radical-right and mainstream-left parties, and to higher support for Green parties.

In an extension of the analysis, we augment the baseline specifications by interacting predicted greenness and brownness scores with region-specific, time-varying shifters that capture variation in the opportunities stemming from the ecological transition. To build these shifters, we first measure the suitability of regions for solar and wind energy production, based on geographic characteristics and on the local intensity of solar radiation and wind speed, respectively. Then, we interact these time-invariant regional features with the growth of green patents issued in the US over time. We use green patents to proxy for global trends in green investments and green technologies adoption, which capture the salience of the ecological transition. We find that individuals residing in regions that are better placed to gain from the green transition tend to have greener vote preferences as the green transition becomes more salient. This is true in particular for individuals with brown profiles, whose preferences get closer to those of green profiles in such contexts. These findings further corroborate the relevance of occupation-based material interest for voting.

This study contributes to a growing stream of research that investigates the drivers of green voting and environmental attitudes. A first strand of this literature has initially focused on individual characteristics driving environmental attitudes, such as gender, age, cultural traits, and education (for a review, see Drews and van den Bergh, 2016). These studies typically provide descriptive evidence on the role of these factors, while a recent contribution by Angrist et al. (2024) provides the first causal evidence on the effect of education on green voting, exploiting compulsory schooling law data across 16 European countries. A second, and more recent, strand of this literature has highlighted the role of personal experiences with temperature anomalies and extreme events (e.g., Baccini and Leemann, 2021; Hazlett and Mildenberger, 2020; Hoffmann et al., 2022; Pianta and Rettl, 2025).

Less attention has been paid to the economic determinants of environmental voting. Some recent contributions have started to investigate the role of the distributional consequences of climate policies (Bolet, Green and González-Eguino, 2023; Colantone et al., 2024; Duijndam and van Beukering, 2021; Gaikwad, Genovese and Tingley, 2022; Stokes, 2016; Voeten, 2025). Other studies have focused on the distributional consequences of trade shocks (Bez et al., 2023; Vona, 2019), on cross-sectoral dynamics (Bayer and Genovese, 2020; Bechtel, Genovese and Scheve, 2019; De Sario, Marin and Sacchi, 2023), on region-specific impacts of the green transition (Rodríguez-Pose and Bartalucci, 2023; Gazmararian and Krashinsky, 2023), and on the general economic context (Duijndam and van Beukering, 2021; Kenny, 2020). The role of individual occupational dynamics in affecting environmental voting has remained largely unexplored thus far. One exception is Heddesheimer, Hilbig and Voeten (2024), who find that a targeted campaign by the AfD in Germany against energy transition policies increased support for the far right among workers employed in a brown job.

In this paper, we contribute to this literature by providing the first cross-country evidence on the role of material interest as related to individual positions in the labor market, exploiting plausibly exogenous variation in occupational profiles, and evaluating them along both a greenness and a brownness scale. We argue that this comprehensive occupational perspective is key when it comes to exploring the political consequences of the green transition, given its heterogeneous implications on different segments of the population. In this respect, our work is also connected to the broader stream of literature on the political consequences of structural changes with winners and losers, which has thus far mostly focused on globalization and automation (Colantone and Stanig, 2018; Colantone, Ottaviano and Stanig, 2022; Gallego and Kurer, 2022; Walter, 2021). We contribute to this literature by focusing on an additional dimension of structural change: the green transition. This is arguably the most relevant structural transformation ongoing world-wide, and something with which governments of all countries will need to deal with.

2 Labor market and environmental voting

The green transition has pervasive implications for the labor market. As the economy moves away from polluting activities and decarbonization progresses, jobs in emission-intensive occupations are threatened, while new opportunities become available in green occupations (e.g., Vona, 2019; Xie et al., 2023). Individuals with green occupational profiles are more likely to benefit from this transition, while individuals with brown profiles are more likely to be penalized by it. These are the distributional consequences of the green transition, which tends to create cleavages in the labor market between winners and losers. In this paper, we study the political effects of these distributional consequences. Specifically, we investigate to what extent holding greener vs. browner occupational profiles has an impact on vote for Green parties, and more generally for parties with more vs. less environmentalist policy platforms.

Material interest has been shown to matter for the political effects of environmental and climate policies. Citizens negatively affected by these policies have been shown to display diminished support for environment-friendly parties, and higher vote for environmental-skeptic parties, especially of the radical right. Evidence of such effects has been found, for instance, with respect to the losers of: traffic bans on polluting vehicles (Colantone et al., 2024); the installation of renewable energy facilities at a very local level (Germeshausen, Heim and Wagner, 2023; Isaksson and Gren, 2024; Mitsch and McNeil, 2022; Stokes, 2016); and carbon taxes (De Groote, Gautier and Verboven, 2024; Voeten, 2025).[3]

In this paper, we focus on material interest from a different angle, that is, occupational positioning in the labor market as related to the green transition. A large literature on the economic drivers of voting behavior has provided evidence on the role played by an individual's occupation in shaping voting behavior. Key factors at the occupation level include unemployment risk (e.g., Rehm, 2009) and broader contract conditions (e.g., Häusermann, 2020); decision autonomy and authority relations (e.g., Oesch and Rennwald, 2018); as well as direct exposure to economic shocks, particularly import competition, offshoring, and automation (e.g., Gallego and Kurer, 2022; Margalit, 2019). One key pattern documented by the literature is that voters can have quite sophisticated and multi-dimensional policy preferences, which in turn are shaped by their labor market experience and situation (Häusermann and Kriesi, 2015). In light of this, it is plausible to think that considerations regarding whether one stands to gain or lose from the green transition are consequential for vote choice in the context of advanced democracies.

In line with much of the literature on class politics, we start with the assumption that positioning in the labor market acts as a central material factor shaping policy preferences and political allegiances. Importantly, we reckon that the individual considerations that

[3] See Bosetti et al. (2025) for an extensive review.

might ultimately be most consequential go beyond current employment. How individuals form preferences and react to economic shocks is shaped by their labor market experience, which includes not only the occupation they are currently employed in, but also the occupations that people like them tend to have and, relatedly, the type of occupations in which they could realistically be employed, in the near future or in the longer span of their career. We posit that voters can become cognizant of their interests, and make choices as a consequence of objective labor market opportunities. In turn, comprehensive empirical measures of these objective conditions, such as the ones we propose, can be used to study this issue.

Some contributions investigating the effects of occupation-based material interest assign to survey respondents an objective characteristic specific to the occupation in which they are currently employed—e.g., employment rate as in Rehm (2009), offshorability as in Rommel and Walter (2018), or routine-task intensity as in Im et al. (2019) and Thewissen and Rueda (2019)—showing that this contributes to shaping policy preferences or vote choices. Other contributions, like ours, rely on more indirect objective measures, predicted or assigned based on observable individual characteristics that allow to reach beyond the current occupation. The underlying idea is that one can attribute to an individual an objective labor market condition based on observable characteristics of the individual themselves, combined with context-level data, e.g., at the local labor-market or occupation level.

For instance, Schwander and Häusermann (2013) create cells based on the combination of three individual features (social class, gender, and age) and for each cell they calculate the unemployment rate and the prevalence of atypical employment. They then attribute to individual survey respondents the measure for their cell. They discuss how individuals might develop political preferences depending on their expectations about labor market risks; these expectations, in turn, "are strongly linked to the labor market prospects of their social group or 'milieu'" (p. 251). In the same spirit, Anelli, Colantone and Stanig (2021) introduce a measure of individual exposure to automation that is not based on the current occupation, but hinges upon individual demographic characteristics and the occupational composition of the region of residence. This objectively assigned measure of automation exposure predicts individual perceptions of unemployment risk, and labor market outcomes such as actual type of contract and salary. In turn, exposure to automation is found to affect individual voting behavior. In addition, recent work documents that individuals can be self-conscious about their objective labor market situation. For instance, Steiner, Mader and Schoen (2024) show that, in Germany, the subjective perception of individuals as globalization losers is related to their objective position in social structure in terms of education, income, occupational class, sector of employment, and region. This subjective perception also predicts vote choice.

Along these lines, we suggest that individuals form expectations about the direct consequences of environmental policies on their occupational prospects, and support or oppose parties with specific policy platforms based on the effect that these policies are expected to exert on their occupational experience. In this respect, the overall labor market context matters. For instance, an individual in a local labor market where brown jobs are common among people with their characteristics, and green jobs seem out of reach, might feel particularly threatened by green transition policies. A similar individual, operating in a local labor market in which people with their characteristics tend to have green jobs, might instead be more positive about these policies. The measures of predicted greenness and browness are designed to capture these types of considerations. That is, they are meant to take into account in a comprehensive way the full spectrum of occupational opportunities that are available to individuals beyond the current occupation.

Recent findings by Egli, Schmid and Schmidt (2022) corroborate the importance of considering outside options and broader local labor market conditions when assessing the political implications of green policies. Their analysis focuses on the electoral effects of coal phasing-out in the Appalachian region of the US, where 54% of coal mining jobs were lost between 2011 and 2016 (32k out of 60k). This led to an increase in Republican vote reaching around three times the number of jobs lost. The effect was stronger in counties where coal mining jobs constituted an important share of total employment, and alternative job opportunities were scarcer. Overall, these findings suggest that individuals tend to react not just to own job loss, but to the overall labor market reshuffling as a consequence of green policies.

