Do Green Immigrants Foster Green Communities?

Origin Countries' Comparative Advantage, Green Innovation, and Renewable Energy in the United States

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Abstract

How does immigration contribute to the green economy? This paper examines the effect of immigration on green innovation and renewable electricity generation in the U.S., using patent and power plant data at the county level in 1995–2020. I differentiate between immigrants from countries with a comparative advantage in renewable energy goods ("green immigrants") and those from countries without ("nongreen immigrants"). I apply a leave-one-out push-pull 2SLS design using ancestry data: I predict immigration based on the coincidence between the timing of emigration waves from each origin country and when each U.S. county was historically attractive to other origins. Green immigrants increase green patenting, and when they go to counties where plants are operated, they also increase renewable electricity generation, whereas nongreen immigrants have no effect on either outcome. Moreover, green immigration does not increase fossil patenting or brown electricity. These findings indicate that immigration can be an important driver of the green transition on the production side, with contributions tied to origin countries' capabilities rather than to immigration in general.

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1 Introduction

The green transition is increasingly driven not only by the urgent need to reduce emissions (UNFCCC, 2023), but also by energy security and industrial competitiveness. Yet, policy support alone cannot be taken for granted, as the United States illustrated when it repealed some energy tax credits in 2025 (International Energy Agency, 2026b). Such policy shifts highlight the need to understand the underlying economic forces that sustain clean energy innovation and diffusion. Immigration may be one such force. Some countries are farther ahead in the transition to a green economy.[1] Through immigration, comparative advantage in clean technologies can cross borders. Immigrants carry with them the knowledge and experience of their countries of origin in advancing and producing renewable energy, and benefit from the cross-border connections they maintain.

Do immigrants from countries with a comparative advantage in renewable energy goods increase green innovation and renewable electricity deployment in the United States? Answering this question is challenging for two reasons. First, identifying a causal effect is difficult because immigration is endogenous: immigrants may settle in counties where green activity is already growing, which makes it hard to separate their contribution from the economic opportunities that draw them there. Second, origin countries differ along many dimensions, making it hard to isolate the contribution of green comparative advantage from other country characteristics. To overcome these challenges, I adapt a recent instrumental variables strategy from the immigration literature (Burchardi et al., 2019; Terry et al., 2026), and rely on the concept of revealed comparative advantage as a summary measure of a country's technological edge in the green economy. I then proceed in two main steps. First, at the individual worker level in the cross-section, I confirm that immigrants from countries with a stronger comparative advantage in renewable energy goods are more likely to work in green occupations in the United States, even after controlling for other origin-country characteristics. Second, at the county level in a panel, I estimate the causal effects of green and nongreen immigration on green innovation and renewable electricity deployment. I also examine the geographic patterns of these effects, along

[1] Green-production capabilities differ sharply across countries: Denmark exported EUR 5.9 billion in wind technology and services in 2023 (State of Green, 2025). At the end of 2022, Germany accounted for approximately 40% of Europe's manufacturing capacity for wind turbine nacelles—the units behind the blades where electricity is generated (Rystad Energy and WindEurope, 2023). In 2024, China accounted for approximately 85% of global manufacturing capacity across the stages of solar panel production (International Energy Agency, 2026a).

with fossil fuel outcomes, to assess whether they reflect productive capabilities tied to immigrants' origin countries rather than simply higher local energy demand.

In the first step, using international trade data, I measure each origin country's revealed comparative advantage (RCA) as the share of renewable energy goods in its exports relative to the world export share, classifying immigrants from origins with RCA ≥ 1 as "green immigrants" and those with RCA < 1 as "nongreen immigrants." Linking individual-level American Community Survey (ACS) data to O*NET occupation definitions, I find that immigrants from higher-RCA origins are more likely to work in green occupations, even after controlling for individual characteristics and origin GDP per capita. To test whether this pattern simply reflects sorting into areas where green jobs are abundant, I further include residential area (PUMA) fixed effects. The positive relationship persists: moving from the 25th to the 75th percentile of origin RCA is associated with a 1.37 percentage-point higher probability of working in a green occupation (11 percent of the sample mean). This evidence indicates that green immigrants' propensity to work in green jobs reflects capabilities tied to their origin countries, even conditional on the "greenness" of their chosen destinations. Still, while these individual-level patterns are suggestive, they are not causal because migration and occupational choices are endogenous.

In the second step, I estimate the *causal* effect of green and nongreen immigration on green innovation and renewable electricity deployment across U.S. counties. I construct a five-year county panel combining Census and ACS immigration data with USPTO patent data (1991–2020) and EPA and EIA power plant data (1996–2020). Green patent counts capture the development of new technologies, while renewable electricity generation (electricity actually produced) and installed capacity (the maximum output that installed equipment can produce) capture renewable energy deployment, measured both in the counties where plants are physically located and in those where they are operated. I instrument for immigration using historical ancestry patterns, following Burchardi et al. (2019) and Terry et al. (2026). The approach predicts ancestry from the coincidence between the timing of emigration waves from each origin country and periods when a U.S. county attracted immigrants from other origins, and combines this predicted ancestry with contemporary immigrant stocks from the same origin to construct separate instruments for green and nongreen immigration. Both immigrant groups enter the same two-stage least squares (2SLS) specification, allowing me to

estimate the effect of each while controlling for the other.

The 2SLS results show that green immigration increases both green innovation and renewable electricity production, whereas nongreen immigration has a small and insignificant effect on either outcome. Controlling for nongreen immigrants, an additional 1,000 green immigrants aged 25 or older increases broad green patenting by 9.9 percent of the sample mean, with positive and significant effects for narrower green energy and renewable patent categories as well. For renewable electricity, when generation and capacity are assigned to the counties of the operating organizations, an additional 1,000 green immigrants increases average annual nonhydro renewable generation by 57.1 GWh (roughly the annual electricity purchases of 5,300 U.S. residential customers; U.S. Energy Information Administration 2024) and installed capacity by 27.7 MW.

The geographic patterns of these effects shed light on how green immigrants contribute to the green transition. Plants outside the operator county account for 78.6 percent of renewable generation and 84.1 percent of installed capacity attributed to operator counties in my sample. Whereas the effects on renewable generation and capacity are positive and statistically significant when these outcomes are assigned to operator counties, there are no statistically significant effects when they are assigned to plant counties. These positive effects persist even when I consider only plants located outside the counties where immigrants settle, making it difficult to explain the results solely by higher local residential demand for electricity. Moreover, green immigration has no statistically significant effect on fossil fuel patenting or brown electricity production. Taken together, these patterns suggest that green immigrants advance the green transition by bringing origin-linked capabilities—potentially through technical know-how, cross-border knowledge transfer, or business connections—to organizations that innovate in and deploy clean technologies.

