ROCKWOOL Foundation Berlin
Institute for the Economy and the Future of Work (RFBerlin)

DISCUSSION PAPER SERIES 63/25

Demand for Green Skills in an Evolving Landscape

Esther Arenas-Arroyo, Jacob Fabian, Friederike Mengel, Bernhard Schmidpeter, Michel Serafinelli

www.rfberlin.com SEPTEMBER 2025

Demand for Green Skills in an Evolving Landscape

Authors

Esther Arenas-Arroyo, Jacob Fabian, Friederike Mengel, Bernhard Schmidpeter, Michel Serafinelli

Reference

JEL Codes: J23, Q54, L20, J24

Keywords: Green skills, Green transition, Online job postings

Recommended Citation: Esther Arenas-Arroyo, Jacob Fabian, Friederike Mengel, Bernhard Schmidpeter, Michel Serafinelli (2025): Demand for Green Skills in an Evolving Landscape. RFBerlin Discussion Paper No. 63/25

Access

Papers can be downloaded free of charge from the RFBerlin website: https://www.rfberlin.com/discussion-papers

Discussion Papers of RFBerlin are indexed on RePEc: https://ideas.repec.org/s/crm/wpaper.html

Disclaimer

Imprint

RFBerlin
ROCKWOOL Foundation Berlin –
Institute for the Economy
and the Future of Work

Gormannstrasse 22, 10119 Berlin
Tel: +49 (0) 151 143 444 67
E-mail: info@rfberlin.com
Web: www.rfberlin.com

Demand for Green Skills in an Evolving Landscape[*]

Esther Arenas-Arroyo[†] Jacob Fabian[‡] Friederike Mengel[§]
Bernhard Schmidpeter[¶] Michel Serafinelli[‖]

September 2025

Abstract

How does firms' skill demand change as the business landscape evolves? We present evidence from the green transition by analyzing how hurricanes impact demand for green skills. These disasters signal the risks of not acting on environmental issues. Using data from U.S. online job postings (2010–2019) and hurricane paths, we create a new measure of green job postings. Firms in areas affected by hurricanes are 6.4% more likely to post jobs that require green skills after the event, particularly those serving local markets.

Keywords: Green skills, Green transition, Online job postings, Hurricanes

JEL Codes: J23, Q54, L20, J24

[*]The authors are grateful to Pamela Campa, Carlos Carrillo-Tudela, Alex Clymo, Emma Duchini, Aseem Patel, and seminar participants at Birmingham, Brown, Collegio Carlo Alberto, EALE, EEA, MiSoC, Pescara, QMUL, and RWI Essen for their comments. This paper has not been funded or endorsed by ISO New England.

[†]Vienna University of Economics and Business (WU)
[‡]Market Development, ISO New England
[§]University of Essex and Erasmus University Rotterdam
[¶]Vienna University of Economics and Business (WU)
[‖]King's College London, ESCoE, RFBerlin, CESifo

1 Introduction

In many developed countries, the landscape in which most businesses operate is becoming increasingly dynamic. New technologies, geopolitical tensions, and the environmental transition are enhancing the pace at which a variety of industries are experiencing changes in their business outlook (Fine 1998; Garrett and Pavan 2012; Tooze 2022; World Economic Forum 2023).
The environmental transition, the main context of this study, requires a shift toward greener jobs and skills (Masterson, Victoria 2021; LinkedIn Corporation 2022; Organisation for Economic Co-operation and Development 2023). Although there is evidence that green jobs and demand for green skills have grown over the past years (Bergant, Mano, and Shibata 2022; Curtis and Marinescu 2022; LinkedIn Corporation 2022), the determinants of the demand for green skills remain unclear.

This paper provides direct evidence showing how skill demand changes in an evolving business landscape. Specifically, we study the role played by hurricanes, arguing that these disasters *convey new information* regarding the dangers of inaction on the environmental transition (Gagliarducci, Paserman, and Patacchini 2019; Hong, Wang, and Yang 2023).

A simple theoretical framework illustrates how experiencing a disaster can shift people's beliefs and lead to heightened concern about the environment. This heightened concern subsequently increases customer demand for clean products, the attractiveness of green vacancies for job applicants, and possibly the desire of the workforce and management to reduce the environmental footprint of the firm. The central empirical goal of the paper is to measure how demand for green skills changes after a hurricane. Our data set combines, for the period 2010–2019, data on jobs posted online in the United States, as collected by the labor market analytics company Lightcast[1], and information on hurricane trajectories. Using skill requirements, we create a new measure of green job postings and document how the occurrence of disasters affects the demand for green skills. Our green skills requirements are based on *requirements specified in firms' job advertisements*, rather than on occupational classification or industry. [2] Our unit of analysis is the county x industry. The empirical strategy exploits the timing and location of the occurrences of hurricanes within a difference-in-difference and event-study framework. We use data on the recorded paths of tropical and subtropical cyclones in the Atlantic and Pacific Oceans from 2010 to 2019. This data is provided by the National Oceanic and Atmospheric Administration's (NOAA) National Hurricane Center (NHC).

[1]The Lightcast brand takes the place of Emsi Burning Glass, a name established in 2021 following the merger of Emsi and Burning Glass Technologies.
[2]Lightcast employs a proprietary algorithm to extract skills from textual data.

Our results can be summarized as follows. Our difference-in-difference estimates indicate an increase in the share of posted jobs with at least one green skill of 0.28 percentage points following a hurricane. This is equivalent to a 6.4% increase relative to the mean. [3] The event-study estimates show that: (a) there is no pretreatment trend in the coefficients; (b) there is an upward shift in the share of green vacancies after the hurricane; and (c) the effect is persistent over time.[4]

We also show estimates indicating that the effect is larger for firms in the non-tradable sector, that is, firms that sell more locally. This evidence is consistent with previous research in the context of the media effects on corporate environmental decisions by Campa (2018). Moreover, we show that the estimated hurricane effect is qualitatively similar when we restrict the control group to a specific radius, namely, counties within 500, 250, or 100 km from the centroid of the treated county. These estimates suggest that geographic spillovers are not particularly relevant. Overall, these two pieces of evidence (i.e., for the non-tradable sector and using the nearby counties as the control group) confirm the localized nature of the impact.

Furthermore, we investigate whether or not the effect is limited to particular sectors of the economy and skills. Our results indicate that the effect is not confined to the construction sector, which typically experiences an overall increase in labor demand after a hurricane, nor to the utilities sector, which has recently exhibited an increase in green jobs in some segments of the industry (solar and wind) (Curtis and Marinescu 2022). Moreover, we document that the effect is not limited to vacancies that require skills related to regulation, for which demand is predicted to increase in expectation of environmental policy changes (Gagliarducci, Paserman, and Patacchini 2019).

Our paper relates to several bodies of work. First, it relates to the literature on drivers of labor demand, and in particular, firms' skill requirements (e.g., Deming and Kahn 2018; Hershbein and Kahn 2018; Modestino, Shoag, and Ballance 2020). We contribute by focusing on green skills and providing evidence on how firms react to new information during the environmental transition.

Our paper also relates to the literature on the green transition and the labor market (e.g., Basso, Colonna, Depalo, and Mendicino 2023), particularly the body of work documenting changes in green jobs over the past years (Bowen, Kuralbayeva, and Tipoe 2018; Vona, Marin, and Consoli 2019; Elliott et al. 2024; Bergant, Mano, and Shibata 2022; Curtis and Marinescu 2022; Saussay et al. 2022; Bachmann et al. 2024). These papers

[3] To contextualize the estimated effect, prior studies show varied impacts of labor market shocks on firms' skill demand. Hershbein and Kahn (2018) find deep recessions cause a persistent 8%–12% rise in demand for cognitive and IT skills. In contrast, Clemens, Kahn, and Meer (2021) report minimum wage hikes do not significantly change demand for cognitive or non-cognitive skills, though they do increase high school diploma requirements for some workers.

[4] Our baseline event-study analysis uses the conventional two-way fixed effects (TWFE) estimator; however, we show that the conclusions are unchanged when using the interaction weighted estimator (Sun and Abraham 2021).

deliver valuable insights into the emergence, growth, geography, and characteristics of green jobs. We build on this body of work and exploit spatiotemporal variation in the occurrence of hurricanes to understand the factors underlying firms' demand for green *skills*. Focusing on green skills presents the advantage of capturing firms' actual demand for these competencies and avoiding the complex task of classifying different occupations as "green". Our research design allows us to test for the presence of pre-trends in the outcomes and enables us to recover the dynamics of the effects of interest.

Our work also speaks to the literature that evaluates the consequences of disasters, for example, the impact on fiscal costs (Deryugina 2017) and the pick-up of elective medical services (Deryugina, Gruber, and Sabety 2020), as well as household finances and business survival (Gallagher and Hartley 2022), firms' location and sourcing decisions (Balboni, Boehm, and Waseem 2024), politicians' support for climate legislation (Gagliarducci, Paserman, and Patacchini 2019), innovation (Hu 2024), and social cohesion (Calo-Blanco et al. 2017). Our contribution is to analyze how disasters affect firms' skill demand.[5]

The remainder of this paper is organized as follows. In Section 3, we describe the data and present descriptive statistics. Section 4 discusses our econometric strategy. The main empirical results and various extensions and robustness checks are presented in Sections 5. Section 6 concludes the paper.