We expect individuals with browner occupational profiles to display less electoral support for Green parties, and to support on average parties featuring less environmentalist elements in their platforms. Conversely, individuals with greener occupational profiles should hold more favorable stances regarding the green transition, and therefore be more supportive of Green parties and environmentalist platforms.

A link between employment conditions and preferences for green policies has been documented in the literature. For instance, Bechtel, Genovese and Scheve (2019) find that individuals employed in polluting industries are in general less supportive of climate cooperation, and more sensitive to cost considerations when evaluating climate policies. De Sario, Marin and Sacchi (2023) find that individuals employed in emission-intensive activities tend to be against stringent climate measures, whereas people in jobs that require high levels of green skills are in favor of them. We extend this type of analysis by broadening the assessment of occupation-related material interest, and by considering the impact on voting behavior.

Green transition initiatives are "steering" policies, by which government intervention directs, shapes, and influences the speed of structural change. Seen in this way, they are similar to trade policy, which is a clear instance of a policy that steers structural change. Specifically, green transition policies aim at shaping economic incentives that in turn affect the occupational structure of the economy, in particular by promoting the growth of greener sectors and encouraging the downsizing or the demise of the most polluting or carbon-intensive ones. This is the core engine of the distributional consequences we focus on in the analysis. Indeed, the measures of predicted greenness and predicted brownness are connected to what has been identified as the "industrial" element of the green transition (e.g., Zimmermann and Gengnagel, 2023). In other words, they focus on the first-order effects of green policies, net of any compensation policies.

In fact, there is also a second, more "social" element of the green transition, that entails compensation of negatively affected individuals and communities, along with retraining schemes for displaced workers. These initiatives are a key component of the so-called "just transition" approach (e.g., Im et al., 2024). While compensation has been found to be politically consequential in the short run in some specific contexts (e.g., Bolet, Green and González-Eguino, 2023), a vast literature in labor economics has documented the long-term negative consequences of involuntary occupational separation (e.g., Jacobson, LaLonde and Sullivan, 1993; Davis and Von Wachter, 2011). For instance, Autor et al. (2014) find that US workers displaced due to globalization faced permanent income losses, even upon finding new jobs. In light of this, even if environmental platforms are paired with compensation or retraining plans, it is fully understandable that voters might be opposed to policies that penalize them in the first place. For instance, in a study of coal phasing-out in Germany, Stutzmann (2025) finds that, in spite of generous compensation (especially in the form of early retirement schemes), plant closures reduced vote for the SPD, and increased abstention. These results are in line with evidence by Heddesheimer, Hilbig and Voeten (2024) pointing to a shift of German brown workers towards the environmental-skeptic AfD party. That said, voter considerations about compensation policies—and their combination with environmentalist stances in party bundles—are going to be reflected in the analysis of how predicted greenness and browness affect vote for different party families.

3 Data and measurement

We employ individual-level data from five waves of the European Social Survey (ESS). We focus on 14 countries of Western Europe.[4] This is a particularly interesting context to investigate this research question, as it is the area of the world, along with North America, where the climate movement is most active and environmental issues have become most salient in national politics, as reported for instance by a recent survey of the Pew Research Center.[5]

The ESS is carried out every two years. It collects an extensive range of data at the individual level. These include demographic characteristics such as age, gender, education, and region of residence, along with occupation and industry of employment. Crucially for our purposes, the ESS provides information on the party voted in the last national elections

[4]These are: Austria, Belgium, Switzerland, Germany, Spain, Finland, France, United Kingdom, Ireland, Italy, Netherlands, Norway, Portugal, Sweden.

[5]Pew Research Center, *Climate Change Remains Top Global Threat Across 19-Country Survey* (link).

before the interview date. Elections covered in the sample span the period 2010-2019.

3.1 Environmental voting

In the econometric analysis we investigate the impact of green vs. brown occupation-based material interest on voting. Specifically, we focus on two main outcome variables, described in what follows.

The first outcome variable is an indicator variable taking value one if the individual reports voting for a Green party. To construct this variable, we define as Green any party belonging to the European Green Party, the political group including the majority of European parties committed to environmental values. In addition, we also consider as Green all the remaining parties classified as members of the Green family by the Manifesto Project (MP, Volkens et al., 2016). The full list is provided in Table A2 of the Online Appendix.

The second outcome variable is the environmentalism score of the party voted by the respondent, based on MP data. In fact, the MP provides human coding of statements made in party manifestos, allowing to compute measures of the ideological leaning of parties along several dimensions. We use the MP environmental protection item of Domain 5 (501), which captures the number of environmentalist claims contained in each party manifesto. Specifically, this item counts all quasi-sentences in favor of protecting the environment, fighting climate change, and other green policies.[6] We scale the item following the methodology proposed by Lowe et al. (2011), i.e., we take the log of $(0.5 + \frac{\text{per501}}{100} \cdot \text{total})$, where *per501* is the percentage of claims classified in the category, and total is the overall number of quasi-sentences in the manifesto. Figure 1 shows the distribution of this environmentalism score for Green vs. non-Green parties. Green parties tend to have higher scores, as one would expect. Yet focusing on the environmentalism score, on top of the indicator variable for supporting a Green party, allows us to provide a more comprehensive, non-binary characterization of party choice along the environmental dimension.

[6] More in detail, item 501 of the MP captures the number of quasi-sentences on *"General policies in favour of protecting the environment, fighting climate change, and other "green" policies. For instance: General preservation of natural resources; Preservation of countryside, forests, etc.; Protection of national parks; Animal rights. May include a great variance of policies that have the unified goal of environmental protection."*

In an extension of the analysis, we also consider a broader score of environmentalism. This combines the environmentalism item considered above with other MP scores regarding anti-growth policies and regulation of economic activity.[7] This broader index of environmentalism is highly correlated with the baseline environmentalism score (0.91, significant at 1%), but captures additional nuances in party stances that are worth taking into account in the analysis.[8]

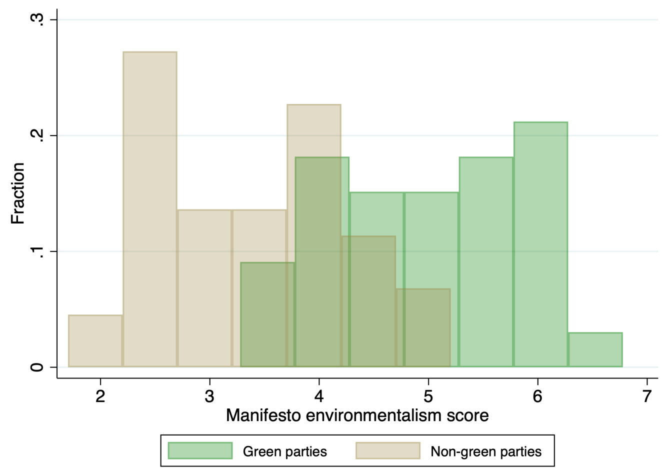

Figure 1: Distribution of environmentalism score by type of party

Notes: The figure shows environmentalism score distributions for Green vs. non-Green parties.

3.2 Conceptual considerations on job greenness and brownness

Measuring workers' exposure to the green transition is not a trivial task. As a matter of fact, there is no widespread agreement on which occupations should be considered "green" vs. "brown", perhaps with the exception of some cases that appear obvious at a first glance. For instance, uncontroversial examples of brown occupations would be coal miners or chemical engineers, that are concentrated in heavily-polluting industries. In contrast, wind turbine technicians or roofers provide prototypical examples of green occupations,

[7] Specifically, the index aggregates claims in support of environmentalism (item 501), market regulation (item 403), and anti-growth/sustainable growth policies (item 416). It is computed following the approach by Lowe et al. (2011).

[8] See Table A5 of the Online Appendix for the full correlation matrix of the outcome variables. See Figure A1 for the distribution of the broad environmentalism score.

since their activities are contributing to greenhouse gas emission reductions. Beyond such polar examples, though, most occupations cannot be uncontroversially considered as dichotomically green or brown (Vona et al., 2021).

Against this backdrop, the prevalent approach in labor economics research dealing with the green transition evaluates occupations along two different dimensions, the green and the brown one (Vona, Marin and Consoli, 2019; Vona et al., 2021). The green dimension, based on the task content of jobs, captures the association of occupations with the production of goods and services that reduce harmful environmental impacts, and thus highlights the potential job creation effect of the green transition. The brown dimension, based on the pollution content of jobs, underscores the potential loss of job opportunities associated with the green transition. In this approach, each occupation can be potentially considered to some degree both green and brown at the same time. We adopt this bi-dimensional approach in the empirical analysis, measuring separately both greenness and brownness scores for each occupation.