This paper makes three contributions to the existing literature. First, to my knowledge, this paper is the first to provide causal evidence on the effects of green immigration on green innovation and renewable electricity deployment *at the local level* (across U.S. counties) over time. Identifying these local effects matters because national-level assessments can obscure heterogeneity across individual receiving communities (OECD, 2022). By tracing changes in green patenting at the county level, I connect international labor mobility to the development of local green technological capabilities, going beyond evidence across countries (Etzo and Takaoka, 2025) and European regions (Cornejo Costas

et al., 2026).[2] Examining renewable electricity generation and installed capacity alongside patenting further shows that the benefits of green immigration extend to energy production and infrastructure. Together, these findings identify green immigration as a driver of the green transition, highlighting the importance of immigrants' contributions for environmental policy design.

Second, this paper contributes to the broader literature on immigrants' economic contributions to receiving economies by distinguishing between green and nongreen immigration. Existing studies show that immigration in general fosters patenting and knowledge spillovers (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Terry et al., 2026; Mayda et al., 2026) and that immigrants transmit their origin countries' productive capabilities across borders (Bahar and Rapoport, 2018; Bahar et al., 2020). These two strands of research raise the question of whether a sector benefits from immigration in general or specifically from immigrants whose origin countries have strong capabilities in that sector. To answer this question, I estimate the contributions of immigration from origins with and without the relevant comparative advantage within the same specification, with a separate instrument for each group.[3] I find that green immigration increases green patenting and renewable electricity deployment, whereas nongreen immigration has no effect. This contrast does not simply reflect differences in economic development across origin countries: both groups include origins with high and low GDP per capita. I also examine whether the positive effects of green immigration extend to fossil innovation and brown electricity deployment: neither group has a significant effect on fossil patenting or brown electricity generation and capacity. These patterns indicate that immigrants' contributions to the green transition are tied specifically to their origin countries' comparative advantage. Policy assessments of immigration's role in the green transition should therefore consider the productive capabilities of immigrants' origin countries, not only the number of immigrants.

Third, this paper highlights the importance of considering where immigrants' economic contributions are realized. The economic effects of immigration need not be confined to the places where

[2] Terry et al. (2026) analyze the impact of non-European immigration on overall U.S. patenting activity at the U.S. county level. My focus is more specifically on green immigration and the green economy, looking at both patenting and renewable energy production.

[3] Prior studies on the international transmission of productive capabilities typically relate destination outcomes in a given product or technology to immigration from origins specialized in that field (e.g., Bahar and Rapoport, 2018; Bahar et al., 2020; Etzo and Takaoka, 2025), rather than jointly estimating the effects of immigration from origins with and without the relevant comparative advantage.

immigrants settle. This possibility is consistent with evidence that larger cities increasingly specialize in corporate management while smaller cities specialize in production (Duranton and Puga, 2005), and that firms transmit local shocks across their establishments in different regions (Giroud and Mueller, 2019). I connect renewable electricity plants to the counties where their operators are based, allowing the analysis to capture changes in electricity generation and installed capacity beyond the receiving county. Green immigration increases renewable generation and capacity associated with operators in receiving counties, and these effects remain positive and statistically significant when the outcomes include only plants outside the operator county. For research on the green transition, these findings highlight the value of linking renewable infrastructure to the communities where its operating organizations are based. More broadly, they suggest that assessments of immigrants' economic contributions should account for the connections between the places where immigrants settle and the locations where economic outcomes are observed.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 defines green and nongreen immigrants based on origin countries' comparative advantage. Section 4 presents the empirical framework, OLS estimates, and threats to identification. Section 5 details the identification strategy and pretreatment exercises. Section 6 presents the empirical results, including individual-level evidence on green employment, the main 2SLS estimates, placebo-style tests on fossil and brown outcomes, and robustness checks. Section 7 concludes.

2 Data

In the main county-level analysis, the unit of observation is county d in a five-year period ending in t. I combine data on international trade, contemporary immigrant stocks, historical immigration patterns, ancestry, corporate patents, and renewable electricity generation and nameplate capacity. These data provide the origin-country trade measures used to classify immigrants (described in Section 3), the contemporary and historical data used to measure immigration and construct the instruments, and the county-level outcomes for green innovation and renewable electricity deployment.

2.1 International Trade

I use bilateral merchandise trade data from the BACI database maintained by CEPII (Gaulier and Zignago, 2010) to measure origin countries' revealed comparative advantage in renewable energy exports. BACI provides annual trade flows at the six-digit Harmonized System (HS) product level by reconciling exporter- and importer-reported data from UN Comtrade. I identify renewable energy goods using the renewable energy plant category of the OECD Combined List of Environmental Goods (Sauvage, 2014) and map these products to six-digit codes in the 1996 revision of the HS classification (HS96).[4]

2.2 Immigrant Stocks and Ancestry

I use contemporary immigrant stocks to measure immigration in the outcome regressions and historical immigration and ancestry data to construct the instruments. These measures differ in their definitions, source years, and roles in the analysis.

Contemporary immigrant stocks count foreign-born residents aged 25 or older by country of birth and county of residence. For the 1995–2020 analysis, I use the 1990 and 2000 Censuses and the 2006–2010, 2011–2015, and 2016–2020 ACS five-year samples, obtained through IPUMS (Ruggles et al., 2025). I assign the ACS samples to 2010, 2015, and 2020, respectively, and linearly interpolate the 1995 and 2005 stocks within county-origin cells using the adjacent Census and ACS observations. Immigrant stocks are expressed in thousands.

To construct the historical immigration and ancestry measures used in the instruments, I adapt the data construction procedures of Terry et al. (2026), which build on Burchardi et al. (2019). The historical immigration data come from the 1880, 1900, 1910, 1920, 1930, 1970, 1980, 1990, and 2000 Censuses and the 2006–2010 ACS, supplemented by the 2011–2015 ACS. Historical immigration is organized by origin and arrival period to measure the timing and geographic distribution of earlier immigration. These data provide the historical push and pull components used to predict ancestry.

Ancestry measures the number of residents who report a given origin as their primary ancestry, including U.S.-born descendants of immigrants. Ancestry counts therefore include both foreign-born

[4]The full list of renewable energy export goods used in this classification is reported in Appendix Table A.1.

and U.S.-born residents, whereas immigrant stocks include only foreign-born residents. I use ancestry measures for 1990, 1995, 2000, 2005, 2010, and 2015, which enter with a five-year lag in constructing the instruments for the 1995–2020 analysis periods.[5]

2.3 Green Patenting

Patent data come from the United States Patent and Trademark Office (USPTO).[6] I use granted corporate utility patents, combining patent-level records with information on application dates, assignees, assignee locations, and International Patent Classification (IPC) codes. Each patent is assigned to a U.S. county using its recorded corporate-assignee location, harmonized to 1990 county boundaries. Patents are dated by application year; the main analysis covers applications filed during 1991–2020 that are observed as granted.