2 Theoretical Framework

Our interest in this paper is with firms' decisions to invest or not in green skills. We assume that firm j's objective function is given by

$$\Pi_j = \pi_j^t(y_j^t, \alpha_j^t, g_j^t) + \gamma E(z_j^t),$$

where y_j^t is aggregate demand for j's product(s) at time t; g_j^t is the amount of green skill that the firm has invested in at t; and α_j^t is a function-valued parameter encompassing technology parameters, the efficiency of internal processes, as well as the quality and motivation of the workforce. $\pi_j^t(y_j^t, \alpha_j^t, g_j^t)$ represents the firm's profits. The second term in the firm's objective function captures possible ethical benefits $E(z_j)$ to the management from reducing the environmental footprint z_j of the firm. $E(z_j)$ is decreasing in z_j^t. The relative importance of profits versus ethical concerns is captured by parameter γ. It is possible to assume ethical concerns away and think of $\gamma = 0$

Investing in green skill g is costly but reduces the environmental footprint (z_j) of the firm. This matters not only because the management might derive benefit from it, but

[5]More broadly, we contribute to the literature at the intersection of environmental and labor economics (Greenstone 2002; Walker 2011; Curtis 2018; Vona et al. 2018).

also because it positively impacts y_j^t as customers care about the firm's environmental footprint. It also affects α_j^t due to possible direct impacts on production technology (positive or negative) and because a more environmentally friendly firm may attract a higher quality workforce (Krueger, Metzger, and Wu 2023; Colonnelli et al. 2023).

Natural disasters matter as they impact how much people (customers, employees, job applicants, or the management) care about the environmental footprint of the firm. The extent to which they care depends on the state $\omega \in \Omega$. For simplicity, we assume there are only two states $\Omega = \{\omega_0, \omega_1\}$. The "low" state ($\omega_0$) indicates situations where people do not worry much about the environment. This could include situations where, although climate change is considered real and human-caused, people believe it mainly affects those far away (both in time and geographic distance) from them. The "high" state (ω_1) is associated with strong concern about the environment and hence strong concern about z_j^t. Each state ω induces a probability distribution over local natural disasters. The induced probability of a local disaster happening is $p(D|\omega)$, which is independent and identically distributed over time.[6]

The state is unknown and does not change over time.[7] $\mathcal{F}^0(\omega)$ is the prior distribution over the states. The prior probability of a disaster occurring locally is then $p^0 = \sum_{\omega \in \Omega} f^0(\omega)p(\omega)$, where $f^0(\omega)$ is the probability attached to state ω at time $t = 0$. People update their beliefs about $\mathcal{F}(\omega)$ at the end of every period, after observing whether a disaster occurred locally ($D^t = 1$) or not ($D^t = 0$). If they are Bayesian, then upon observing a disaster, they update

$$f_i^t(\omega_1|D^{t-1} = 1) = \frac{p(D|\omega_1)}{p^0} f_i^{t-1}(\omega_1).$$

In summary, a disaster increases people's posterior on the high state. They are now more likely to believe that climate change can affect them, and this heightens their concern about the environment. This heightened concern then increases customer demand for clean products, the attractiveness of green vacancies for job applicants, and possibly also the desire of the existing workforce and management to reduce the environmental footprint of the firm.

[6] An alternative interpretation of states would be that low states indicate situations where climate change is not human-caused or not very severe. In this case, consumers should learn not only from local disasters, but also from disasters occurring further away, as long as consumers have enough information about these disasters. A second implication of this alternative interpretation is that effect sizes should be larger for more climate-sceptic people, which under this interpretation would be people whose prior places strong weight on ω_0.

[7] This is a simplifying assumption allowing us to focus on a single variable for belief updating.

3 Data

3.1 Data on Job Postings and Green Skills Requirement

We use the near universe of online job postings in the United States collected and provided by Lightcast. Lightcast gathers data by scraping over 45,000 company career sites and online job boards. It deduplicates and further cleans the job postings and then enriches the data by extracting a wide range of information about the vacancies, such as company information, required educational level, employment type, and location. We use the Lightcast data from 2010 to 2019.

Multiple features make the Lightcast data particularly useful for our analysis. First, Lightcast extracts rich information about skills from the advertisement texts, which it dynamically updates. This allows us to identify firms' actual demand for green skills based on job postings rather than relying on broad industry or occupational classifications, as in traditional data sets. Concentrating on occupational or industry classifications to define green skills can also lead to biased estimates when firms shift their hiring strategies and require non-environmental jobs to become greener. For example, firms may search for maintenance and repair workers who also possess environmental risk assessment skills.

Second, the Lightcast data provides information on actual labor demand rather than observed firm-worker matches, as in more traditional data sets.[8] If firms rapidly increase demand for green skills after being exposed to a hurricane, demand for green skills may outstrip supply, and some jobs may not be filled. Therefore, using observed matches may lead to the underestimation of firms' demand for green skills. The geographical information provided in the data also allows us to consider the occurrence of hurricanes on a fine level.

We perform further cleaning and apply restrictions to the Lightcast data similar to those employed in Hershbein and Kahn (2018) and Modestino, Shoag, and Ballance (2020). First, we drop all postings without stated skill requirements from the data. Second, we also drop observations in counties where the total number of job postings was less than 42 during our sample period. This corresponds to eliminating the bottom 5% of the sample. This ensures that we capture meaningful differences in the demand for green skills.

We use Lightcast's definition to define all job postings requiring at least one environmental skill.[9] Concentrating on posted environmental skills allows for a more nuanced view of how exposure to hurricanes can affect firms' labor demand. Our classification is broader than that reported in Curtis and Marinescu (2022), who also use the Lightcast

[8] The Lightcast data does not contain information on the vacancy duration, whether or not the vacancy was filled, and if so, who filled the position. Since we are interested in the demand for green skills, the lack of this information is not an issue in our analysis.

[9] Table A.1 in the appendix lists environment skills in the job ads.

data but concentrate on solar and wind jobs. Our definition also differs from that in Bowen, Kuralbayeva, and Tipoe (2018) and Vona et al. (2018). These studies employ the predefined industry and occupational classification of green jobs and green skills, such as those derived from O*NET. Our definition is based on firms' descriptions of jobs, regardless of the occupational classification. Using all environmental skills in a job posting allows us to investigate further whether jobs have become "greener" after the occurrence of a hurricane or whether firms change their hiring practices.

Our outcome of interest—demand for green skills—is then constructed as the number of posted jobs demanding at least one green skill in a given year, county and industry divided by the total number of job postings in the particular year, county, and industry. Dividing by the total number of job postings ensures that our outcome does not reflect any mechanical increase in job postings after the occurrence of a disaster, for example, when firms increase postings to find workers to repair any damages. We then merged our vacancy data with our disaster incident data.

Our data allows us to identify firms' actual demand for green skills. However, the Lightcast data is not representative of (online) job vacancies, given that coverage depends on (a) the number of sites scraped and (b) the algorithm used to identify and eliminate duplicates and to extract information from the postings. In general, the Lightcast data has a similar occupation-industry distribution as other benchmark data, such as the Job Openings and Labor Turnover Survey, Occupational Employment Statistics, and Help Wanted Online (Carnevale, Jayasundera, and Repnikov 2014; Hershbein and Kahn 2018; Modestino, Shoag, and Ballance 2020). While the Lightcast data tends to over-represent computational, mathematical, and financial occupations in earlier years, he extent of this over-representation has declined for more recent years. In addition, by auditing an early sample of the Lightcast data, Carnevale, Jayasundera, and Repnikov (2014) show that information on skills has an accuracy of at least 80%. This accuracy is likely to have improved over time. The Lightcast data has also been used in numerous other works exploring changes in skill requirements associated with, for example, technological change, "upskilling" during the Great Recession, the introduction of Medicaid, and the demand for green energy jobs (Hershbein and Kahn 2018; Modestino, Shoag, and Ballance 2020; Dillender 2020; Curtis and Marinescu 2022).

3.2 Best Track Data – Hurricanes

We use data on the recorded paths of tropical and subtropical cyclones in the Atlantic and Pacific oceans from 2010 to 2019. This hurricane database (HURDAT2) is constructed and provided by NOAA NHC, with historical data going back as far as 1851. For each storm, HURDAT2 contains data (at six-hour intervals) on the location, maximum winds, central pressure, and (beginning in 2004) size of all known tropical cyclones and subtropical cyclones (Landsea and Franklin 2013; National Hurricane Center 2025a). Using the provided geo-located storm points, we are able to construct wind speed quadrants and radii according to the reported directional wind speeds at each point of the storm's path. We can then intersect these new area-based wind shapes with the reported geographic location of each job posting, allowing us to create a treatment measure. We focus on wind speeds greater than or equal to 74 miles per hour (64 knots), as this is the level at which a tropical storm is considered a Category 1 hurricane according to the Saffir–Simpson Hurricane Wind Scale[10] (National Hurricane Center 2025b). Therefore, our baseline treatment is defined as the first instance a county geographic shape intersects with Category 1 hurricane wind speeds (74mph, 64 knots) in the 2010-2019 period. Counties are considered treated in each year following the initial hurricane exposure. Figure 1 illustrates both the HURDAT2 data and county treatment definitions of a representative subset of hurricanes.