3.3 Greenness

To assign a greenness score to occupations, we rely on the Occupational Information Network (O*NET) database of the US Bureau of Labor Statistics. This provides detailed information on the tasks performed by workers in each occupation, and on their relative importance. Crucially, the green economy program of O*NET makes it possible to identify, out of all the tasks performed within each occupation, those that are green. Based on this information, we follow the state-of-the-art labor economics approach (i.e., Vona et al., 2018 and Vona, Marin and Consoli, 2019) and measure the greenness of each occupation j as:

$$\text{greenness}_j = \sum_{k=1}^{n} w_{jk} \times \mathbb{1}(k \in \text{green}) \tag{1}$$

where k denotes tasks; w_{jk} are occupation-task-specific weights, given by the importance scores attributed to each of the n occupation-specific tasks and normalized to sum up to 1; and $\mathbb{1}(k \in \text{green})$ is an indicator equal to 1 if task k is green. The resulting measure is a continuous score ranging between 0 and 1. This captures the relative importance of green

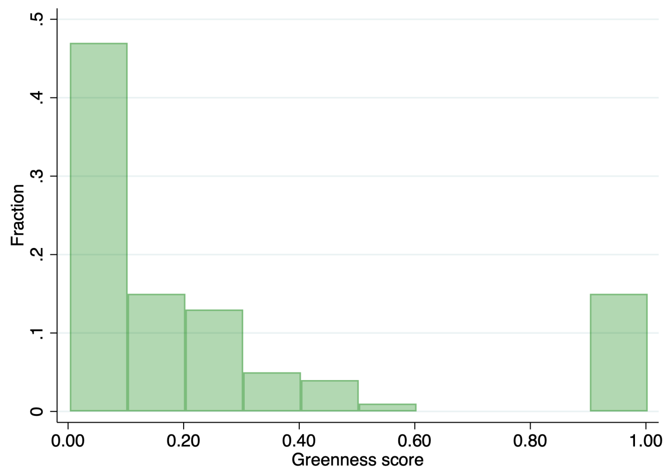

Figure 2: Distribution of greenness score

Notes: The figure shows the distribution of greenness score across ISCO08 occupations, for occupations with a score greater than zero.

tasks for individuals working in occupation j.

O*NET provides data on occupations according to the Standard Occupational Classification System (SOC), at the 6-digit level of disaggregation. Hence, as a first step, we obtain greenness scores for each 6-digit SOC occupation code. We then convert them into the classification of occupations employed in the ESS data, the International Standard Classification of Occupations (ISCO), at the 4-digit level of disaggregation. For the conversion, following common practice in the literature (e.g., Goos, Manning and Salomons, 2014), we rely on official crosswalks, complemented by a one-by-one manual revision to ensure that the resulting classification is coherent with the European labor market framework.

We have a total of 813 ISCO 4-digit occupations observed in the ESS. Across these occupations, the greenness measure has a simple average of about 0.06. It ranges between zero, e.g., for livestock and dairy producers, and 1, e.g., for environmental engineers. Figure 2 plots the distribution of the greenness score across occupations with score greater than zero. These are around 24% of the total. A full list with scores is reported in Table A1 of the Online Appendix.

3.4 Brownness

To measure the brownness of occupations, we rely on recent work that classifies as brown those occupations that are likely to be negatively affected by the ecological transition in the labor market. While for the measurement of greenness the characterization of occupations is based on their task content, for brownness the focus is on their pollution content. In particular, brown occupations are identified as those that are more prevalent in the most polluting industries.

Specifically, we adopt the approach developed by Vona et al. (2018). They first define the most polluting industries, at the NAICS 4-digit level, as those above the 95th percentile of pollution intensity for at least three pollutants among CO2, CO, VOC, NOx, SO2, PM10, PM2.5, and lead. They then compute, for each 6-digit SOC occupation, the share of total employees employed in any of the most polluting industries. This computation is based on US data (BLS-OES) for the years 2006-2014. They define as brown all the 6-digit SOC occupations for which the share of employment in polluting industries is at least 7 times higher than the average share across all occupations.[9]

We adapt this binary measure of brownness to the European context using appropriate crosswalks from the SOC to the ISCO classification used in the European data. Given the m-to-n correspondence between the 6-digit SOC and the 4-digit ISCO occupations, we obtain a continuous score of brownness for each occupation in the ISCO classification. This continuous score essentially captures the unweighted probability for workers within a given occupation of being employed in a polluting industry.

The brownness score has a simple average of around 0.13 across all occupations. It ranges between zero, e.g., for bicycle and related repairers, and 1, e.g., for miners and quarriers, or petroleum and natural gas refining plant operators. Importantly, relatively high brownness scores are observed not only for occupations related to fossil fuels, but also for occupations in livestock farming and the food industry. For instance, livestock and dairy producers, along with poultry producers and food machine operators, get a brownness score of 1.

[9] More details are provided in Section 2.5 and Web Appendix C of Vona et al. (2018).

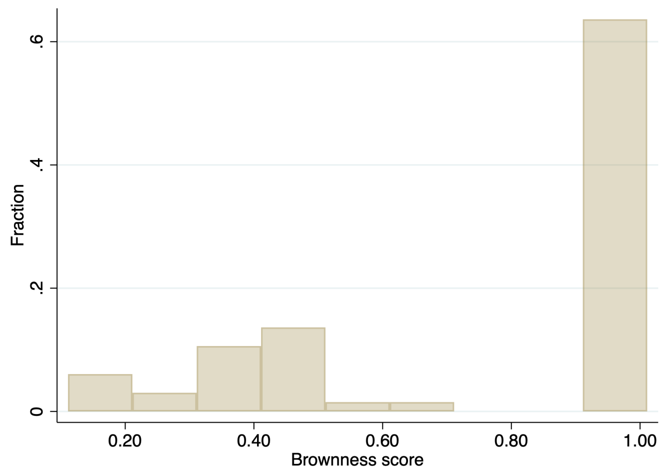

Figure 3: Distribution of brownness score

Notes: The figure shows the distribution of brownness score across ISCO08 occupations, for occupations with a score greater than zero.

Figure 3 plots the distribution of the brownness score across occupations with score greater than zero. These are around 16% of the total. Their list is reported in Table A1 of the Online Appendix, which shows the greenness and brownness scores for all occupations with at least one of the two scores being greater than zero. For a robustness check, we also employ a discrete measure of brownness, with an indicator variable equal to one if the brownness score is greater than 0.3. The choice of this threshold is based on the distribution of brownness scores reported in Figure 3. Through this approach we end up labeling around 17% of all occupations as brown. These occupations, flagged in Table A1, account for 6.7% of employment in the sample.

4 Empirical strategy

Our aim is to investigate whether occupation-related material interest matters for environmental voting. In particular, we want to study to what extent voter support for parties proposing environmentalist platforms is related to the greenness vs. brownness of their occupational profile: two measures capturing how likely individuals are to benefit from the green transition, or be penalized by it in the labor market.

As we previewed, focusing on current occupation may deliver only a partial, and potentially imprecise, measure of the greenness and brownness of an individual's occupational profile. For instance, two workers currently employed in the same occupation may differ in terms of age, gender, education, and region of residence. These factors have a strong influence on their likelihood of employment in different occupations, and therefore on their labor market opportunities beyond the current one. These are very important in terms of outside options in case the current job is lost, and in general for any job switches in search of better career opportunities. Our conceptualization of occupational profile encompasses the full spectrum of opportunities, which allows to assess individual material interest in a comprehensive way.

Besides capturing only partial, and potentially noisy, information on the occupational profile, focusing on the current occupation of individuals would also be problematic for two additional reasons. First, it would necessarily lead to the exclusion of unemployed individuals from the analysis. Yet this is a very interesting social group to be included in the investigation of the impact of occupational material interest on environmental voting. Second, there may be confounding factors that simultaneously influence both voting behavior and current occupation. For example, individuals with a relatively greener disposition might be more inclined to self-select into greener (rather than browner) occupations, and by the same token they may also be more likely to support more environmentalist parties.

For these reasons, we compute a measure of predicted greenness and one of predicted brownness that do not depend on the current observed occupation, but are based on a vector of predicted probabilities for each individual to be employed in each occupation. These probabilities are predicted from a multinomial logit model of occupational choice that is estimated, country by country, from pre-sample labor force survey data.

We predict occupation probabilities based on individual characteristics and region fixed effects, which account for the composition of employment at the occupation level in the different regions. Specifically, we first estimate the parameters of an occupation model as a function of age, gender, education, and region of residence, using European Labor Force Survey (EU-LFS) data from 2005-2006. We then use such estimates to make out-of-sample predictions of the probabilities of working in each occupation for the ESS respondents included in the analysis, who are interviewed between 2010 and 2020.[10] Predicted greenness and brownness are then obtained as the scalar product between this vector of probabilities and the vector of greenness or brownness scores for each occupation. In other words, the predicted greenness (brownness) of a given individual is a weighted average of the greenness (brownness) scores of each occupation, where the weights are given by the individual-specific predicted probabilities of employment in each occupation.