I identify green patents using the World Intellectual Property Organization's (WIPO) IPC Green Inventory, which maps IPC codes to environmentally sound technologies (World Intellectual Property Organization, n.d.). This classification system identifies environmental technologies within the broader IPC framework, allowing green patents to be identified from their technology codes rather than from keywords in patent titles or abstracts. My broadest measure, *broad green patents*, includes all patents in the inventory and spans multiple fields, including energy production, transportation, energy conservation, and waste management.

I construct two additional outcomes to examine energy-related innovation more specifically. *Green energy patents* cover eight topics within the inventory's Alternative Energy Production category: solar energy, wind energy, geothermal energy, biofuels, energy from manmade waste, fuel cells, use of waste heat, and natural heat. *Renewable (nonhydro) patents*, which I refer to as *renewable patents* hereafter, focus on renewable electricity generation technologies covering solar energy, wind energy, geothermal energy, and energy from manmade waste. For all three measures, a patent qualifies if at least one of its IPC codes matches the corresponding technology categories, and each qualifying patent is counted only once within a given outcome. Appendix Table A.2 summarizes the three

[5]Following Terry et al. (2026), ancestry counts for 1995 and 2005 are constructed from the 2000 Census and the 2006–2010 ACS, respectively, by excluding individuals who arrived after the target year and children younger than five.

[6]Patent records are obtained through PatentsView (U.S. Patent and Trademark Office, n.d.).

definitions.

For each patent category—broad green, green energy, and renewable—I aggregate patents assigned to county d into five-year counts by application year. Period t denotes the endpoint of the window: for example, $t = 1995$ corresponds to applications filed during 1991–1995. The analysis uses six periods ending in 1995, 2000, 2005, 2010, 2015, and 2020. To account for differences in county size, I express the outcomes as five-year patent counts per 100,000 residents, using fixed 1990 Census county population (U.S. Census Bureau, n.d.).

Figure 1 plots national five-year counts for the three patent categories by application year. Green patenting began to expand more rapidly in the early 1990s. The main analysis therefore begins with the 1991–1995 period to examine immigration's contribution during this expansion. By 2016–2020, broad green, green energy, and renewable patent counts had reached approximately 6.2, 2.8, and 4.7 times their respective 1991–1995 levels.

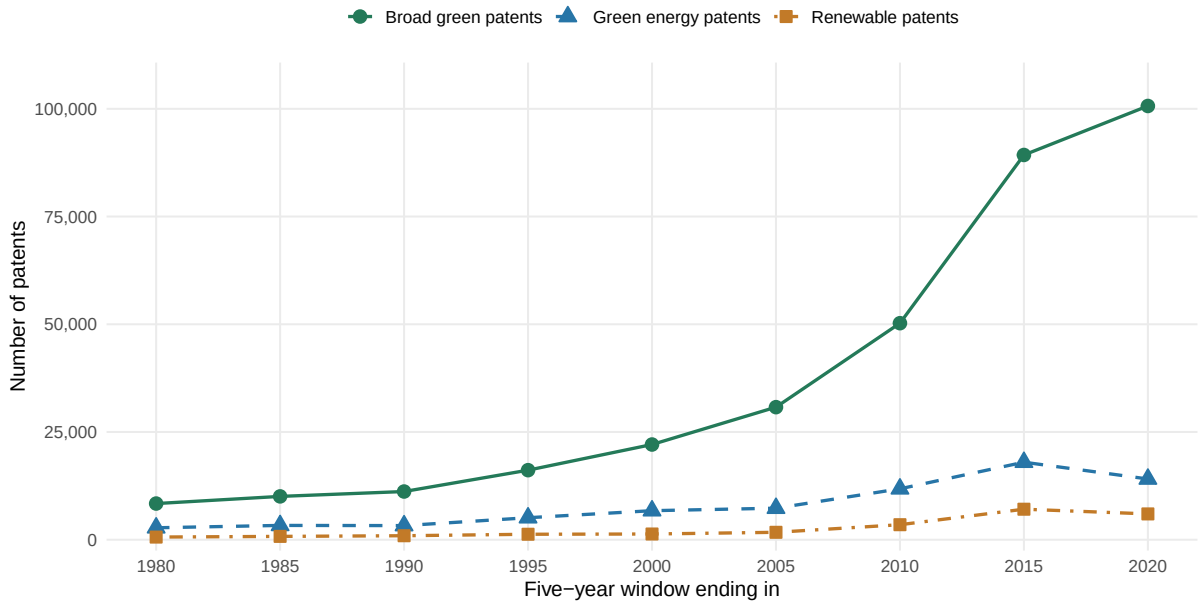


Figure 1: National Green Patenting, 1980–2020

Notes: Counts include granted corporate utility patents dated by application year. All observations are five-year counts; for example, 1995 covers application years 1991–1995.

2.4 Renewable Electricity Generation and Capacity

I measure renewable electricity deployment using electricity generation and installed capacity. Because wind and solar generation vary with weather conditions even for a given level of installed capacity (Kumler et al., 2019), I also examine end-period capacity, which reflects cumulative installations and changes over time through new additions and retirements. Examining capacity alongside generation helps assess whether changes in renewable electricity output are accompanied by corresponding changes in installed generating capacity.

I obtain electricity generation from the EPA's eGRID database and installed capacity from the EIA's Form EIA-860. These data draw on electricity producers' reports to the federal government about their generating facilities and operations (U.S. Environmental Protection Agency, 2026; U.S. Energy Information Administration, 2026). Both outcomes sum across wind, solar, geothermal, and biomass facilities and exclude hydroelectric power.

For generation, I use eGRID's annual plant-level net generation—total electricity produced minus the electricity used to operate the plant—measured in megawatt-hours (MWh). After assigning plant output to counties as described below, I average annual county totals within each five-year period ending in 2000, 2005, 2010, 2015, and 2020. Because eGRID is not available for every year, these averages use the observed years within each period.

For capacity, I use annual EIA-860 records covering 1996–2020, supplemented in the early years by eGRID records to cover plants not owned by traditional utilities. Using generator-level fuel and technology information, I sum the nameplate capacities—the maximum rated output, measured in megawatts (MW)—of qualifying renewable generators. I use records for 2000, 2005, 2010, 2015, and 2020 to measure installed capacity at the end of each five-year period.