4 Empirical Strategy

We use difference-in-difference and event-study approaches to estimate the impact of exposure to a hurricane on the demand for green skills. Our baseline approach exploits the geographic and temporal variation in the hurricane incidents on the local demand for green skills:

$$G_{i,c,t} = \beta D_{c,t} + \Gamma_i + \gamma_c + \theta_t + \epsilon_{i,c,t} \tag{1}$$

where $G_{i,c,t}$ is the share of green vacancies at time t, county c and industry i; and $D_{c,t}$ is an indicator variable equal to one in the year a hurricane happens in county c and each of the following years, and zero otherwise. This paper focuses on the estimation of the effects of the hurricane on the demand for green skills, and thus the parameter of interest is β, which tests for a *mean shift* in the share of green vacancies in the affected locality after the disaster. If agents are fully aware of the dangers of inaction on the environmental transition before disasters, we should expect $\beta = 0$. If disasters convey new information, we should expect $\beta > 0$. Identification of β relies on a standard parallel trends assumption: in the absence of hurricane exposure, treated counties' average share of green vacancies would have evolved in the same way as the observed path of the untreated counties in our control group. Both the exact timing of hurricanes and their

[10]The Saffir–Simpson Hurricane Wind Scale is a 1 to 5 rating based only on a hurricane's maximum sustained wind speed. This is used to categorize hurricane intensity and estimate property damage. Hurricanes that are Category 3 or higher are considered major hurricanes (National Hurricane Center 2025b).

paths are relatively unpredictable, helping to dampen threats to identification in the form of anticipation, selection, and time-varying confounders.

We also include industry-fixed effects Γ and county-fixed effects γ_c to address any unobserved industry and county-specific characteristics that are potentially correlated with the outcome. The temporal fixed effects θ_t account for aggregate-level shocks potentially impacting skill demand. We cluster all standard errors at the county level.

The coefficient $\widehat{\beta}$ captures the average effect of hurricanes on the demand for green skills. To investigate any potential demand dynamics and to assess the potential existence of pre-trends in our analysis, we also estimate a dynamic event-study specification:

$$\begin{aligned} G_{i,c,t} = \sum_{\substack{a=-3 \\ a\neq -1}}^{4} \delta_a \mathbb{1}(t - DY_c = a) + \delta_{-4}\mathbb{1}(t - DY_c < -3) \\ + \delta_5 \mathbb{1}(t - DY_c > 4) + \gamma_{i,c}^{ES} + \theta_t^{ES} + \epsilon_{i,c,t}^{ES} \end{aligned} \tag{2}$$

where DY_c is the year when the hurricane in county c occurred. As we only have a limited number of observations for years distant from the actual treatment year, we bin all time periods with a relative treatment time longer than five years prior to or five years after the hurricane. In our event study, we include the same set of control variables as in equation (1).

5 Evidence

5.1 Main Estimates

The main difference-in-difference estimates (equation (1)) are shown in Table 1. Specifically, the first column reports the estimated mean shift parameter, β, and its standard error (in parentheses) in the *mean shift* row. Experiencing a hurricane increases the share of green vacancies in a locality on average by 0.28 percentage points. This is equivalent to a 6.4% increase relative to the mean.[11] The mean shift estimate is highly statistically significant.

To put the magnitude of the estimated effect into context, it is useful to compare it with findings from previous studies on how labor market shocks affect firms' skill demand in various settings. Hershbein and Kahn (2018) show that structural changes resulting from deep recessions lead to a persistent increase in firms' demand for cognitive and IT skills of approximately 8% to 12%. In contrast, Clemens, Kahn, and Meer (2021),

[11] The mean share of green vacancies is 0.04 throughout the examined data set.

using broad skill measures, find that minimum wage increases do not significantly change employers' demand for cognitive and non-cognitive skills.[12]

Figure 2 shows the corresponding event-study estimates (equation 2). Three important features emerge. First, there is no pretreatment trend in the coefficients, lending support to the validity of our research design. Second, there is an upward shift in the share of green vacancies after the hurricane. Third, the effect is persistent during the period post-event, represented by the year of the event and the following five years. This evidence is consistent with the prediction of our theoretical model.

In Columns 2 and 3 of Table 1 and Figure 3 we show differences-in-difference and event-study estimates for firms in the tradeable versus non-tradeable sector, following the classification by Jensen et al. (2005). The estimates indicate that the effect is larger for firms in the non-tradable sector, namely, those that mainly sell to a local market. Specifically, the coefficient for non-tradable industries is significant at 1%, indicating an increase by 0.43 percentage points. This is equivalent to an 8.4% increase relative to the mean. The coefficient for tradable industries is significant at 5%, indicating an increase of 0.17 percentage points. This is equivalent to a 4.8% increase relative to the mean. The difference in the increase between the tradable and non-tradable industries is equal to 0.26 percentage points (The p-value of the test of equality of the coefficients for the tradable and non-tradable industries is equal to 0.05).

In the remainder of Table 1 and in Figure 4 we show differences-in-difference and event-study estimates when we restrict the control group counties to those within a progressively small radius from the centroid of the treated county. When restricted to 500, 250, or 100 km, the estimates are similar to the baseline ones. These estimates suggest that spillovers to nearby counties are not particularly relevant. Overall, the two pieces of evidence for the non-tradable sector, as well as using the nearby counties as a control group, confirm the localized nature of the impact.

Next, we investigate whether or not the effect is limited to particular parts of the economy and skills. Specifically, we exclude industries or skills that in principle may drive the bulk of the estimated effects. We first exclude the construction and utility industry. The construction industry is excluded as it typically experiences an overall increase in labor demand after a hurricane due to reconstruction efforts. The effect we uncovered above could be confined to "build-back-better (greener)"-type efforts. The exclusion of the utility industry is motivated by the evidence of the increase in green jobs in some segments of the industry, namely solar and wind (Curtis and Marinescu 2022). The results, shown in Column 1 of Table A.2 and Panel A of Figure A.1, indicate that when excluding the construction and utility industries, the results are very similar. Finally, in

[12] Clemens, Kahn, and Meer (2021) find, however, that employers increase the requirement for a high school diploma among low- and medium-wage workers in response to a minimum wage hike.

Column 2 of Table A.2 and Panel B of Figure A.1, we exclude vacancies that require skills related to regulation, as the demand for these skills is predicted to increase in expectation of changes in environmental policy (Gagliarducci, Paserman, and Patacchini 2019). The estimates indicate that the hurricane effect is not limited to these types of skills.

5.2 Robustness: interaction weighted estimator

Our baseline analysis uses the conventional two-way fixed effects (TWFE) estimator. Hurricanes that occur later may be different from those occurring earlier, generating cohort-specific treatment effects. We therefore present estimates using the interaction weighted estimator. Sun and Abraham (2021) prove that this estimator is consistent for the average dynamic effect at a given relative time even under heterogeneous treatment effects.[13] We use the "never treated as the control" cohort. Figures A.2–A.5 display the interaction weighted estimator version of Figures 2–4 and Figure A.1, respectively. The estimates are highly similar to those of the baseline.

6 Conclusions

We document that firms in localities hit by a hurricane are more likely to increase the share of green vacancies in the period after the disaster. Overall, the evidence indicates that new information regarding the dangers of inaction on the environmental transition increases firms' demand for green skills. The effect is larger for firms in the non-tradable sector.

In terms of policy implications, our evidence indicates that altering the way agents understand the dangers of inaction may be an effective strategy to promote transition.[14] This could be obtained through info campaigns and by shifting the way environmental issues are presented in media, education, and product commercials, with emphasis on the local impacts.

[13] We use the "eventstudyinteract" Stata routine available at https://economics.mit.edu/grad/lsun20/stata.

[14] See Grewenig, Lergetporer, and Werner (2020) for policy implications of a similar spirit in a different context (gender norms and labor-supply expectations).

References

Bachmann, Ronald, Markus Janser, Florian Lehmer, and Christina Vonnahme. 2024. *Disentangling the greening of the labour market: The role of changing occupations and worker flows.* 1099. Ruhr Economic Papers.

Balboni, Clare, Johannes Boehm, and Mazhar Waseem. 2024. *Firm Adaptation and Production Networks: Evidence from Extreme Weather Events in Pakistan.* Working Paper. Private Enterprise Development in Low Income Countries. https://pedl.cepr.org/publications/firm-adaptation-production-networks-evidence-extreme-weather-events-pakistan.