Formally, we define:

$$\text{predicted greenness}_i = \sum_{j=1}^{N} \hat{P}r(o_i = j|\text{age}, \text{gender}, \text{edu}, \text{reg}) \times \text{greenness}_j \tag{2}$$

$$\text{predicted brownness}_i = \sum_{j=1}^{N} \hat{P}r(o_i = j|\text{age}, \text{gender}, \text{edu}, \text{reg}) \times \text{brownness}_j \tag{3}$$

where i indexes individuals, j occupations (at the ISCO 2-digit level), and r regions (NUTS-2). $\hat{P}r(o_i = j|\text{age}, \text{gender}, \text{edu}, \text{reg})$ is individual i's probability of working in occupation j. The variables $greenness_j$ and $brownness_j$ are the continuous measures for occupation j presented in Sections 3.3 and 3.4. Since employment probabilities are predicted at the ISCO 2-digit level, the measures of greenness and browness are also aggregated at the same level.[11]

The resulting variables, *predicted greenness*$_i$ and *predicted brownness*$_i$, assign higher values to individuals with a higher probability of employment in occupations with higher greenness or brownness scores, respectively. They capture the average (in)compatibility with the green transition of the occupations that individuals with the same characteristics, in the same regional labor market, would more likely be employed in.

This counterfactual methodological approach, which borrows from Anelli, Colantone and Stanig (2021), allows to capture variation in individual material interests in a broader

[10] More details on this empirical approach are available in Section A of the Online Appendix.

[11] To obtain greenness and brownness scores for each occupation at the 2-digit level, we take the weighted average of the 4-digit level scores within each 2-digit occupation. We use as weights the relative frequency of each 4-digit occupation in the countries under study, based on ESS data and taking into account post-stratification weights.

way compared to the information provided by the individual current occupation. In fact, it takes into account the whole structure of available opportunities for individuals in the labor market, which shapes the greenness and brownness of their occupational profiles. Predicted greenness and brownness scores can be assigned also to unemployed individuals, as they do not hinge on information about the current occupation of employment. Moreover, by the same token, they provide plausibly exogenous variation in material interest to be exploited in the vote regressions. In fact, employment probabilities are based on plausibly pre-treatment individual characteristics—i.e., age, gender, education, and region of residence—combined with pre-sample labor market characteristics.

4.1 Specifications

The baseline specifications that we estimate have the following form:

$$\text{green voting}_{icrt} = \beta_1 \,\text{predicted brownness}_i + \mathbf{X}_i' \lambda + \omega_{ct} + \delta_r + \varepsilon_{irct} \quad (4)$$

$$\text{green voting}_{icrt} = \beta_2 \,\text{predicted greenness}_i + \mathbf{X}_i' \lambda + \omega_{ct} + \delta_r + \varepsilon_{irct} \quad (5)$$

where i indexes individuals, c countries, r NUTS-2 regions, and t election years. The variable $\textit{green voting}_{icrt}$ is either a dummy for voting a Green party or the environmentalism score of the party voted, as introduced in Section 3.1. $\textit{predicted brownness}_i$ and $\textit{predicted greenness}_i$ are the scores for individual i, as introduced above. $\mathbf{X}_i$ is a vector of (plausibly) pre-treatment individual-level controls: age group, gender, and years of education. ω_{ct} are country-election year (i.e., election) fixed effects, while δ_r are region fixed effects. The estimation sample includes individuals in the voting and working age population at the time of the elections, i.e., between 16 (which is the minimum voting age in Austria) and 64. It includes both employed and unemployed individuals.[12]

In an extension of the analysis, we interact greenness and brownness with region-specific,

[12] Specifically, the estimation sample includes these categories of the ESS *mnactic* variable: paid work; unemployed looking for job; unemployed not looking for job; community or military service; housework, looking after children, other. Excluded categories are: education; permanently sick or disabled; retired; and other.

time-varying shifters that capture variation in the salience of the ecological transition and in the opportunities stemming from it. The intuition is that these contextual conditions may moderate the relationship between the predicted greenness and brownness of occupational profiles and voting behavior. Specifically, we estimate:

$$\begin{aligned} \text{green voting}_{icrt} = \beta_1 \, & \text{predicted brownness}_i + \\ & + \beta_2 \, \text{predicted brownness}_i \times \mathrm{S}_r \times \Delta \text{ green patents}_t + \\ & + \mathbf{X}_i' \lambda + \omega_{ct} + \delta_r + \varepsilon_{irct} \end{aligned} \tag{6}$$

$$\begin{aligned} \text{green voting}_{icrt} = \beta_3 \, & \text{predicted greenness}_i + \\ & + \beta_4 \, \text{predicted greenness}_i \times \mathrm{S}_r \times \Delta \text{ green patents}_t + \\ & + \mathbf{X}_i' \lambda + \omega_{ct} + \delta_r + \varepsilon_{irct} \end{aligned} \tag{7}$$

where S_r is the regional suitability for either solar or wind energy production, depending on the estimated model. We compute such measures of suitability based on geographic characteristics and on the local intensity of solar radiation and wind speed, respectively. Full details on the methodology are provided in Section D of the Online Appendix. These measures of suitability are interacted with Δgreen patents$_t$, that is the change in the number of patents in environment-related technologies issued in the United States. This is computed as $\Delta\text{green patents}_t = \ln\left(\sum_{s=t-10}^{t-1} \text{new green patents}_s\right) - \ln\left(\sum_{s=t-20}^{t-11} \text{new green patents}_s\right)$. We use green patents to proxy for global trends in green investments and green technologies adoption, which capture the salience of the ecological transition. We focus on US green patents as these are not directly related to potentially endogenous policy decisions specific to the sample countries.

5 Results

Table 1 displays the baseline estimates of Equations (4) and (5). In the odd-numbered columns the outcome variable is a dummy equal to 1 if the individual reports voting for a Green party; in the even-numbered columns the outcome is the environmentalism score of the party voted. In columns 1-2 we focus on predicted brownness; in columns 3-4 on predicted greenness; in columns 5-6 we include both scores jointly.

Higher predicted brownness leads to less environmentalist voting, while higher predicted greenness leads to more environmentalist voting. These findings are consistent across the two different outcome variables. In terms of magnitudes, considering fixed effects and using variation in the residualized variables following Mummolo and Peterson (2018), according to the estimates in columns 1-2 an increase by one standard deviation in the predicted brownness score decreases the probability of voting for a Green party by 0.95 percentage points, and the environmentalism score of the party voted by 4.6% of a standard deviation. According to the estimates in columns 3-4, an increase by one standard deviation in the predicted greenness score increases the probability of voting for a Green party by 3.7 percentage points, and the environmentalism score of the party voted by 11.9% of a standard deviation.

In the baseline specifications we include predicted greenness and predicted brownness separately. In fact, as discussed above, these scores reflect two alternative ways of evaluating occupational profiles as related to the green transition, along the green vs. brown dimension. If anything, including both scores jointly in the same regression leads to stronger results in absolute value, as can be seen in columns 5-6. Yet, in the model including both scores the coefficients are identified only from variation in either predicted score conditional on the other. This is potentially problematic in terms of the effective sample on which the estimation is based (Aronow and Samii, 2016). Therefore we prefer to adopt a conservative approach and focus on the baseline specifications in the rest of the analysis.

5.1 Robustness

In Table 2 we augment the baseline specifications with controls for the brownness and greenness scores of the current occupation. The estimation sample is therefore restricted to individuals in paid work. The baseline results on predicted brownness and greenness are essentially unaffected in terms of significance and magnitude. As for current brownness and greenness, there is only one association that is close to statistical significance, in column 2 (p-value=0.109), suggesting that a higher brownness score of the current occupation is negatively associated with the environmentalism score of the party voted. Overall, these results point to the importance of focusing on occupational profiles, rather than on current occupation, for assessing the role of material interest in the context of the green transition.

Table 1: Baseline estimates

VARIABLES	(1) Green party	(2) Environ	(3) Green party	(4) Environ	(5) Green party	(6) Environ
Pred. brownness	-0.325***	-1.829***			-0.511***	-2.552***
	(0.090)	(0.403)			(0.094)	(0.420)
Pred. greenness			1.485***	5.543***	1.705***	6.645***
			(0.197)	(0.832)	(0.205)	(0.866)
Observations	40,060	39,968	40,060	39,968	40,060	39,968
R^2	0.091	0.338	0.092	0.338	0.093	0.339
Individual controls	✓	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Mean	0.083	3.573	0.083	3.573	0.083	3.573

Notes: Individual controls include age group, gender, and years of education. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In Table 3 we perform a number of additional robustness checks. All of them confirm the main results. Specifically, in row 1 we include fixed effects for the current industry of employment, at the NACE 2-digit level. By doing so, we are identifying the effects of predicted brownness and greenness from variation across individuals within the same industry. The sample is therefore restricted to individuals in paid work. In row 2, we expand

Table 2: Controlling for current brownness and greenness

VARIABLES	(1) Green party	(2) Environ	(3) Green party	(4) Environ
Pred. brownness	-0.338***	-1.849***		
	(0.100)	(0.434)		
Brownness	-0.010	-0.076		
	(0.008)	(0.048)		
Pred. greenness			1.406***	4.651***
			(0.217)	(0.914)
Greenness			0.007	-0.020
			(0.011)	(0.050)
Observations	32,961	32,889	32,961	32,889
R^2	0.092	0.339	0.093	0.339
Individual controls	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Mean	0.087	3.596	0.087	3.596

Notes: Individual controls include age group, gender, and years of education. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

the estimation sample and replicate the baseline regressions including retired people.