I construct two geographic assignments for each outcome. The *plant-county* measure assigns generation and capacity to the county where the generating facility is physically located. The *operator-county* measure uses linked EIA entity records and reported business addresses to assign these outcomes to the reporting organization's county. I refer to these linked organizations collectively as *plant operators*.[7] When a plant is linked to operators in multiple counties, I apply the correspond-

[7]EIA-860 distinguishes the reporting entity's business address from the physical plant address. Reporting entities may be owners, operators, or asset managers; "plant operators" is used here as a collective label. See U.S. Energy Information Administration (n.d., Schedule 1, items 3–4, and Schedule 2).

Table 1: Summary Statistics

Variable	*N*	Mean	SD
Panel A. Immigrant stocks (thousands), 1995–2020			
Aggregate immigrant (green + nongreen)	18,828	8.7	66.2
Green immigrant (18 origins)	18,828	5.0	41.6
Nongreen immigrant (68 origins)	18,828	3.7	26.9
Unclassified immigrant (108 origins)	18,828	1.2	13.7
Panel B. Five-year patent outcomes per 100,000 fixed-1990 residents, 1995–2020			
Broad green patents	18,828	4.098	14.8
Green energy patents	18,828	0.843	3.3
Renewable patents	18,828	0.323	1.4
Panel C. Renewable electricity deployment outcomes, 2000–2020			
Plant-county renewable capacity (MW)	15,695	23.8	127.9
Plant-county renewable generation (MWh)	15,695	66,584	390,064
Plant operator-county renewable capacity (MW)	15,695	23.5	304.2
Plant operator-county renewable generation (MWh)	15,695	60,368	678,723

Notes: The unit of observation is a county-period. Aggregate immigrant is the sum of green immigrant and nongreen immigrant stocks. Origin groups are defined in Section 3.2. Patent outcomes are five-year counts per 100,000 fixed-1990 residents. Renewable capacity is end-period installed nameplate capacity, and renewable generation is average annual generation over each five-year period. Deployment outcomes exclude hydroelectric power and include solar, wind, biomass, and geothermal power.

ing county allocation weights before aggregating to the county level. The operator-county measure therefore captures generation and capacity from all plants linked to operators in that county, whether the plants are located within the county or elsewhere.

Appendix Table A.3 decomposes the operator-county outcomes by plant location using the same plant–operator links, allocation weights, and estimation sample as Panel A of Table 8. Plants in the same county as the associated operator account for 21.4 percent of renewable generation and 15.9 percent of installed capacity. Plants in a different state account for 51.6 percent of generation and 57.9 percent of capacity. This geographic separation motivates examining deployment outcomes at both plant and operator locations.

Table 1 reports summary statistics for the immigrant stocks, patent outcomes, and renewable deployment outcomes used in the analysis. Green, nongreen, and unclassified immigrant stocks use the origin groups defined in Section 3.2.

3 Classification of Green and Nongreen Immigrants

To distinguish immigrants by the productive capabilities of their origins, I use origin-country revealed comparative advantage in renewable energy goods. RCA provides an observable indicator of the productive environment from which immigrants come. This environment may be associated with relevant knowledge, experience, and connections that are not fully reflected in conventional measures of human capital, such as education and STEM training.

Research on migration and knowledge diffusion suggests several ways in which these backgrounds may contribute to receiving economies. Immigrants may carry productive knowledge and experience that can be applied in their destinations (Bahar and Rapoport, 2018; Bahar et al., 2020). Their networks may also facilitate access to external knowledge, and collaboration in receiving regions may help combine this knowledge with capabilities already present there (Cornejo Costas et al., 2026). These possibilities motivate classifying immigrants by their countries of origin. Consistent with this view, Section 6.1 shows at the individual level that immigrants from countries with a stronger comparative advantage in renewable energy goods are more likely to work in green occupations in the United States.

3.1 Measurement of Origin-Country Comparative Advantage

Using the trade data described in Section 2.1, I construct each origin country's revealed comparative advantage in renewable energy goods from export values aggregated across destinations and pooled over 1996–1999, the first four years available in the BACI HS96 data. Pooling over four years avoids relying on a single year of trade flows, which can fluctuate from year to year. For each origin country o, RCA is defined as

$$RCA_o^{Renewable} = \frac{X_o^{Renewable}/X_o}{X_W^{Renewable}/X_W}. \tag{1}$$

All export measures are based on the dollar value of exports. Here, $X_o^{Renewable}$ denotes the value of renewable energy goods exports from country o, and X_o denotes the value of its total merchandise exports. The corresponding world aggregates are denoted by $X_W^{Renewable}$ and X_W, respectively.

3.2 Classification of Origins

I classify origins into green and nongreen groups based on their revealed comparative advantage in renewable energy goods. Green origins have $RCA_o^{Renewable} \geq 1$, meaning that the share of renewable energy goods in their total exports is at least as large as the corresponding world share, whereas nongreen origins have $RCA_o^{Renewable} < 1$.

To ensure that this classification reflects sufficient export activity, an origin must have cumulative exports over 1996–1999 of at least US $1 billion in total goods and US $10 million in renewable energy goods, with positive exports in at least five renewable product categories. Applying these criteria yields 18 green origins and 68 nongreen origins. The remaining 108 origins are referred to as *unclassified* origins and are assigned to neither group. I refer to immigrants from green and nongreen origins as green and nongreen immigrants, respectively. Applying this classification to the contemporary immigrant stocks described in Section 2.2 yields green and nongreen immigrant stocks, I_{dt}^G and I_{dt}^{NG}. Their sum, $I_{dt} = I_{dt}^G + I_{dt}^{NG}$, is the aggregate immigrant stock from the 86 classified origins. In the county-level analysis, unclassified immigrants do not enter either treatment stock and are used only to construct the instruments.

One natural concern is whether this classification simply reflects differences in income across countries. Figure 2 plots the RCA of the classified countries on the vertical axis against log GDP per capita in 1996–1999 on the horizontal axis. Green countries are shown as green circles at or above the $RCA = 1$ threshold, and nongreen countries as orange triangles below it. The figure shows that both groups span a wide range of GDP per capita and include high-income economies: for example, Germany and Denmark are classified as green, whereas France, Canada, and Australia are classified as nongreen. The nongreen group also includes major oil and gas producers such as Qatar, Saudi Arabia, and Norway. The full list of countries in each group is provided in Appendix Table A.4. Section 6.6 further examines whether the county-level findings are confined to higher-income green origins.