Basso, Gaetano, Fabrizio Colonna, Domenico Depalo, and Graziella Mendicino. 2023. *The Green Transition and the Italian Labour Market.* Technical report. Bank of Italy, Economic Research and International Relations Area.

Bergant, Katharina, Rui Mano, and Mr Ippei Shibata. 2022. *From Polluting to Green Jobs: A Seamless Transition in the US?* International Monetary Fund Working Paper No. 2022/129.

Bowen, Alex, Karlygash Kuralbayeva, and Eileen L. Tipoe. 2018. "Characterising Green Employment: The Impacts of 'Greening' on Workforce Composition." *Energy Economics* 72:263–275.

Calo-Blanco, Aitor, Jaromır Kovářık, Friederike Mengel, and José Gabriel Romero. 2017. "Natural Disasters and Indicators of Social Cohesion." *PloS one* 12 (6): e0176885.

Campa, Pamela. 2018. "Press and Leaks: Do Newspapers Reduce Toxic Emissions?" *Journal of Environmental Economics and Management* 91:184–202. https://doi.org/https://doi.org/10.1016/j.jeem.2018.07.007.

Carnevale, Anthony P., Tamara Jayasundera, and Dmitri Repnikov. 2014. *Understanding Online Jobs Ad and Data.* Technical Report. Georgetown University Center on Education and the Workforce. https://cew.georgetown.edu/wp-content/uploads/2014/11/OCLM.Tech_.Web_.pdf.

Clemens, Jeffrey, Lisa B Kahn, and Jonathan Meer. 2021. "Dropouts need not apply? The minimum wage and skill upgrading." *Journal of Labor Economics* 39 (S1): S107–S149.

Colonnelli, E., T. McQuade, G. Ramos, T. Rauther, and O. Xiong. 2023. *Polarizing Corporations: Does Talent Flow to "Good" Firms?* Working Paper 31913. National Bureau of Economic Research. http://www.nber.org/papers/w31913.

Curtis, E. Mark. 2018. "Who Loses under Cap-and-Trade Programs? The Labor Market Effects of the NO_X Budget Trading Program." *Review of Economics and Statistics* 100 (1): 151–166.

Curtis, E. Mark, and Ioana Marinescu. 2022. *Green Energy Jobs in the US: What Are They, and Where Are They?* Working Paper 30332. National Bureau of Economic Research. http://www.nber.org/papers/w30332.

Deming, David, and Lisa B. Kahn. 2018. "Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals." *Journal of Labor Economics* 36 (S1): S337–SS369.

Deryugina, Tatyana. 2017. "The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurances." *American Economic Journal: Economic Policy* 9 (3): 168–198.

Deryugina, Tatyana, Jonathan Gruber, and Adrienne Sabety. 2020. *Natural Disasters and Elective Medical Services: How Big is the Bounce-Back.* Working Paper 27505. National Bureau of Economic Research. http://www.nber.org/papers/w27505.

Dillender, Marcus. 2020. "How Do Medicaid Expansions Affect the Demand for Health Care Workers? Evidence from Vacancy Postings." *Journal of Human Resources,* 0719–10340R1. https://doi.org/10.3368/jhr.57.4.0719-10340R1.

Elliott, Robert JR, Wenjing Kuai, David Maddison, and Ceren Ozgen. 2024. "Eco-innovation and (green) employment: A task-based approach to measuring the composition of work in firms." *Journal of Environmental Economics and Management* 127:103015.

Fine, Charles H. 1998. *Clockspeed: Winning Industry Control in the Age of Temporary Advantage.* Perseus Books.

Gagliarducci, Stefano, M Daniele Paserman, and Eleonora Patacchini. 2019. *Hurricanes, Climate Change Policies and Electoral Accountability.* Working Paper 25835. National Bureau of Economic Research. http://www.nber.org/papers/w25835.

Gallagher, Justin, and Daniel Hartley. 2022. *Natural Disasters, Local Bank Market Share, and Economic Recovery.* Working Paper 2024-17. Federal Reserve Bank of Chicago. https://ssrn.com/abstract=4941756.

Garrett, Daniel F, and Alessandro Pavan. 2012. "Managerial Turnover in a Changing World." *Journal of Political Economy* 120 (5): 879–925.

Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufatureres." *Journal of Political Economy* 110 (6): 1175–1219.

Grewenig, Elisabeth, Philipp Lergetporer, and Katharina Werner. 2020. *Gender Norms and Labor-Supply Expectations: Experimental Evidence from Adolescents.* Rationality and Competition Discussion Paper Series 259. CRC TRR 190 Rationality and Competition. https://ideas.repec.org/p/rco/dpaper/259.html.

Hershbein, Brad, and Lisa B. Kahn. 2018. "Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings." *American Economic Review* 108 (7): 1737–1772. https://doi.org/10.1257/aer.20161570.

Hong, Harrison, Neng Wang, and Jinqiang Yang. 2023. "Mitigating Disaster Risks in the Age of Climate Change." *Econometrica* 91 (5): 1763–1802.

Hu, Yuan. 2024. "Green Technological Change After Natural Disasters: Evidence from Hurricane Katrina." *Mimeo.*

Jensen, J Bradford, Lori G Kletzer, Jared Bernstein, and Robert C Feenstra. 2005. "Tradable services: Understanding the scope and impact of services offshoring." In *Brookings trade forum,* 75–133. JSTOR.

Krueger, Philipp, Daniel Metzger, and Jiaxin Wu. 2023. *The Sustainability Wage Gap.* Working Pape No. 21-17. Swiss Finance Institute. https://ssrn.com/abstract=3672492.

Landsea, Christopher, and James Franklin. 2013. "Atlantic Hurricane Database Uncertainty and Presentation of a New Database Format." *Monthly Weather Review* 141:3576–3592. https://doi.org/10.1175/MWR-D-12-00254.1.

LinkedIn Corporation. 2022. *Global Green Skills Report 2022.* LinkedIn. https://economicgraph.linkedin.com/content/dam/me/economicgraph/en-us/global-green-skills-report/global-green-skills-report-pdf/li-green-economy-report-2022.pdf.

Masterson, Victoria. 2021. "These Are the Skills Young People Will Need for the Green Jobs of the Future." *World Economic Forum* (August). https://www.weforum.org/stories/2021/08/these-are-the-skills-young-people-will-need-for-the-green-jobs-of-the-future/.

Modestino, Alicia Sasser, Daniel Shoag, and Joshua Ballance. 2020. "Upskilling: Do Employer Demand Greater Skill When Workers Are Plentiful?" *Review of Economics and Statistics* 102 (4): 793–805.

National Hurricane Center. 2025a. *NHC Data Archive - Best Track Data (HURDAT2).* https://www.nhc.noaa.gov/data/.

———. 2025b. *Saffir-Simpson Hurricane Wind Scale.* https://www.nhc.noaa.gov/aboutsshws.php.

Organisation for Economic Co-operation and Development. 2023. *Job Creation and Local Economic Development 2023.* OECD Publishing. https://www.oecd-ilibrary.org/content/publication/21db61c1-en.

Saussay, Aurélien, Msato Sato, Francesco Vona, and Layla O'Kane. 2022. *Who's Fit for the Low Carbon Transition? Emerging Skills and Wage Gaps in Job Vacancy Data.* Working Paper No. 31. https://ssrn.com/abstract=4260227.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects." *Journal of Econometrics* 225 (2): 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006.

Tooze, Adam. 2022. "Welcome to the World of the Polycrisis." *Financial Times* (October). https://www.ft.com/content/498398e7-11b1-494b-9cd3-6d669dc3de33.

Vona, Francesco, Giovanni Marin, and Davide Consoli. 2019. "Measures, Drivers and Effects of Green Employment: Evidence from US Local Labor Markets, 20062014." *Journal of Economic Geography* 19 (5): 1021–1048.