Next, we address the potential concern that the region of residence might be endogenous to labor market opportunities, as individuals may migrate across regions in search of (better) jobs. Specifically, in row 3 we exclude region fixed effects from the multinomial logit models that we estimate for the prediction of individual probabilities of employment in each occupation. This entails estimating such probabilities based on the pre-sample *national* composition of the labor market, rather than on the regional one. In the same spirit, in row 4 we exclude migrants from the sample. We define migrants as individuals who were born in a country that is different from their current country of residence (international migration), or individuals who were born in a region different from their current region of residence within the same country (internal migration). While identifying international migrants is relatively straightforward, isolating internal migrants is more complicated, as the ESS does not provide information on the region of birth. We then use self-reported ethnic identification and exclude from the sample individuals who identify as members of an ethnic group that is not the majority in their current region of residence. For instance, we exclude Walloons living in Flanders, Catalans living in the Madrid region, or Scots living in the London region.

In rows 5 and 6, we use older labor force survey data to estimate the occupational models. Specifically, in row 5 we use EU-LFS data from 2000-2001, while in row 6 we use EU-LFS data from 1995-1996. In row 7, we control for (NUTS-2) region-specific time trends, while in row 8 we include region-year fixed effects, thus allowing for region-specific trajectories in a more flexible way. In row 9, we exclude individuals born after 1980, who might have adjusted their educational choices foreseeing the challenges and opportunities brought by the green transition. In row 10, we include as control an indicator variable for unionized workers. In row 11, we cluster the standard errors at the occupation-country level. In row 12 we account for the uncertainty of predicted brownness and greenness scores deriving from the estimation of employment probabilities in the occupational models. The posterior simulation approach for uncertainty propagation is explained in Section B of the Online Appendix.

Row 13 presents an additional robustness check on predicted brownness, where we employ a discrete version of the predicted brownness score. This is obtained by multiplying the individual probabilities of employment by the indicator variable for brown occupations, instead of the continuous measure of brownness employed in the main analysis. Results are substantively unaffected. Finally, in row 14 we show that results are robust to using the broad environmentalism score introduced in Section 3.1 as outcome variable.

5.2 Party families and policy preferences

To further characterize the implications of environmental material interest for voting behavior, in Table 4 we assess the effects of predicted brownness and greenness on support for parties belonging to different party families. Specifically, panel A focuses on predicted brownness, while panel B focuses on predicted greenness. In column 1, the dependent variable is a dummy equal to 1 if the individual reports voting for a radical-right party. In

Table 3: Robustness checks

	(1)	(2)	(3)	(4)
Dependent Variable:	Green party	Environ	Green party	Environ
Explanatory Variable:	Pred. brownness		Pred. greenness	
1) Including current industry FE	-0.223**	-1.518***	1.420***	4.754***
	(0.100)	(0.440)	(0.219)	(0.927)
2) Including the retired	-0.281***	-0.823***	1.429***	4.111***
	(0.058)	(0.291)	(0.141)	(0.625)
3) Excluding region FE from occupational models	-0.564***	-2.192***	1.527***	5.829***
	(0.102)	(0.440)	(0.207)	(0.911)
4) Excluding migrants	-0.327***	-1.848***	1.551***	5.648***
	(0.093)	(0.418)	(0.204)	(0.863)
5) Using EU-LFS data from 2000-2001	-0.312***	-1.648***	1.245***	5.512***
	(0.084)	(0.393)	(0.199)	(0.849)
6) Using EU-LFS data from 1995-1996	-0.224***	-2.119***	0.800***	4.509***
	(0.084)	(0.398)	(0.171)	(0.794)
7) Controlling for region-specific time trends	-0.329***	-1.859***	1.485***	5.599***
	(0.091)	(0.402)	(0.197)	(0.829)
8) Controlling for region-year FE	-0.325***	-1.828***	1.483***	5.675***
	(0.091)	(0.402)	(0.197)	(0.830)
9) Excluding born after 1980	-0.312***	-1.461***	1.500***	4.980***
	(0.102)	(0.452)	(0.220)	(0.953)
10) Controlling for union membership	-0.322***	-1.805***	1.459***	5.467***
	(0.092)	(0.407)	(0.200)	(0.846)
11) Clustering at occupation-country level	-0.325***	-1.829***	1.485***	5.543***
	(0.095)	(0.430)	(0.230)	(0.894)
12) Accounting for uncertainty in occupational models	-0.332***	-1.845***	1.480***	5.574***
	(0.091)	(0.407)	(0.204)	(0.846)
13) With discrete measure of brownness	-0.144***	-1.137***	-	-
	(0.049)	(0.220)		
14) Using broad environmentalism score	-	-1.448***	-	6.108***
		(0.347)		(0.698)

Notes: All specifications include individual controls (age group, gender, and years of education). Country-year FE and region FE are always included, except for rows 7-8. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

columns 2-4 the focus is on parties of the radical left, mainstream right, and mainstream left, respectively. For completeness of exposition, column 5 replicates the baseline results on Green parties.[13]

[13]Radical-right parties are identified based on consensus in the literature; their list is reported in Table A3 of the Online Appendix. Radical-left parties are those classified as communist and socialist by the Manifesto

Individuals with higher predicted brownness scores are more likely to support radical-right parties, and less likely to support mainstream-right parties. At the same time, they are less likely to support Green parties and more likely to support mainstream-left parties. These results are consistent with a re-shuffling of preferences within the right camp and the left camp, respectively, and are in line with existing evidence by Dickson and Hobolt (2024) on the link between climate attitudes and vote choice. Individuals with higher predicted greenness scores are less likely to support radical-right and mainstream-left parties, and more likely to support Green parties.

As a further extension of the analysis, in Table 5 we focus on policy preferences related to the green transition. In particular, we use two items in wave 8 of the ESS. The first item measures support for increases in fossil fuel taxes to reduce climate change; the second measures support for subsidies in favor of renewable energy to reduce climate change. Answers to both items are provided on a 5-point Likert scale, from "strongly against" to "strongly in favor". The specifications are the same as in the baseline analysis but country-year fixed effects are not included since the analysis is cross-sectional. Individuals with higher predicted greenness scores are significantly more supportive of both higher taxes on fossil fuels and higher subsidies for renewables. Conversely, individuals with higher predicted brownness scores are significantly less supportive of increases in fossil fuel taxes. These results are in line with the evidence on voting behavior, and provide a further validation of our measures of material interest in the context of the green transition.

5.3 Analysis including shifters

In this section, we augment the baseline specifications with region-specific, time-varying shifters that capture variation in the opportunities stemming from the ecological transition. By interacting these shifters with predicted scores of greenness and brownness, we explore heterogeneous effects related to residing in regions that are better or worse placed to gain

Project, plus others according to the classification by Rooduijn et al. (2024); their list is reported in Table A4 of the Online Appendix. We classify as mainstream left all parties that, according to the Manifesto Project, belong to the Social-Democratic party family. Similarly, we classify as mainstream right all parties that, according to the Manifesto Project, belong to the Liberal, Christian-Democratic, and Conservative party families, and are not classified as radical-right parties.

Table 4: Party families

Panel A					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Radical right	Radical left	Mainstream right	Mainstream left	Green
Pred. brownness	1.311***	-0.116	-1.452***	0.366**	-0.325***
	(0.101)	(0.091)	(0.177)	(0.160)	(0.090)
Observations	40,060	40,060	40,060	40,060	40,060
R^2	0.099	0.065	0.080	0.077	0.091
Individual controls	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Mean	0.072	0.071	0.429	0.267	0.083
Panel B					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Radical right	Radical left	Mainstream right	Mainstream left	Green
Pred. greenness	-0.521***	-0.048	0.154	-0.998***	1.485***
	(0.163)	(0.205)	(0.353)	(0.320)	(0.197)
Observations	40,060	40,060	40,060	40,060	40,060
R^2	0.093	0.065	0.078	0.077	0.092
Individual controls	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓
Mean	0.072	0.071	0.429	0.267	0.083

Notes: All specifications include individual controls (age group, gender, and years of education), country-year FE, and region FE. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

from the green transition, as this becomes more salient.