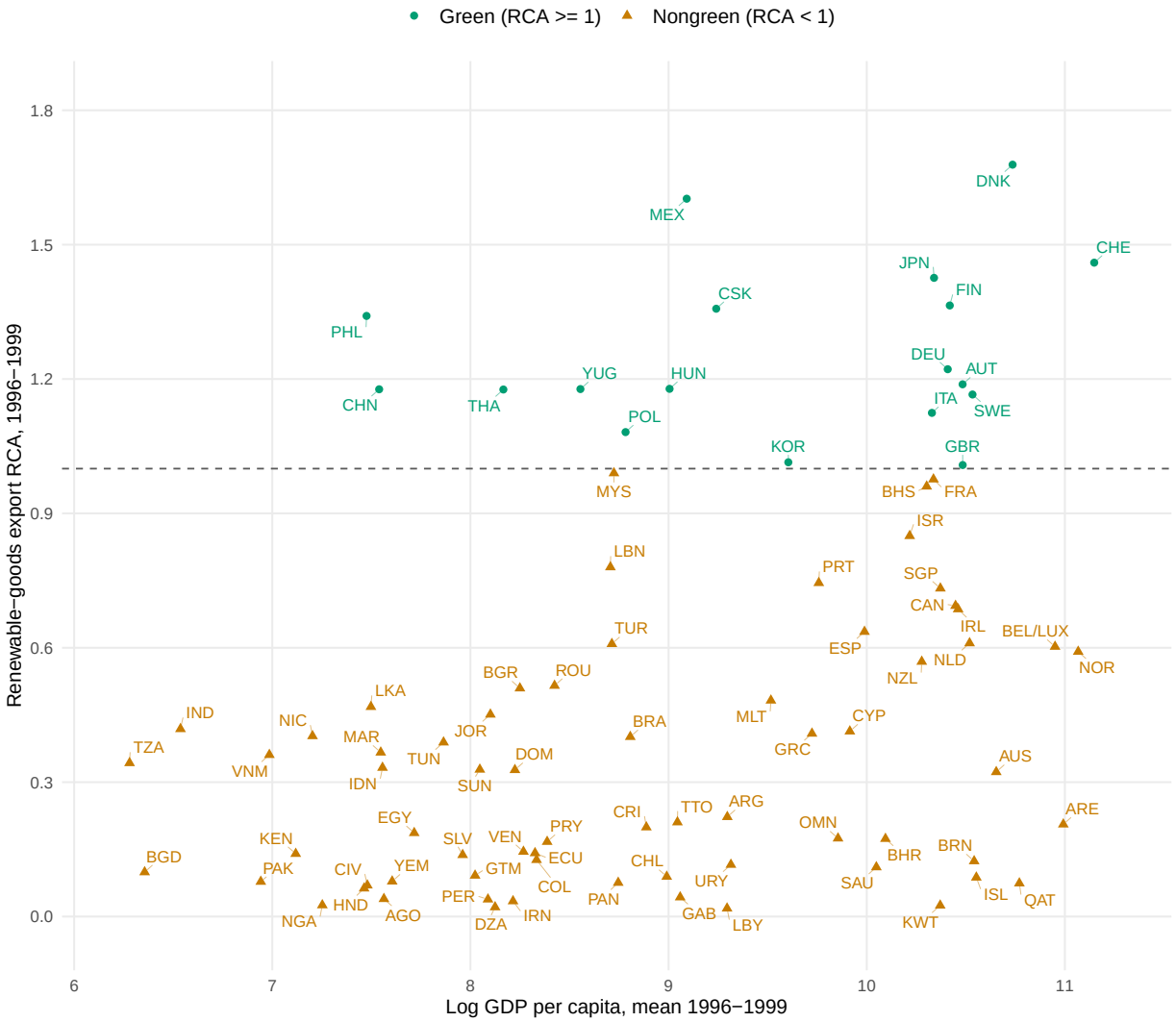


Figure 2: Renewable Energy Export RCA and GDP per Capita, 1996–1999

Notes: All 86 origins with comparable GDP data are labeled: 18 green and 68 nongreen origins. The dashed line marks $RCA = 1$. GDP per capita is the 1996–1999 mean in constant 2015 U.S. dollars (World Bank WDI). Labels use ISO alpha-3 codes.

Using these green and nongreen immigrant measures, the next section presents the county-level empirical framework, OLS estimates, and threats to identification.

4 Empirical Framework

4.1 Empirical Specification

A large literature finds that immigrants raise innovation in destination economies, both through their own inventive activity and through spillovers to other workers (Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010; Bernstein et al., 2022; Terry et al., 2026). This paper asks whether green immigrants, defined by their origins' RCA in renewable energy goods, contribute to green innovation and renewable electricity deployment in U.S. counties, controlling for nongreen immigrants. The main specification is

$$Y_{dt} = \alpha_d + \alpha_{s(d)t} + \beta_G I^G_{dt} + \beta_{NG} I^{NG}_{dt} + X'_{d0}\gamma_t + \varepsilon_{dt}, \tag{2}$$

where Y_{dt} is a patent or renewable energy outcome in county d and period t, and I^G_{dt} and I^{NG}_{dt} are the stocks of green and nongreen immigrants, in thousands of residents aged 25 or older. County fixed effects, α_d, absorb permanent county characteristics, and state-by-period fixed effects, $\alpha_{s(d)t}$, absorb shocks common to counties in the same state and period. I cluster standard errors by state. Rather than controlling for contemporaneous county characteristics that may themselves respond to immigration, I control for characteristics reflecting counties' initial levels of economic development and allow their effects to vary across periods. Specifically, X_{d0} includes college share, manufacturing employment share, and per capita personal income[8], all measured in 1990, before the analysis period. I interact these characteristics with period indicators.

Including both immigrant groups in equation (2) estimates the contribution of each group while accounting for the other, allowing the effects of immigration on green activity to differ by origin-country RCA rather than imposing a common effect.

To connect the analysis with the existing literature on overall immigration, I also estimate an

[8]Per capita personal income comes from the Bureau of Economic Analysis (BEA), table CAINC1, line 3, Personal Income by County. It is residents' total personal income divided by midyear population, expressed in 1990 U.S. dollars.

aggregate specification that pools the two groups:

$$Y_{dt} = \alpha_d + \alpha_{s(d)t} + \beta I_{dt} + X'_{d0}\gamma_t + \varepsilon_{dt}, \qquad I_{dt} = I^G_{dt} + I^{NG}_{dt}. \tag{3}$$

The aggregate specification imposes $\beta_G = \beta_{NG}$ and therefore estimates the effect of aggregate immigration without distinguishing between green and nongreen immigrants.