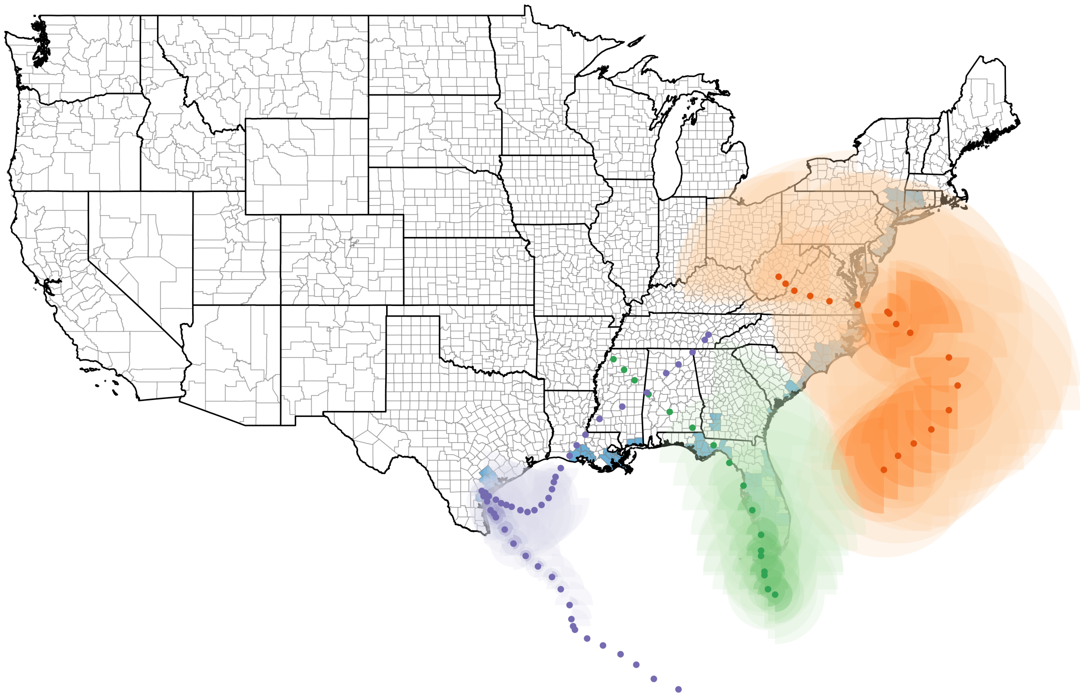
Vona, Francesco, Giovanni Marin, Davide Consoli, and David Popp. 2018. "Enivornmental Regulation and Green Skills: An Empirical Exploration." *Journal of the Association of Enivornmental and Resource Economists* 5 (4): 713–753.

Walker, W. Reed. 2011. "Environmental Regulation and Labor Reallocation: Evidence from the Clean Air Act." *American Economic Review* 101 (3): 442–447.

World Economic Forum. 2023. *Global Risks Report.* World Economic Forum. https://www.weforum.org/publications/global-risks-report-2023.

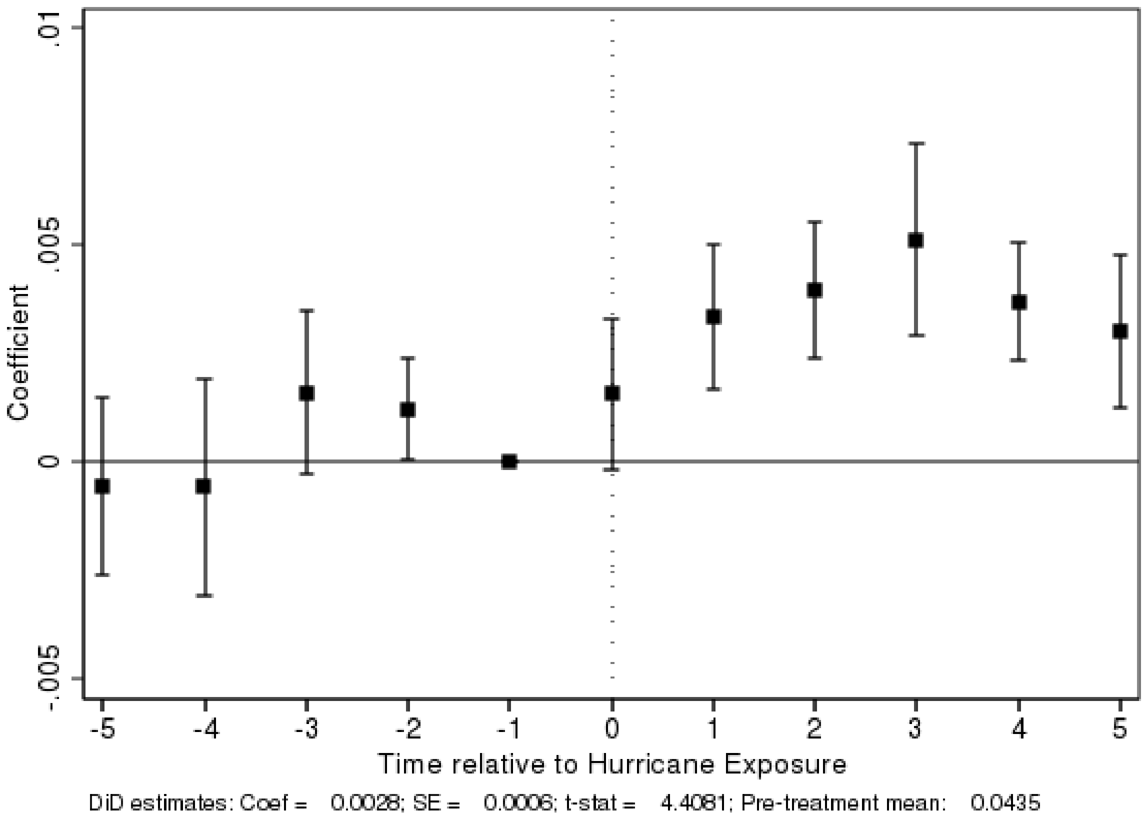
Figures

Figure 1: Example of Hurricane Paths and Wind Speed



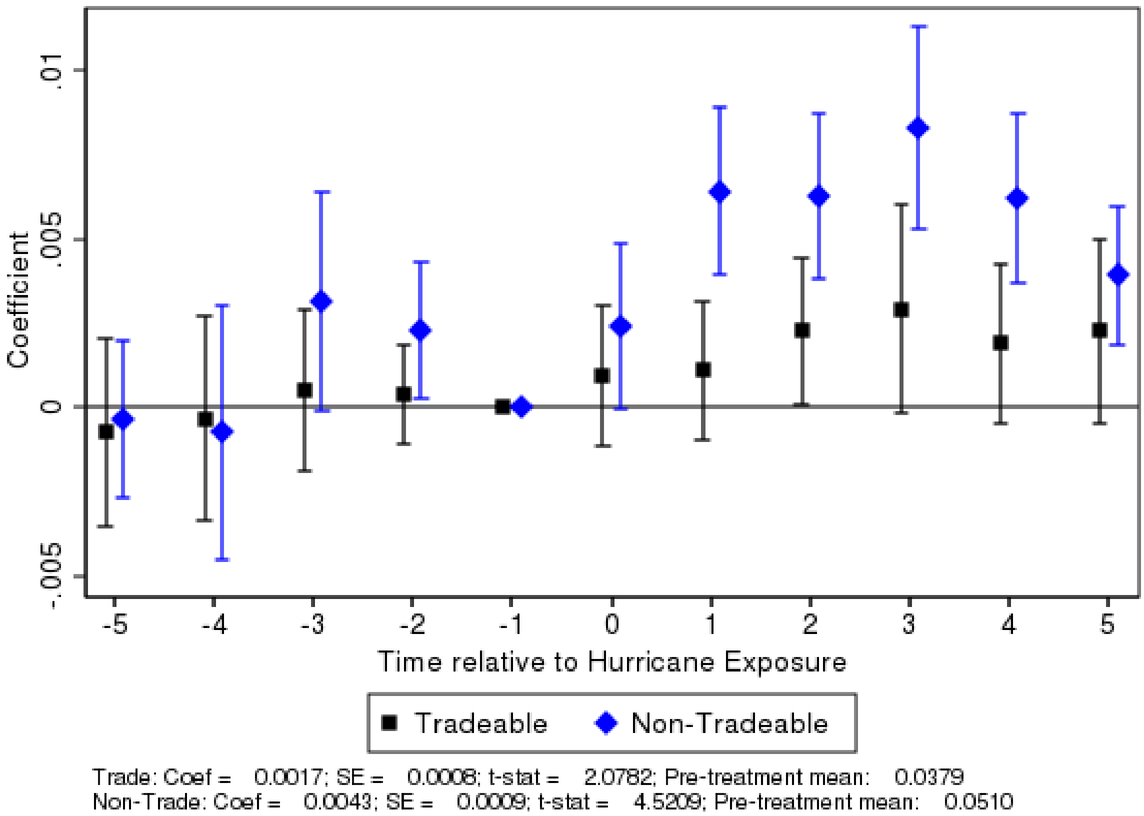
Note: The figure shows the track and wind speed for three major hurricanes: Sandy in 2012 (orange); Irma in 2017 (green); and Harvey in 2017 (purple). Darker shaded regions imply higher wind speed. Treated counties are shown in blue.

Figure 2: Share of Job Postings Requiring Green Skills, Relative to the Year of a Hurricane



Notes: The figure plots the event-study coefficients δ_a from equation (2), using the share of job postings requiring environmental skills as the outcome variable; see Section 3 for further details. The event-study specifications include year and county-by-industry fixed effects and are weighted by the size of the county labor force in 2006. Standard errors are clustered at the county level.