Tables 6 and 7 present estimates of Equations (6) and (7). Table 6 uses regional suitability for solar energy as a proxy for S_r, while Table 7 uses regional suitability for wind energy. The two tables provide very similar evidence. The baseline results on the linear terms of predicted brownness and greenness are confirmed. In both tables, the interaction terms are significant in columns 1 and 3, i.e., where the outcome variable captures voting for a Green party. In particular, the interactions with predicted greenness are positive, suggesting that the positive link between predicted greenness and environmentalist voting

Table 5: Policy preferences

	(1)	(2)	(3)	(4)
VARIABLES	Pro fossil fuel tax		Pro subs. renewable	
Pred. brownness	-4.815***		-0.714	
	(0.715)		(0.628)	
Pred. greenness		3.279**		3.818***
		(1.364)		(1.107)
Observations	15,883	15,883	15,962	15,962
R^2	0.130	0.127	0.075	0.075
Individual controls	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Mean	2.876	2.876	4.035	4.035

Notes: Individual controls include age group, gender, and years of education. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

is stronger in regions that are better placed to gain from the green transition, as the green transition becomes more salient. Interestingly, the interactions with predicted brownness are also positive. This suggests that individuals with browner occupational profiles display voting preferences that are closer to those of less brown profiles in contexts where the positive effects of the green transition are more likely to be tangible.

To get a sense of the substantive implications, the average change in (log) patents is approximately equal to 2. In a low suitability region (i.e., at the 10th percentile of the distribution of solar suitability), the probability of supporting a Green party is 1.5 percentage points lower for individuals a one standard deviation higher in terms of predicted brownness. In a higher suitability region (i.e., at the 90th percentile) the effect of higher brownness is essentially zero and not statistically significant. That is, higher suitability attenuates, and mutes in the limit, the effect of differences in brownness. The divergence between high and low suitability regions in terms of how much brownness matters would be amplified in years characterized by higher changes in patents. The same exact pattern emerges with wind suitability.[14] These findings offer additional evidence highlighting the relevance of

[14]These results are robust to including all the double interaction terms. According to those estimates, at the mean of change in log patents, in a low-suitability region the probability of supporting a Green party is

occupation-based material interest in shaping voting behavior in the context of the green transition.

Table 6: Regional shifters – Solar suitability

VARIABLES	(1) Green party	(2) Environ	(3) Green party	(4) Environ
Pred. brownness	-0.667***	-1.743***		
	(0.105)	(0.451)		
Pred. brownness $\times$ S_r $\times$ Δ green patents$_t$	0.006***	-0.001		
	(0.001)	(0.004)		
Pred. greenness			1.171***	6.053***
			(0.216)	(0.877)
Pred greenness $\times$ S_r $\times$ Δ green patents$_t$			0.004***	-0.006
			(0.001)	(0.004)
Observations	39,939	39,849	39,939	39,849
R^2	0.092	0.339	0.092	0.339
Individual controls	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Mean	0.083	3.574	0.083	3.574

Notes: Individual controls include age group, gender, and years of education. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusion

We investigate the role of material interest in shaping environmental voting, using individual-level data from 14 Western European countries over 2010–2019. Our focus is on occupation-related material interest. This is measured by the greenness vs. brownness of occupational profiles, which capture the extent to which individuals are expected to benefit rather than be penalized as the green transition impacts the labor market.

2.3 percentage points lower for individuals one standard deviation higher in brownness. In a high-suitability region the effect is negligible in size and not statistically significant at conventional levels. The implications regarding the effects of greenness and brownness at low and high levels of renewable suitability are always identical in the models with and without the two-way interaction terms.

Table 7: Regional shifters – Wind suitability

VARIABLES	(1) Green party	(2) Environ	(3) Green party	(4) Environ
Pred. brownness	-0.603***	-1.410***		
	(0.105)	(0.452)		
Pred. brownness $\times$ S_r $\times$ Δ green patents$_t$	0.007***	-0.009		
	(0.001)	(0.006)		
Pred. greenness			1.183***	6.041***
			(0.216)	(0.878)
Pred. greenness $\times$ S_r $\times$ Δ green patents$_t$			0.006***	-0.007
			(0.001)	(0.006)
Observations	39,939	39,849	39,939	39,849
R^2	0.091	0.339	0.092	0.339
Individual controls	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓
Region FE	✓	✓	✓	✓
Mean	0.083	3.574	0.083	3.574

Notes: Individual controls include age group, gender, and years of education. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We argue that current occupation alone does not fully characterize an individual's occupational profile, as it fails to account for the broader job market opportunities available to individuals based on their demographic characteristics and the composition of the labor market in their region of residence. Moreover, relying on current occupation excludes unemployed individuals and introduces endogeneity concerns in vote regressions, as occupational choices and voting behavior may share common confounders.

To address these issues, we propose a novel approach that isolates plausibly exogenous variation in occupation-related material interest. We compute predicted greenness and brownness scores that reflect labor market opportunities without relying on the current observed occupation. Specifically, we estimate each individual's probability of employment in all occupations by combining individual characteristics with pre-sample employment data in their region of residence. Predicted greenness and brownness are then constructed as weighted averages of occupation-specific greenness and brownness scores, with weights given by individual employment probabilities.

We find that individuals with higher predicted brownness are less likely to vote for Green parties and for parties with more environmentalist agendas, while those with higher predicted greenness show the opposite pattern. Studying vote choice by party family, we find that in the right camp higher predicted brownness increases support for radical-right parties and reduces support for mainstream-right parties. In the left camp, it is associated with less support for Green parties and more support for mainstream-left parties. Conversely, higher predicted greenness reduces support for both radical-right and mainstream-left parties, while increasing support for Green parties. We also document how policy preferences for green subsidies and fossil fuel taxes are shaped by the greenness and browness of one's occupational profile, in a direction fully consistent with the voting behavior results: browner profiles oppose fossil fuel taxes, while greener profiles favor green subsidies and fossil fuel taxes.

We further interact predicted greenness and brownness with region-specific, time-varying shifters that capture variation in opportunities from the green transition. We document that individuals in regions better positioned to gain from the green transition tend to develop greener preferences as the transition becomes more salient. In particular, individuals with higher predicted brownness scores display voting preferences that converge towards those of less brown profiles. These results corroborate the significance of occupation-based material interest for voting behavior in the context of the green transition.

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Green Collars at the Voting Booth: Material Interest and Environmental Voting

Online Appendix

Table of content

A: Estimation of individual greenness and brownness

B: Uncertainty propagation

C: Additional information

D: Measuring wind and solar suitability at the regional level

A Estimation of individual greenness and brownness

In the individual-level analysis, we use data from waves 5-9 of the European Social Survey (ESS), covering elections spanning the period 2010-2019. For each individual, we observe voting behavior along with demographic characteristics and region of residence. The computation of predicted greenness and predicted brownness scores relies on estimates of the individual probabilities of employment in each occupation. To obtain these estimates, we proceed in two steps.

We first estimate multinomial logit models of occupational choice based on European Labor Force Survey (EU-LFS) data for 2005-2006. These models have the set of all occupations as outcome variable, while the predictors are age, gender, educational attainment, and region of residence. Occupations are defined at the 2-digit level of the International Standard Classification of Occupations (ISCO). We estimate the models separately for each country. The parameter estimates obtained from these models reflect the occupational outcomes of workers with a given profile in each country and region, in the labor market immediately prior to the study period.

We then calculate predicted probabilities of being in each occupation for the ESS respondents, based on their observables and the parameter estimates obtained from the LFS estimation. These probabilities are then used as weights to calculate the predicted brownness and predicted greenness of each respondent, based on Equations (2) and (3).

B Uncertainty propagation

In row 12 of Table 3, we incorporate the uncertainty regarding the parameters of the occupational models in the estimation of the voting models. In practice, we want to account for the fact that the measures of individual greenness and brownness are based on predicted probabilities derived from parameters that are themselves estimated.

Formally, the probabilities $\widehat{Pr}(o_i = j|\text{age}, \text{gender}, \text{edu}, \text{reg})$ that appear in Equations (2)-(3) of the main manuscript are based on the estimates of the multinomial logit models: for each country, we estimate a vector of parameters $\hat{\gamma}$ that link observable characteristics of the individuals in the EU-LFS sample to their observed occupation. At a subsequent stage, we predict, out of sample, the $\widehat{Pr}(o_i = j)$ for each individual $i \in$ ESS, and for all occupations j, based on these $\hat{\gamma}$ estimates. These probabilities are used in turn to compute individual predicted greenness and brownness scores, which are the main explanatory variables in the voting models.

To account for the uncertainty of the occupational model estimates, we implement the following algorithm:

For $m \in 1, 2, \ldots, M$ with $M = 100$,

1. draw a vector of parameters $\tilde{\gamma}^{(m)}$ from the posterior distribution of γ;
2. predict $\widetilde{Pr}^{(m)}(o_i = j)$ for all j and for each $i \in$ ESS based on $\tilde{\gamma}^{(m)}$;
3. compute predicted greenness$_i^{(m)}$ and predicted browness$_i^{(m)}$ for each $i \in$ ESS following Equations (2)-(3) of the main manuscript, using the simulated $\widetilde{Pr}^{(m)}(o_i = j)$ instead of the $\widehat{Pr}(o_i = j)$ estimate;
4. get a point estimate $\tilde{\beta}^{(m)}$ and variance estimate $\tilde{V}_{\beta}^{(m)}$ for the parameters β_1 and β_2 in the voting models of Equations (4)-(5) in the main text, using predicted greenness$_i^{(m)}$ and predicted browness$_i^{(m)}$ as predictors.