4.2 OLS Estimates

Table 2 reports the OLS estimates for green patenting in (a) and renewable electricity deployment in (b). Aggregate immigration is positively and significantly associated with broad green and renewable patents and both operator-county deployment outcomes; its association with green energy patents is positive but statistically insignificant. When green and nongreen immigrants are included together, neither group has a significant coefficient for green energy or renewable patents, whereas both groups have positive and significant coefficients for operator-county generation and capacity. Only the nongreen coefficient is significant for broad green patents. Green immigrants are also positively and significantly associated with both plant-county outcomes, while the nongreen coefficients for these outcomes are negative and significant. These associations cannot distinguish the contribution of immigrants from the conditions that shaped where they settled, which I discuss next.

Table 2: Immigration, Green Patenting, and Renewable Electricity Deployment, OLS

(a) Green Patenting

Dependent variable	Broad green patents	Green energy patents	Renewable patents
Panel A. Aggregate immigration			
Aggregate immigrant	0.102**	0.012	0.007**
	(0.043)	(0.007)	(0.003)
Panel B. Green and nongreen immigration			
Green immigrant	0.031	0.012	0.004
	(0.082)	(0.013)	(0.006)
Nongreen immigrant	0.182**	0.012	0.011
	(0.090)	(0.016)	(0.007)
Observations	18,828	18,828	18,828
County FE	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes

(b) Renewable Electricity Deployment

Location	Operator county		Plant county	
Dependent variable	Generation (MWh)	Capacity (MW)	Generation (MWh)	Capacity (MW)
Panel A. Aggregate immigration				
Aggregate immigrant	24,923***	11.1***	4,148*	1.6*
	(7,927)	(3.3)	(2,405)	(0.9)
Panel B. Green and nongreen immigration				
Green immigrant	8,633*	4.2*	15,475**	6.1***
	(4,538)	(2.3)	(6,796)	(2.2)
Nongreen immigrant	40,027***	17.5***	−6,355*	−2.6**
	(14,259)	(5.3)	(3,619)	(1.3)
Observations	15,695	15,695	15,695	15,695
County FE	Yes	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes	Yes

Notes: In (a), patent outcomes are five-year patent counts per 100,000 residents, using fixed 1990 Census population, for 1995–2020. In (b), energy outcomes are average annual nonhydro renewable generation in MWh and end-period installed nonhydro nameplate capacity in MW, for 2000–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. The controls are the 1990 college share among residents aged 25 or older, the manufacturing share among residents aged 16 or older, and income, each interacted with period indicators. Within each block, Panel A reports separate regressions of each outcome on the sum of green and nongreen immigrants; Panel B includes both immigrant groups together. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.3 Threats to Identification

The green and nongreen immigrant stocks, I_{dt}^{G} and I_{dt}^{NG}, in equation (2) are potentially endogenous: immigrants choose where to settle, and their choices may be related to local green outcomes for reasons other than their own contribution. First, local green activity may itself attract immi-

grants. Immigrants choose destinations partly in response to current and anticipated local economic opportunities, and expanding innovative firms or renewable energy businesses can raise employment and earnings prospects. OLS may therefore attribute to immigration some of the green growth that helped attract immigrants in the first place.

Second, unobserved local economic conditions may affect both green outcomes and immigrant settlement. Although equation (2) accounts for time-invariant county characteristics, state-by-period shocks, and differential trends associated with initial 1990 economic conditions, counties still evolve differently over time. Immigrants may therefore remain correlated with unobserved local conditions that also affect green outcomes. Because these conditions may attract green and nongreen immigrants to different degrees, the resulting omitted-variable bias may differ across the two groups.

The observed settlement patterns are consistent with these concerns. Appendix Tables B.1 and B.2 relate changes in immigrant stocks to changes in green activity over the preceding five-year period. These analyses show that prior growth in broad green patenting and operator-county renewable generation and capacity is positively and significantly associated with subsequent changes in nongreen immigrant stocks, while the corresponding associations for green immigrants are negative. These patterns indicate that the relationship between prior green activity and subsequent immigration differs across groups. If local conditions that raise green activity also attract nongreen immigrants while being negatively associated with green immigrant inflows, OLS would overstate the association for nongreen immigrants and understate it for green immigrants. These patterns do not establish whether green activity attracts immigrants or whether other local changes drive both, but they motivate seeking variation in immigration that is independent of these destination conditions.

5 Identification Strategy

To address these concerns, I adapt the approach of Burchardi et al. (2019) and Terry et al. (2026) to construct separate instruments for the green and nongreen immigrant stocks, I_{dt}^{G} and I_{dt}^{NG}, in equation (2). The construction proceeds in two steps. First, I predict ancestry from each origin in each county using historical push and pull forces. Second, I combine predicted ancestry with contemporary immigrants to construct the instruments. I describe these steps below, followed by the identifying assumptions and supporting evidence.

5.1 Predicted Ancestry

A conventional shift-share construction, following Card (2001), constructs an instrument for immigration from the interaction between preexisting ancestry and contemporary immigration to other parts of the country:

$$A_{od,t-5} \times I_{o,-r(d),t},$$

where $A_{od,t-5}$ is observed ancestry from origin o in county d, and $I_{o,-r(d),t}$ is the contemporary immigrant stock from that origin outside the destination's Census division. An identification concern arises because earlier migrants also chose destinations in response to local economic conditions and industry opportunities. Observed ancestry, $A_{od,t-5}$, can therefore reflect persistent links between particular origins and local industrial structures. When those industries later experience shocks that affect green innovation or renewable deployment, a conventional shift-share instrument based on $A_{od,t-5}$ can reintroduce through the ancestry component the very omitted-variable concern it is meant to address.

Polish immigration to Cook County, Illinois, illustrates this mechanism. Early Polish migrants came to Chicago for industrial employment, while established Polish American organizations later helped postwar arrivals settle (Radzilowski, 2022). Observed Polish ancestry therefore captures not only a community that attracts subsequent immigrants, but also the industrial history that shaped its location. If that industrial legacy shapes the county's exposure to subsequent industry shocks, observed ancestry may remain correlated with changes in green outcomes even after county fixed effects.

To reduce the influence of endogenous historical settlement, I replace the observed ancestry component, $A_{od,t-5}$, in the shift-share construction above with predicted ancestry based on the coincidence between origin-specific historical emigration waves and periods when a destination attracted immigrants from other groups.

For Poland and Cook County, the historical push is Polish immigration to destinations outside the East North Central division, which contains Cook County. The pull is Cook County's share of U.S. immigration from other immigrant groups in the same historical period. Cook County's average attractiveness to European migrants is absorbed by the continent-by-county fixed effects, and Polish

migrants' average propensity to settle in the East North Central division is absorbed by origin-by-division fixed effects. Conditional on these fixed effects and the bilateral controls, the prediction uses the overlap between Polish migration waves outside the division and periods of greater immigration to Cook County from other immigrant groups.