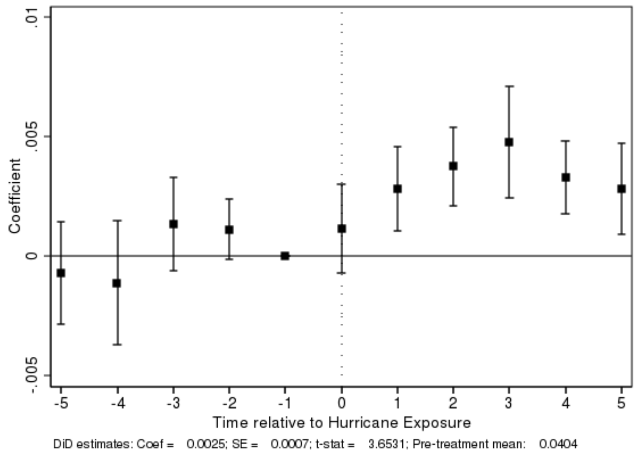
Figure 3: Share of Job Postings Requiring Green Skills: Tradable and Non-Tradable Industries



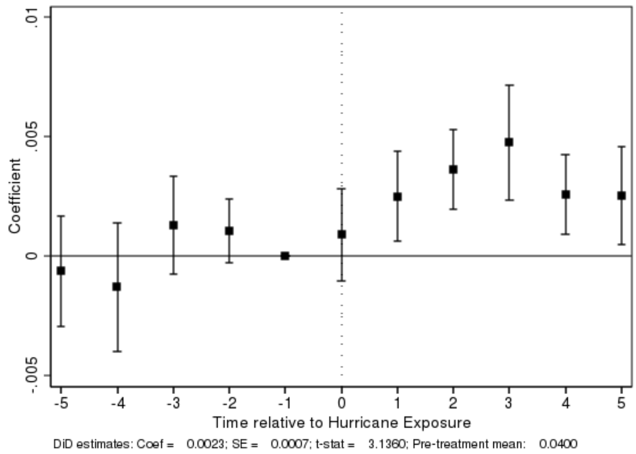
Notes: The figure plots the event-study coefficients δ_a from equation (2), using the share of job postings requiring environmental skills as the outcome variable; see Section 3 for further details. The data is divided into tradable and non-tradable industries following Jensen et al. (2005). (Non-) tradable industries are defined as those within a sector where (at least) less than 50% of employment is geographically concentrated. The event-study specifications include year and county-by-industry fixed effects and are weighted by the size of the county labor force in 2006. Standard errors are clustered at the county level.

Figure 4: Share of Job Postings Requiring Green Skills: Effects by Distance

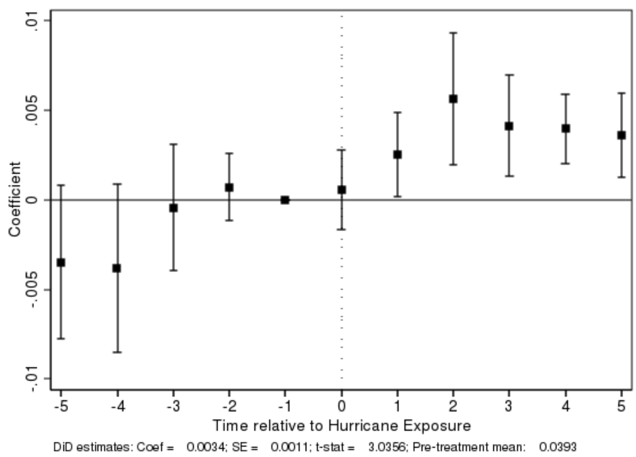
A: 500 km



B: 250 km



C: 100 km



Notes: The figure plots the event-study coefficients δ_a from equation (2), using the share of job postings requiring environmental skills as the outcome variable; see Section 3 for further details. Panel A includes only control counties located within a 500 km radius of a treated county. Panels B and C apply the same strategy, but restrict the control group to counties within 250 km and 100 km, respectively. The event-study specifications include year and county-by-industry fixed effects and are weighted by the size of the county labor force in 2006. Standard errors are clustered at the county level.

Tables

Table 1: Effect of Hurricanes on the Demand for Green Skills: Difference-in-Differences Estimates

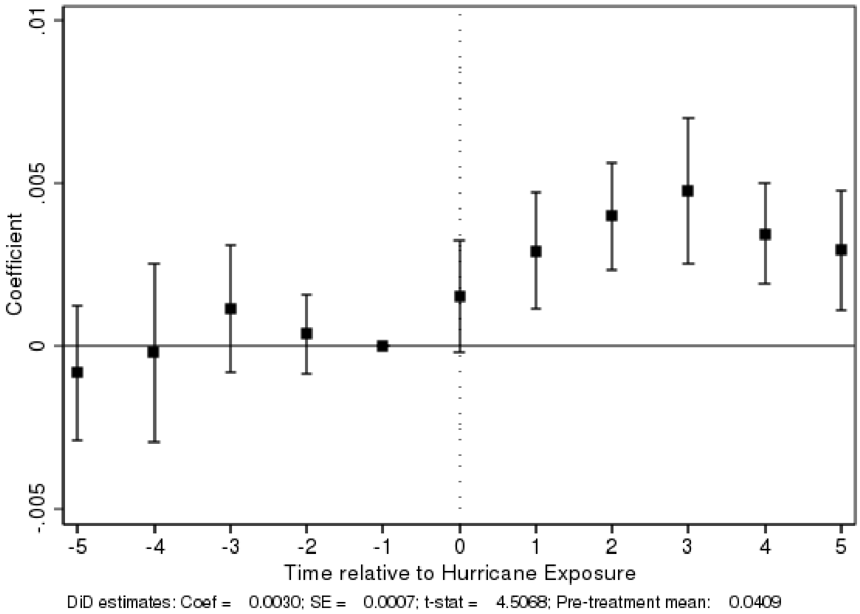
	Main (1)	Tradeable (2)	Non-Tradeable (3)	500 km (4)	250 km (5)	100 km (6)
β: Mean Shift	0.0028***	0.0017**	0.0043***	0.0025***	0.0023***	0.0034***
	(0.0006)	(0.0008)	(0.0009)	(0.0007)	(0.0007)	(0.0011)
% Change	6.4368	4.4845	8.4313	6.1881	5.7500	8.6514
P-value: Equality of Effect		0.0507				
Pretreatment Mean	0.0435	0.0379	0.0510	0.0404	0.0400	0.0393

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome variable is the share of job postings requiring environmental skills. See equation (1) for specification details. Standard errors, clustered at the industry by county level, are in parentheses. Column (1) presents the results for the baseline sample. Columns (2) and (3) split the sample into tradeable and non-tradeable industries, based on the classification in Jensen et al. (2005). Columns (4) to (6) restrict the analysis to treatment and control counties located within a 500 km, 250 km, and 100 km radius, respectively. All regressions are weighted by 2006 county-industry employment.

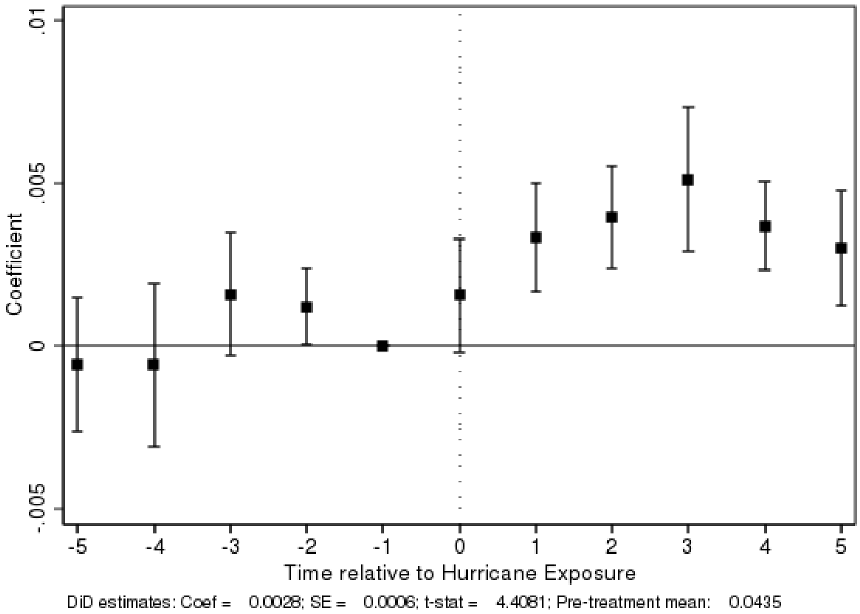
A Supplemental Appendix

Figure A.1: Share of Job Postings Requiring Green Skills: Excluding Utilities/Construction & Environmental Legislation Skills