This procedure yields M estimates $\tilde{\beta}^{(m)}$ of the voting model parameters for each of predicted brownness and predicted greenness. We then compute (and report) the average $\overline{\beta} = \frac{1}{M}\sum_m \tilde{\beta}^{(m)}$, and the standard errors for β_1 and β_2 based on the formula:

$$\mathrm{SE}_{\mathrm{fi}}^{\mathrm{sim}} = \left(\frac{1}{M} \sum_m \tilde{V}_{\beta}^{(m)} + (1 + \frac{1}{M}) \frac{1}{M-1} \sum_m (\tilde{\beta}^{(m)} - \overline{\beta})^2 \right)^{\frac{1}{2}}$$

We perform this exercise for the baseline regressions of columns 1-4 in Table 1. Incorporating this additional source of uncertainty turns out to be fundamentally inconsequential for the findings, with only slightly wider confidence intervals. A full data package with the simulated coefficients of the occupational model and the simulated individual vulnerabilities will be made available in the replication package.

C Additional information

Table A1: Greenness and brownness scores by occupation

ISCO08 Title	ISCO08 Code	Greenness	Brownness	Brown dummy
Agricultural and forestry production managers	1311	.0481256	0	0
Agricultural and industrial machinery mechanics and repairers	7233	.1111111	.3333333	1
Agricultural technicians	3142	.0550568	0	0
Air conditioning and refrigeration mechanics	7127	.0657744	0	0
Air traffic safety electronics technicians	3155	.100273	0	0
Animal producers n.e.c.	6129	0	1	1
Aquaculture and fisheries production managers	1312	.0481256	0	0
Bicycle and related repairers	7234	1	0	0
Biologists, botanists, zoologists and related professionals	2131	.0690929	.1111111	0
Blacksmiths, hammersmiths and forging press workers	7221	0	1	1
Bleaching, dyeing and fabric cleaning machine operators	8154	0	1	1
Bricklayers and related workers	7112	0	.5	1
Building and related electricians	7411	.5	0	0
Building architects	2161	.2682825	0	0
Building construction labourers	9313	.0263455	0	0
Building frame and related trades workers n.e.c.	7119	.5887991	0	0
Bus and tram drivers	8331	1	0	0
Business services agents n.e.c.	3339	.0615079	0	0
Business services and administration managers n.e.c.	1219	.0660316	0	0
Butchers, fishmongers and related food preparers	7511	0	.25	0
Cement, stone and other mineral products machine operators	8114	0	1	1
Chemical and physical science technicians	3111	.0572719	1	1
Chemical engineering technicians	3116	.1064441	1	1
Chemical engineers	2145	0	1	1
Chemical processing plant controllers	3133	0	1	1
Chemical products plant and machine operators	8131	0	1	1
Chemists	2113	0	.5	1
Civil engineering technicians	3112	.0446421	0	0
Civil engineers	2142	.3267401	0	0
Commercial sales representatives	3322	.055	0	0
Construction managers	1323	.2260342	0	0
Crane, hoist and related plant operators	8343	0	.2	0
Customs and border inspectors	3351	.0062789	0	0
Dairy-products makers	7513	0	1	1
Database and network professionals n.e.c.	2529	.0030657	0	0
Earthmoving and related plant operators	8342	0	.4	1
Electrical engineering technicians	3113	.089361	0	0
Electrical engineers	2151	.1606959	0	0
Electrical line installers and repairers	7413	1	0	0
Electrical mechanics and fitters	7412	.1348	.1538462	0
Electronics engineering technicians	3114	.100273	0	0
Electronics engineers	2152	.0491788	0	0
Electronics mechanics and servicers	7421	.1348	.1428571	0
Engineering professionals n.e.c.	2149	.1423095	0	0
Environmental and occupational health and hygiene professionals	2263	1	0	0
Environmental and occupational health inspectors and associates	3257	.1198021	0	0
Environmental engineers	2143	1	0	0
Environmental protection professionals	2133	1	0	0
Farming, forestry and fisheries advisers	2132	.2072786	0	0
Fibre preparing, spinning and winding machine operators	8151	0	1	1
Financial analysts	2413	.0672838	0	0
Financial and insurance services branch managers	1346	.0566944	0	0
Financial and investment advisers	2412	.1563042	0	0
Food and related products machine operators	8160	0	1	1
Forestry and related workers	6210	1	0	0
Forestry labourers	9215	1	0	0
Forestry technicians	3143	1	0	0

ISCO08 Title	ISCO08 Code	Greenness	Brownness	Brown dummy
Garbage and recycling collectors	9611	.5	0	0
Garden and horticultural labourers	9214	0	0	0
Gardeners, horticultural and nursery growers	6113	1	0	0
Garment and related pattern-makers and cutters	7532	0	.3333333	1
Geologists and geophysicists	2114	.2149376	1	1
Glass and ceramics plant operators	8181	0	1	1
Glass makers, cutters, grinders and finishers	7315	0	1	1
Government licensing officials	3354	.0094184	0	0
Government social benefits officials	3353	.0094184	0	0
Heavy truck and lorry drivers	8332	.0427818	0	0
House builders	7111	.2260342	0	0
Incinerator and water treatment plant operators	3132	.240863	.5	1
Industrial and production engineers	2141	.05	0	0
Information and communications technology sales professionals	2434	.055	0	0
Information technology trainers	2356	.0862385	0	0
Insulation workers	7124	.3	0	0
Journalists	2642	.0193069	0	0
Landscape architects	2162	.260082	0	0
Legal professionals n.e.c.	2619	.0382507	0	0
Life science technicians (excluding medical)	3141	.5	0	0
Livestock and dairy producers	6121	0	1	1
Locomotive engine drivers	8311	1	0	0
Manufacturing labourers n.e.c.	9329	.25	.25	0
Mechanical engineering technicians	3115	.0462233	0	0
Mechanical engineers	2144	.2947051	0	0
Mechanical machinery assemblers	8211	.0647683	0	0
Metal finishing, plating and coating machine operators	8122	0	1	1
Metal moulders and coremakers	7211	0	.5	1
Metal polishers, wheel grinders and tool sharpeners	7224	0	1	1
Metal processing plant operators	8121	0	1	1
Metal production process controllers	3135	0	1	1
Metal working machine tool setters and operators	7223	.005985	.3636364	1
Meteorologists	2112	.4329176	0	0
Meter readers and vending-machine collectors	9623	0	.5	1
Mineral and stone processing plant operators	8112	0	1	1
Miners and quarriers	8111	0	1	1
Mining and metallurgical technicians	3117	0	1	1
Mining and quarrying labourers	9311	0	1	1
Mining engineers, metallurgists and related professionals	2146	0	1	1
Mining managers	1322	0	1	1
Mining supervisors	3121	0	1	1
Mobile farm and forestry plant operators	8341	1	0	0
Motor vehicle mechanics and repairers	7231	.0340898	0	0
Odd job persons	9622	.13	0	0
Other cleaning workers	9129	0	1	1
Packing, bottling and labelling machine operators	8183	0	1	1
Paper products machine operators	8143	0	1	1
Petroleum and natural gas refining plant operators	3134	0	1	1
Philosophers, historians and political scientists	2633	.0449735	0	0
Physical and engineering science technicians n.e.c.	3119	.1584036	0	0
Physicists and astronomers	2111	.05	0	0
Plastic products machine operators	8142	0	.5833333	1
Plumbers and pipe fitters	7126	.1206143	0	0
Policy administration professionals	2422	.3333333	0	0
Policy and planning managers	1213	.3961895	0	0
Potters and related workers	7314	0	.5	1
Poultry producers	6122	0	1	1
Power production plant operators	3131	.119538	.5	1
Product graders and testers (excluding foods and beverages)	7543	.0613655	0	0
Professional services managers n.e.c.	1349	.3961895	0	0
Public relations professionals	2432	.2130159	0	0
Pulp and papermaking plant operators	8171	0	1	1

ISCO08 Title	ISCO08 Code	Greenness	Brownness	Brown dummy
Railway brake, signal and switch operators	8312	1	0	0
Refuse sorters	9612	1	0	0
Research and development managers	1223	.0893194	0	0
Retail and wholesale trade managers	1420	.1133889	0	0
Roofers	7121	.3009046	0	0
Rubber products machine operators	8141	0	1	1
Sales and marketing managers	1221	.0860184	0	0
Securities and finance dealers and brokers	3311	.006681	0	0
Senior government officials	1112	.0377963	0	0
Senior officials of special-interest organizations	1114	.1698594	0	0
Sewing, embroidery and related workers	7533	0	.3333333	1
Sheet-metal workers	7213	.0713787	.3333333	1
Shotfirers and blasters	7542	0	1	1
Software and applications developers and analysts n.e.c.	2519	.0061315	0	0
Sports, recreation and cultural centre managers	1431	.1980947	0	0
Spray painters and varnishers	7132	0	.5	1
Stationary plant and machine operators n.e.c.	8189	0	.5	1
Stock clerks	4321	.0284543	0	0
Subsistence livestock farmers	6320	0	1	1
Supply, distribution and related managers	1324	.2216368	0	0
Technical and medical sales professionals (excluding ICT)	2433	.055	0	0
Telecommunications engineering technicians	3522	.100273	0	0
Telecommunications engineers	2153	.0983575	0	0
Tobacco preparers and tobacco products makers	7516	0	.6666667	1
Toolmakers and related workers	7222	0	.3333333	1
Town and traffic planners	2164	.3604269	0	0
Trade brokers	3324	.004454	0	0
Training and staff development professionals	2424	.0862385	0	0
Transport conductors	5112	1	0	0
Upholsterers and related workers	7534	0	1	1
Weaving and knitting machine operators	8152	0	1	1
Well drillers and borers and related workers	8113	.0083476	1	1
Wood processing plant operators	8172	0	1	1
Wood treaters	7521	0	1	1
Woodworking-machine tool setters and operators	7523	0	1	1

Notes: The table shows greenness and brownness scores (including the brown discrete measure) for all ISCO08 occupations with at least one of the scores greater than 0.