Formally, let A_{odT} denote the number of residents with ancestry from origin o in county d at time T. For each ancestry year $T \in \{1990, 1995, 2000, 2005, 2010, 2015\}$, I estimate the following regression across origin–county pairs:

$$\begin{aligned} A_{odT} = \delta_{o,r(d)} + \delta_{c(o),d} + X'_{od}\zeta \\ + \sum_{\tau=1880}^{T} a_{r(d),\tau,T} \left(I_{o,-r(d),\tau} \frac{I^U_{d\tau}}{I^U_{US,\tau}} \right) + u_{odT}, \end{aligned} \tag{4}$$

where $I_{o,-r(d),\tau}$ is historical immigration from origin o to destinations outside county d's Census division (the 'push'), and $I^U_{d\tau}/I^U_{US,\tau}$ is county d's share of U.S. immigration from unclassified origins in period τ (the 'pull').[9] I measure the pull using unclassified immigrants (neither green nor nongreen) to capture a county's attractiveness to other immigrant groups without directly using the settlement choices of the green and nongreen immigrants whose effects I estimate.[10] The index τ denotes the available historical periods from 1880 through T.

Here, $r(d)$ denotes the Census division containing county d, and $c(o)$ denotes the continent of origin o. Origin-by-division fixed effects, $\delta_{o,r(d)}$, and origin-continent-by-county fixed effects, $\delta_{c(o),d}$, absorb persistent differences in how origins sort across regions and how counties attract migrants from each continent. The vector X_{od} contains bilateral distance and latitude distance. The coefficients $a_{r(d),\tau,T}$ allow the contribution of each historical push–pull interaction to differ across destination divisions and ancestry years.

I construct predicted ancestry as follows:

$$\widehat{A}_{odT} = \sum_{\tau \leq T} \widehat{a}_{r(d),\tau,T} \left(I_{o,-r(d),\tau} \frac{I^U_{d\tau}}{I^U_{US,\tau}} \right)^{\perp}, \tag{5}$$

[9] Appendix C.1 lists the nine Census divisions used in the leave-division-out construction and their constituent states.

[10] Terry et al. (2026) use a related approach in which European settlement predicts ancestry from non-European origins.

where the superscript $\perp$ indicates that the interaction of push-pull factors has been residualized with respect to all of the controls in equation (4), and $\widehat{a}_{r(d),\tau,T}$ are the coefficients for the historical push-pull interactions. The prediction excludes the fitted geographic components and the common intercept, so its variation comes only from the historical push–pull interactions.

For each outcome period t, I use predicted ancestry at $T = t - 5$ to construct the immigration instruments described in the next subsection.

5.2 Immigration Instruments

In the second step, I apply the standard shift-share structure from Section 5.1, with predicted ancestry replacing observed ancestry as the ancestry component. For the Poland–Cook County example, this step interacts the predicted Polish ancestry of Cook County with the contemporary Polish stock outside East North Central. Using the contemporary immigrant stock from the same origin outside the destination division excludes same-origin settlement within that division from the own-origin push component. Using residents aged 25 or older, I estimate separate equations for green and nongreen immigrants:

$$I^{G}_{odt} = \delta^{G}_{o,r(d)} + \delta^{G}_{c(o),d} + \delta^{G}_{t} + X'_{od}\theta^{G} + b^{G}_{t}\left[\widehat{A}_{od,t-5} \times \tilde{I}_{o,-r(d),t}\right] + \eta^{G}_{odt}, \tag{6}$$

and

$$I^{NG}_{odt} = \delta^{NG}_{o,r(d)} + \delta^{NG}_{c(o),d} + \delta^{NG}_{t} + X'_{od}\theta^{NG} + b^{NG}_{t}\left[\widehat{A}_{od,t-5} \times \tilde{I}_{o,-r(d),t}\right] + \eta^{NG}_{odt}, \tag{7}$$

where $\tilde{I}_{o,-r(d),t} = I_{o,-r(d),t}\left(I^{U}_{r(d),t}/I^{U}_{-r(d),t}\right)$ is the scaled push from origin o. Here, $I_{o,-r(d),t}$ is the contemporary immigrant stock from o outside division $r(d)$, and $I^{U}_{r(d),t}$ and $I^{U}_{-r(d),t}$ are the unclassified immigrant stocks within and outside that division. I use unclassified immigrant stocks to measure the size of the destination division's immigrant population relative to the rest of the country. I then multiply $I_{o,-r(d),t}$ by this ratio. Each regression includes origin-by-division, origin-continent-by-county, and year fixed effects, and time-invariant bilateral distance and latitude distance controls.

I construct the final instruments by aggregating across origins within each group:

$$\widehat{I}_{dt}^{G} = \sum_{o \in G} \widehat{b}_{t}^{G} \left[\widehat{A}_{od,t-5} \times \tilde{I}_{o,-r(d),t} \right], \tag{8}$$

$$\widehat{I}_{dt}^{NG} = \sum_{o \in NG} \widehat{b}_{t}^{NG} \left[\widehat{A}_{od,t-5} \times \tilde{I}_{o,-r(d),t} \right]. \tag{9}$$

I use $\widehat{I}_{dt}^{G}$ and $\widehat{I}_{dt}^{NG}$ as instruments for I_{dt}^{G} and I_{dt}^{NG} in equation (2), and each first stage includes both instruments.[11] Appendix Figure C.1 illustrates the geographic distribution of the green and nongreen immigration instruments after removing county and state-by-period fixed effects.

The identifying assumption is that, conditional on the fixed effects and controls in the outcome equation, the instruments are uncorrelated with unobserved determinants of green innovation and renewable electricity deployment. This requires that the instruments affect these outcomes only through the green and nongreen immigrant stocks.

5.3 Evidence on Instrument Validity

To assess the validity of these instruments, I conduct two exercises examining the timing of green outcomes and instrument-predicted immigration. The first addresses reverse causality by asking whether pre-period or early outcome growth predicts later instrument-predicted immigration, which could arise if growing green activity attracted immigrants and the instruments captured that response. Panel A of Table 3 asks whether patent growth from 1985 to 1990, before the sample period, predicts future instrument-generated changes in green or nongreen immigrant stocks. Across broad green, green energy, and renewable patents, none of the six coefficients is statistically significant. Panel B of Table 3 repeats the exercise for early operator-county capacity and generation growth, and none of the four estimates is statistically significant.

The second exercise provides a falsification check by asking whether subsequent changes in green and nongreen immigrant stocks predict earlier changes in green outcomes. I instrument these stock changes using the corresponding instruments constructed through the procedure described above.

[11] For the aggregate specification, I estimate the immigration prediction equation using green and nongreen origins together. The resulting aggregate instrument is therefore constructed separately, rather than by adding the green and nongreen instruments.