A: Excluding Utility & Construction Sectors

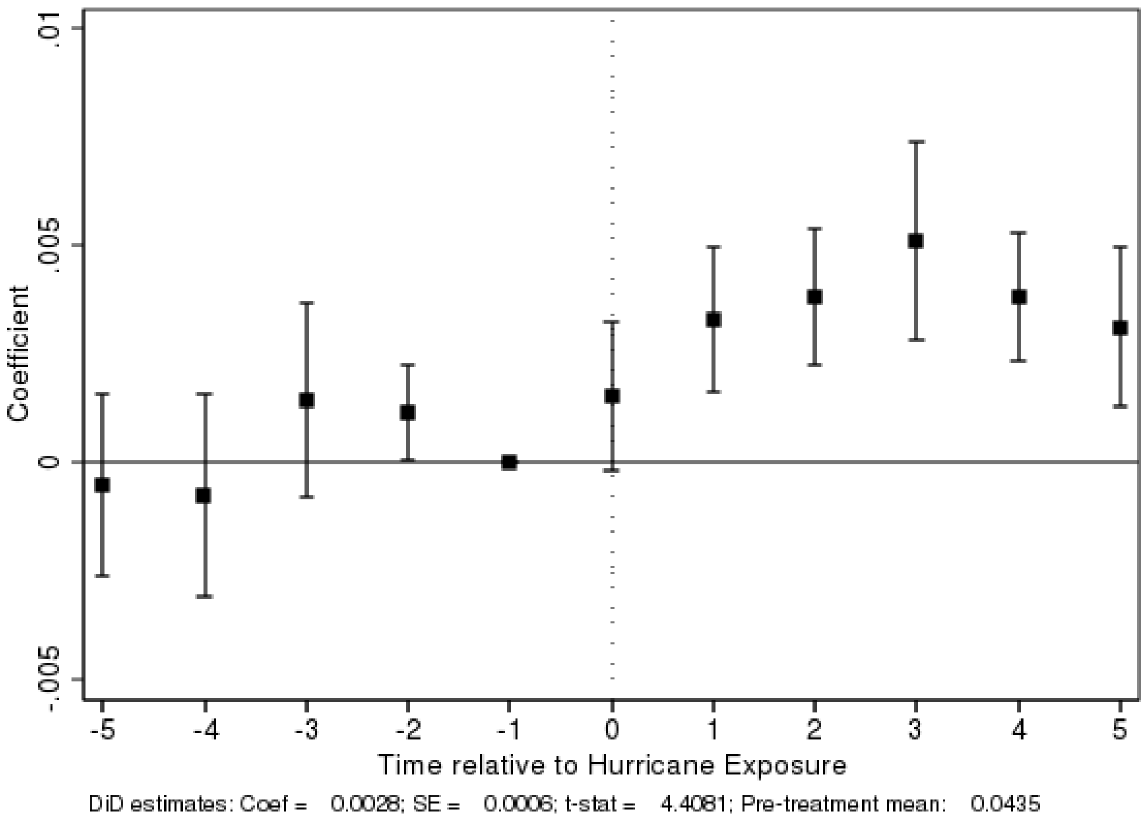


B: Excluding Environmental Regulation Skills



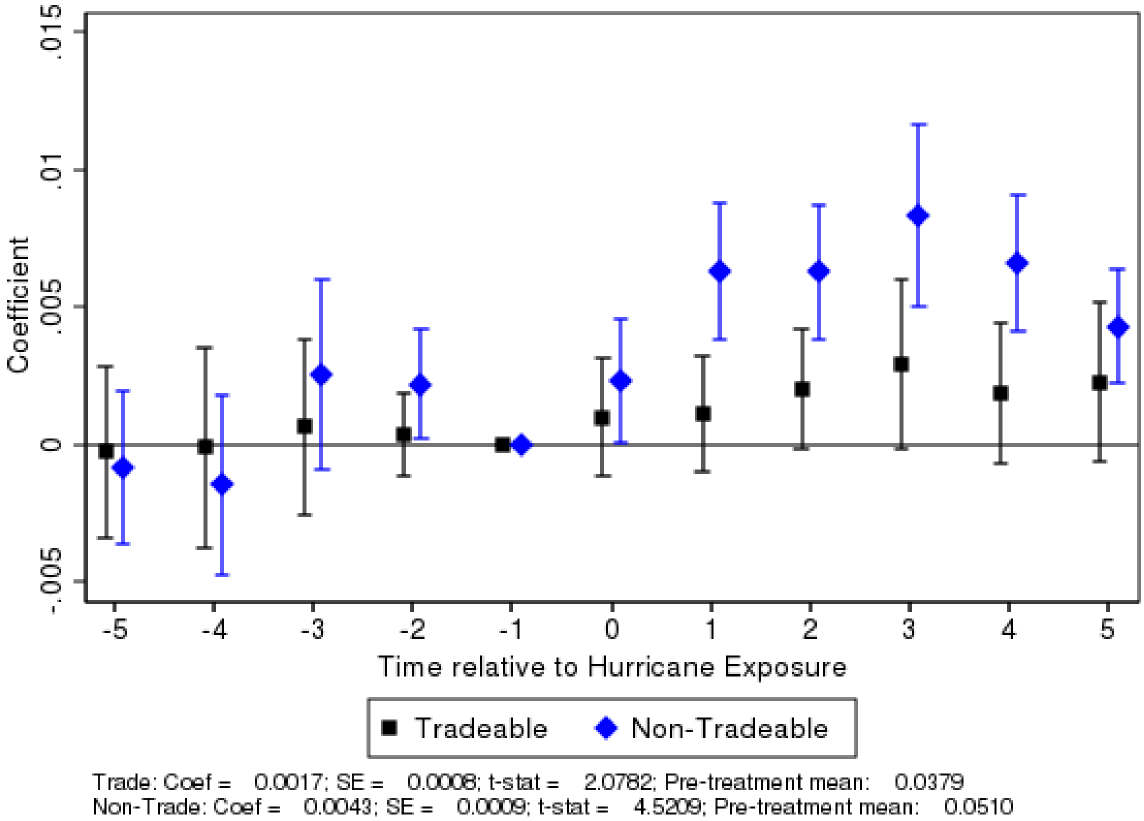
Notes: The figure plots the event-study coefficients δ_a from equation (2), using the share of job postings requiring environmental skills as the outcome variable; see Section 3 for further details. Panel A excludes industries in utilities and construction (NAICS 4-digit codes 2211-2389). Panel B excludes all environmental skills related to legislation and regulation. The event-study specifications include year and county-by-industry fixed effects and are weighted by the size of the county labor force in 2006. Standard errors are clustered at the county level.

Figure A.2: Share of Job Postings Requiring Green Skills–Sun & Abraham Estimator



Notes: The figure plots event-study coefficient using the approach of Sun and Abraham 2021 and never treated counties as the control group. The outcome variable is the share of job postings requiring environmental skills; see Section 3 for further details. The event-study specifications include year and county-by-industry fixed effects and are weighted by the size of the county labor force in 2006. Standard errors are clustered at the county level.

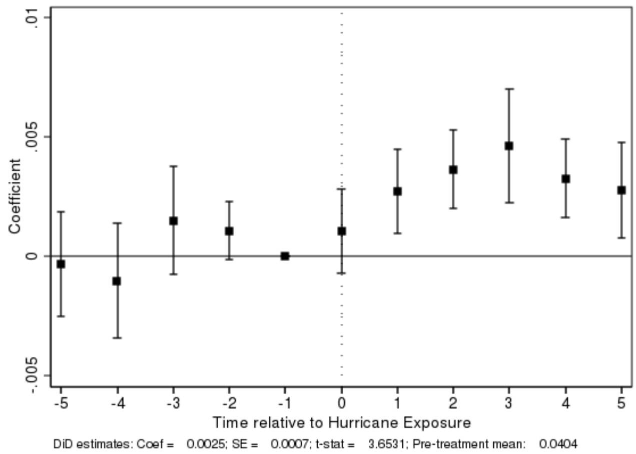
Figure A.3: Share of Job Postings Requiring Green Skills–Sun & Abraham Estimator: Tradable and Non-Tradable Industries



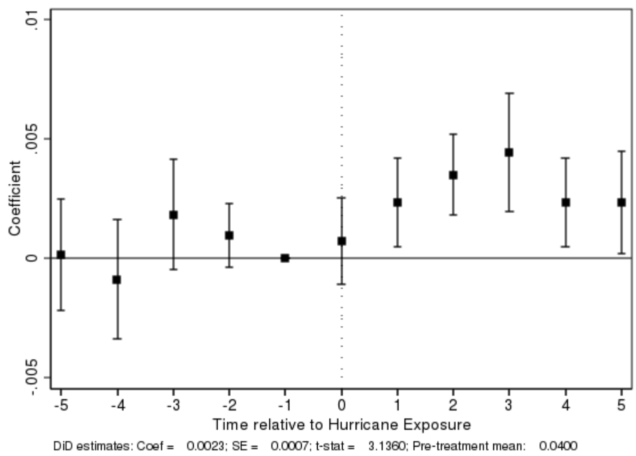
Notes: The figure plots coefficients from separate event-studies using the approach of Sun and Abraham 2021 and never treated counties as the control group. The outcome variable is the share of job postings requiring environmental skills; see Section 3 for further details. The data is divided into tradable and non-tradable industries following Jensen et al. (2005). (Non-) tradable industries are defined as those within a sector where (at least) less than 50% of employment is geographically concentrated. The event-study specifications include year and county-by-industry fixed effects and are weighted by the size of the county labor force in 2006. Standard errors are clustered at the county level.