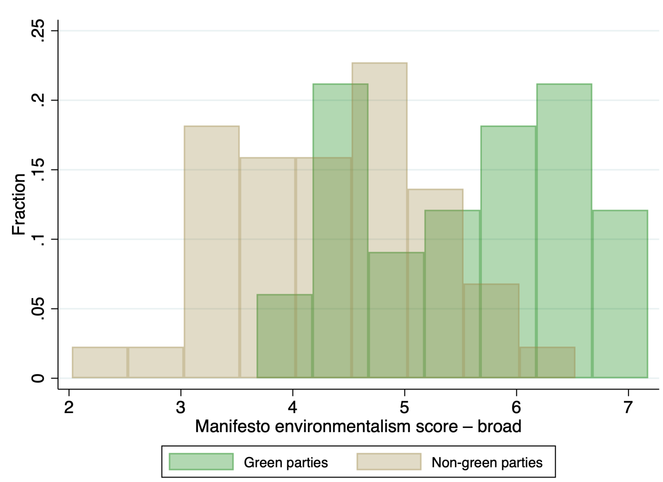

Figure A1: Distribution of broad environmentalism score by type of party

Notes: The figure shows broad environmentalism score distributions for Green vs. non-Green parties.

Table A2: List of Green parties

Party name	Country
Grüne	Austria
Agalev/Groen!	Belgium
Ecolo	Belgium
Green League	Finland
EELV (Europe Ecologie Les Verts)	France
Les Verts	France
Other ecologists movements	France
Alliance 90/The Greens	Germany
Green Party	Ireland
Green Left	Netherlands
Miljøpartiet De Grønne	Norway
PAN - Pessoas-Animais-Natureza	Portugal
PACMA	Spain
Miljöpartiet de gröna	Sweden
Green Liberal Party	Switzerland
Green Party	Switzerland
Green Party	United Kingdom

Notes: Parties are labelled as green either because they belong to the European Green Party or because of the Manifesto Project classification (see Section 3.1). Each of these parties ran for office in at least one election over the sample period while satisfying at least one of these two conditions.

Table A3: List of radical-right parties

Party name	Country
Alliance for the Future of Austria	Austria
Austrian Freedom Party	Austria
Team Stronach for Austria	Austria
Belgian National Front	Belgium
Flemish Interest	Belgium
True Finns	Finland
National Front	France
Alternative for Germany	Germany
National Democratic Party of Germany	Germany
Brothers of Italy	Italy
Casapound	Italy
Northern League	Italy
Forum for Democracy	Netherlands
Party for Freedom	Netherlands
Progress Party	Norway
Vox	Spain
Sweden Democrats	Sweden
Swiss People's Party	Switzerland
United Kingdom Independence Party	United Kingdom

Notes: Radical-right parties are identified based on consensus in the literature.

Table A4: List of radical-left parties

Party name	Country
Workers' Party of Belgium	Belgium
Left Wing Alliance	Finland
French Communist Party	France
Left Front	France
Die Linke	Germany
Sinn Féin	Ireland
Civil Revolution	Italy
Left Ecology Freedom	Italy
Socialist Party	Netherlands
Socialist Left Party	Norway
Left Bloc	Portugal
Portuguese Communist Party	Portugal
En Marea	Spain
Galician Nationalist Bloc	Spain
Izquierda Unida	Spain
Podemos	Spain
Unidas Podemos	Spain
Left Party	Sweden
Swiss Labour Party	Switzerland

Notes: Radical-left parties are those classified as communist and socialist by the Manifesto Project, plus others according to the classification by Rooduijn et al. (2024).

Table A5: Correlation between environmental vote measures

	Green party dummy	Environ score	Broad environ score
Green party dummy	1		
Environ score	0.315***	1	
Broad environ score	0.249***	0.914***	1

Notes: Pairwise correlation coefficients. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

D Measuring wind and solar suitability at the regional level

We calculate two indicators of suitability for renewable energies at the regional level, separately for wind and solar (photovoltaic) power generation, adapting the general lines of the approach suggested by Castillo, e Silva and Lavalle (2016) and taking some inspiration from the report by the European Topic Centre for Air and Climate Change (2009). The suitability is based on three types of information: the intensity of the phenomenon that produces energy (solar radiation, or wind speed); constraints present in areas (e.g., dense urban areas) where installation of equipment is not possible; and geographic characteristics, like elevation of the terrain and distance from existing transportation infrastructure, that affect the cost of setting up and operating a power conversion plant.

Geographic data. We collect the following geographic data for the constraints. From the Harmonized World Soil Database (Fischer et al., 2008)[15], we obtain data about urbanization, forests, and water bodies from the Land Use and Land Cover data at the 5' grid-cell resolution (less than 10km side). We classify as urbanized those cells that are more than 15% builtup, and we classify as forest those cells that are more than 80% covered by forest. From the Common Database on Designated Areas (CDDA) of the European Environment Agency we identify all areas that are classified as "national parks" (type II) according to the International Union for Conservation of Nature classification. Based on these, we defined as constrained those areas that are either urban, forests, national parks, or covered by a water body (also relying on the Fischer et al. (2008) data). For wind power generation, there is one additional constraint highlighted in Baseer et al. (2017): airports. We start with the shapefile of airport locations from GISCO Airports. This is a geographical dataset developed by the European Commission based on Corine Land Cover 2000 and Eurocontrol data. We retain only major ones: those classified as "main" and open to commercial traffic with at least 150,000 passengers as of 2004, or to military traffic. We then classify an area

[15] Available at https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/.

of radius 5km around the listed location of the airport as constrained.

We then collect further geographic data to capture suitability short of all-or-nothing constraints. We collect the Terrain slope classes of the world (FGGD)[16] at the 5' resolution. We rescale them so that 100 corresponds to the minimum and zero to the maximum slope (within the whole set of European countries we consider). Population density in the year 2000 (also at the 5' resolution) comes from CIESIN. Population density is first logged and then scaled so that the minimum corresponds to a value of 100 and the maximum to a value of zero (hence higher values indicate lower population density).

We prepare the data on electrical transmission lines starting from the vector data in SciGRID (Medjroubi and Matke, 2015), which we convert to a shapefile. We calculate, for each 5' cell in the grid, the distance from the closest electrical transmission line located in the same country. We then rescale the distances so that 100 corresponds to the minimum distance and 0 to the maximum distance (over the entire set of countries we consider).

Solar suitability: aggregation. The measure of radiation intensity comes from PVGIS. Specifically, we use the yearly average global irradiance on an optimally inclined surface (W/m2), over the period 2007-2016.[17] We rescale the values so that 0 corresponds to the minimum and 100 to the maximum, and coarsen the original data to the 5' resolution used in the geographic data.

The solar suitability is calculated at the level of the individual 5' cell as the weighted average of the rescaled values of radiation, slope, population density, and distance to transmission lines, where radiation, following Castillo, e Silva and Lavalle (2016), is assigned twice the weight of the others. We then assign suitability zero to all cells that are classified as constrained based on urbanization, forests, national parks, and water bodies. The cell-level suitability thus calculated is then aggregated at the NUTS-2 level by overlaying the Eurostat shapefile and taking the average suitability by region.

[16] http://www.fao.org:80/geonetwork/srv/en/resources.get?id=14131&fname=Map4$_6.zip$.

[17] https://joint-research-centre.ec.europa.eu/photovoltaic-geographical-information-system-pvgis/pvgis-data-download/cm-saf-solar-radiation$_en$

Wind suitability: aggregation. The measure of wind speed comes from ERA5. Neutral wind speeds at 10 meters are reported at the monthly level, decomposed into a north-south and an east-west component, at the resolution of one-tenth of a degree. It is the horizontal speed of air, at a height of ten metres above the surface of the Earth, in metres per second. We first calculate the wind speed for each location and each month, and then take the yearly average by location. We then re-rasterize at the 5' resolution.

As before, we take the weighted average of the wind speed and the geographic features for each cell, assigning double weight to wind speed. We then set suitability equal to zero in all areas that are constrained (including all the constraints for solar but, this time, also areas that are in proximity of a main airport). We then aggregate the data at the NUTS-2 level by overlaying the Eurostat shapefile and taking the average suitability by region.

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