Figure A.4: Share of Job Postings Requiring Green Skills–Sun & Abraham Estimator: Effects by Distance

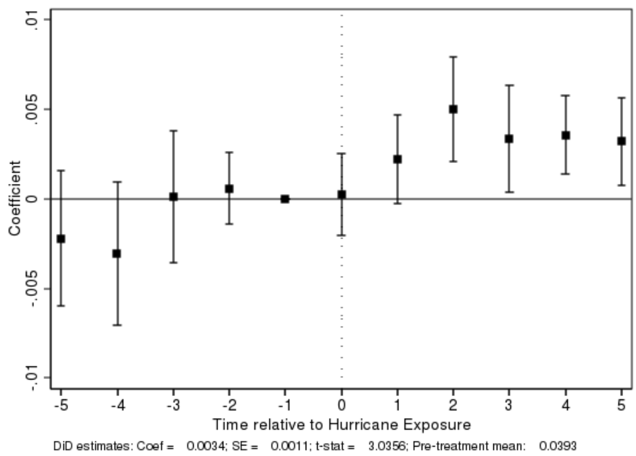
A: 500 km



B: 250 km



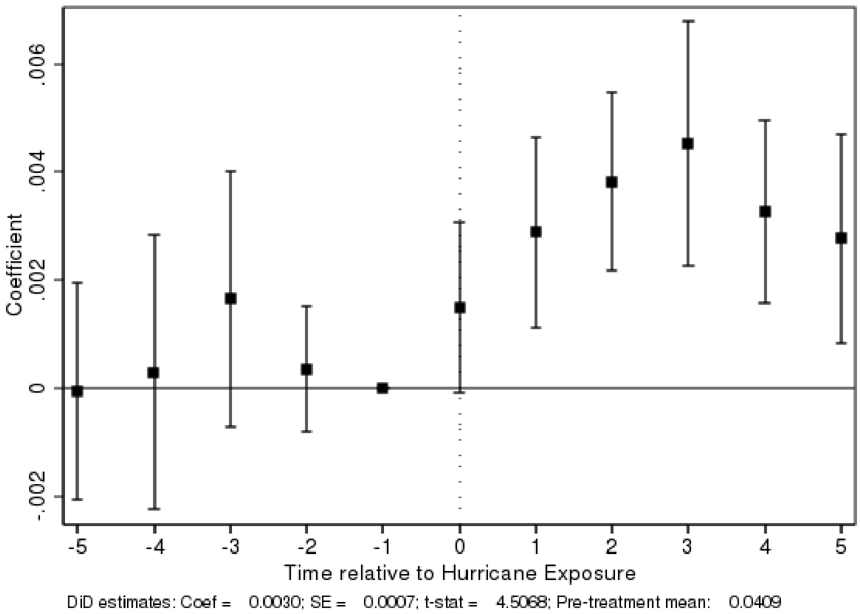
C: 100 km



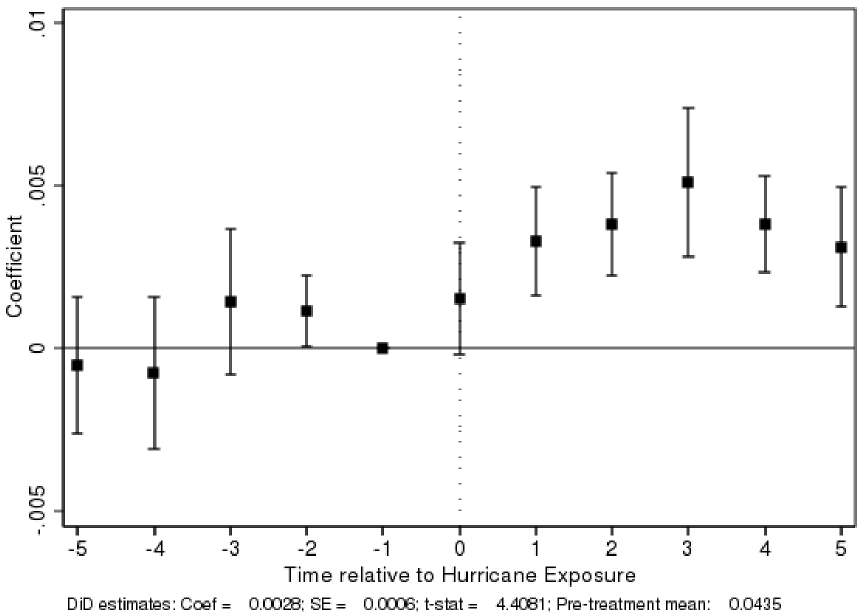
Notes: The figure plots coefficients from separate event-studies using the approach of Sun and Abraham 2021 and never treated counties as the control group. The outcome variable is the share of job postings requiring environmental skills; see Section 3 for further details. Panel A includes only control counties located within a 500 km radius of a treated county. Panels B and C apply the same strategy, but restrict the control group to counties within 250 km and 100 km, respectively. The event-study specifications include year and county-by-industry fixed effects and are weighted by the size of the county labor force in 2006. Standard errors are clustered at the county level.

Figure A.5: Share of Job Postings Requiring Green Skills–Sun & Abraham Estimator: Excluding Utilities/Construction & Environmental Legislation Skills

A: Excluding Utility & Construction Sectors



B: Excluding Environmental Regulation Skills



Notes: The figure plots event-study coefficient using the approach of Sun and Abraham 2021 and never treated counties as the control group. The outcome variable is the share of job postings requiring environmental skills; see Section 3 for further details. Panel A excludes industries in utilities and construction (NAICS 4-digit codes 22112389). Panel B excludes all environmental skills related to legislation and regulation. The event-study specifications include year and county-by-industry fixed effects and are weighted by the size of the county labor force in 2006. Standard errors are clustered at the county level.

Table A.1: Skills listed as Environmental in the Lightcast Data

Air Emissions	Environmental Research	Pollution Control Equipment
Air Permitting	Environmental Risk Assessment	Pollution Prevention
Air Pollution Control	Environmental Science	Pumping Systems
Air Quality Control	Environmental Stewardship	Range Management
Air Sampling	Environmental Stress Screening (ESS)	Reforestation
Aquatic Ecology	Environmental Studies	Refuse Collection
Biosolids	Environmental Sustainability	Remediation Services
Brownfields	Ethanol	Site Investigations
Categorical Exclusions	Fish Hatchery	Site Remediation
Chemical Waste Handing	Fishery Biology	Soil Collection
Clean Air Act	Forestry Operations	Soil Conservation
Clean Water Act	Fume Hoods	Soil Sampling
Climate Change	Geologic Data Interpretation	Soil Science
Conservation Planning	Greenhouse Gas	Soil Processes
Conservation Services	Groundwater Remediation	Stream Restoration
Corrosion Control Systems	Groundwater Sampling	Tree Felling
Emissions Management	Habitat Management	Waste Removal
Emissions Monitoring	Habitat Restoration	Waste Treatment
Environmental Assessments	Hazard Analysis	Waste Reduction
Environmental Compliance	Hazard Risk	Wastewater Engineering
Environmental Concerns	Hazardous Material Handling	Wastewater Treatment
Environmental Consulting	Hazardous Materials Endorsement	Wastewater Treatment Systems
Environmental Education	Hazardous Waste	Water Conservation
Environmental Engineering	Hazardous Waste Management	Water Planning
Environmental Geology	Hydrologic Modeling	Water Quality
Environmental Impact Assessment (EIA)	Industrial Hygiene	Water Quality Analysis
Environmental Impact Statements	Industrial Hygiene Assessment	Water Quality Control
Environmental Laws and Regulations	Industrial Wastewater Treatment Systems	Water Quality Modeling
Environmental Management	Land Management	Water Sampling
Environmental Management Systems	Land Planning	Water Testing
Environmental Permitting	Land Use	Water Treatment
Environmental Planning	Low Impact Development	Watershed Management
Environmental Policy	Methanol	Wetland Delineation
Environmental Protection	Municipal Waste Water Treatment Systems	Wildlife Conservation
Environmental Quality	Natural Resource Management	Wildlife Damage Management
Environmental Regulations	Natural Resources	Wildlife Management
Environmental Remediation	Plant Identification	Wildlife Removal
	Pollution Control	Wildlife Surveys

Table A.2: Difference-in-Differences Estimates: Excluding Utilities/Construction Environmental Legislation Skills

	Excluding	
	Utilities & Construction (1)	Regulation Skills (2)
β: Mean Shift	0.0030***	0.0028***
	(0.0007)	(0.0006)
% Change	7.3350	6.4368
Pretreatment Mean	0.0409	0.0435

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The outcome variable is the share of job postings requiring environmental skills. See equation (1) for details of specification. Standard errors, clustered at the industry by county level, in parentheses. Column (1) excludes industries in utilities and construction (NAICS 4-digit codes 2211-2389). Column (2) excludes environmental skills related to legislation and regulation, such as the Clean Air Act.