Table 3: Reverse Causality Analysis

Prior Green Activity and Future Predicted Immigration, OLS

Panel A. Pre-period patent growth

Dependent variable	Future predicted green immigrant changes			Future predicted nongreen immigrant changes		
	(1)	(2)	(3)	(4)	(5)	(6)
Change in broad green patents, 1985–1990	−0.006			−0.000		
	(0.008)			(0.001)		
Change in green energy patents, 1985–1990		0.026			0.000	
		(0.024)			(0.003)	
Change in renewable patents, 1985–1990			0.039			−0.001
			(0.058)			(0.008)
Observations	15,690	15,690	15,690	15,690	15,690	15,690
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Early renewable energy growth

Dependent variable	Future predicted green immigrant changes		Future predicted nongreen immigrant changes	
	(1)	(2)	(3)	(4)
Change in renewable capacity, 2000–2005 (per 100 MW)	0.186		0.028	
	(0.208)		(0.036)	
Change in renewable generation, 2000–2005 (per 100 GWh)		0.086		0.014
		(0.069)		(0.009)
Observations	9,417	9,417	9,417	9,417
State FE	Yes	Yes	Yes	Yes

Notes: Each column within a panel reports a separate OLS regression of the indicated future five-year change in instrument-predicted immigrant stocks, in thousands, on the single prior-outcome predictor shown and the controls listed below. Panel A uses 1985–1990 changes in five-year patent counts per 100,000 residents, using fixed 1990 Census population, and stacks immigrant changes from 1995–2000 through 2015–2020. In Panel B, capacity is end-2005 minus end-2000 operator-county nonhydro renewable capacity, in units of 100 MW; generation is the change from 1996–2000 to 2001–2005 in average annual operator-county nonhydro renewable generation, in units of 100 GWh (100,000 MWh). Panel B stacks immigrant changes from 2005–2010 through 2015–2020. All regressions include state fixed effects, and the 1990 college share, manufacturing share, and per capita personal income, each interacted with period indicators. State-clustered standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Following Autor et al. (2013) and Mayda et al. (2023), I use patent growth before the estimation period to examine this relationship. Panel A of Table 4 reports 2SLS regressions of 1985–1990 changes in patent counts on instrumented changes in green and nongreen immigrant stocks over 1995–2020. Because comparable energy measures are unavailable before the estimation period, I use early-period energy changes instead. Panel B relates 1999–2000 changes in operator-county renewable generation and capacity to instrumented immigrant stock changes over 2005–2020. Thus, both panels

Table 4: Falsification Tests

Future Immigration and Prior Green Activity, 2SLS

Panel A. Pre-period patent growth (immigrant changes, 1995–2020)

Dependent variable	Change in broad green patents (1985–1990)	Change in green energy patents (1985–1990)	Change in renewable patents (1985–1990)
	(1)	(2)	(3)
Change in green immigrant	−0.002	0.002	0.001
	(0.003)	(0.002)	(0.001)
Change in nongreen immigrant	0.000	−0.001	−0.001
	(0.005)	(0.002)	(0.001)
Observations	3,138	3,138	3,138
KP F	4.1	4.1	4.1
State FE	Yes	Yes	Yes

Panel B. Early renewable energy growth (immigrant changes, 2005–2020)

Dependent variable	Change in renewable generation (1999–2000, MWh)	Change in renewable capacity (1999–2000, MW)
	(1)	(2)
Change in green immigrant	−972	0.1
	(1,514)	(0.3)
Change in nongreen immigrant	1,479	0.3
	(1,590)	(0.3)
Observations	3,139	3,139
KP F	4.7	4.7
State FE	Yes	Yes

Notes: Each column within a panel reports a separate 2SLS regression containing both green and nongreen immigrant changes, in thousands of residents aged 25 or older, instrumented by the corresponding instrument changes. Panel A relates 1985–1990 changes in five-year patent counts per 100,000 residents, using fixed 1990 Census population, to immigrant changes over 1995–2020. Panel B relates 1999–2000 changes in operator-county nonhydro renewable generation (MWh) or capacity (MW) to immigrant changes over 2005–2020. All regressions include state fixed effects and the 1990 college share, manufacturing share, and BEA per capita personal income (in thousands of 1990 dollars). Panel B additionally controls for 1990 population. State-clustered standard errors are in parentheses. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

examine whether later immigration predicts outcome changes that precede the immigration period, although only the patent exercise uses outcomes from before the estimation period. None of the coefficients is statistically significant. Appendix Figures H.1 and H.2 provide visual illustrations of these results. Given the low first-stage F statistics of these falsification exercises, I also report reduced-form regressions of prior outcome changes on subsequent changes in both instruments. Neither instrument coefficient is statistically significant for any outcome (Appendix Table H.1).

6 Empirical Results

This section begins with descriptive individual-level evidence on origin RCA and green employment before turning to the county-level 2SLS analysis based on Section 5. The county-level analysis estimates the effects of green and nongreen immigration on green innovation and renewable electricity deployment, examines fossil innovation and brown electricity deployment as comparison outcomes, and concludes with robustness checks.

6.1 Origin RCA and Green Occupation Employment

I first examine whether immigrants from origins with higher revealed comparative advantage (RCA) in renewable energy goods are more likely to work in green occupations in the United States. Using annual ACS observations for civilian employed workers aged 25–64 during 2005–2020, I measure green employment using all three O*NET green occupation categories: *Green New and Emerging*, *Green Enhanced Skills*, and *Green Increased Demand*. These categories capture new types of green work, substantial changes in existing occupational requirements, and increased demand for existing occupations without substantial changes in their tasks or skill requirements (Dierdorff et al., 2009; National Center for O*NET Development, 2017). Green employment accounts for 13.7 percent of green immigrants, compared with 11.3 percent of nongreen immigrants and 12.5 percent of U.S.-born workers (see Appendix A.5 and Appendix Figure A.1 for measurement details and breakdowns by arrival duration).

To examine whether the relationship between origin RCA and green employment persists after accounting for worker characteristics, residential location, and origin-country GDP per capita, I estimate individual-level OLS regressions using continuous origin RCA. The regression sample includes immigrants from all countries with available RCA and GDP data.[12] Table 5 reports the results. Columns (1)–(5) use the 2005–2020 sample, beginning with RCA alone and sequentially adding age, sex, and education controls; survey-year and arrival-cohort fixed effects; residential PUMA fixed effects; and origin GDP per capita. In particular, PUMA fixed effects address the possibility that the relationship reflects immigrants' sorting into destinations where green jobs are more abundant,

[12] I also estimate the same specifications restricting the sample to immigrants from green and nongreen countries; Appendix Table A.5 reports these estimates.

Table 5: Origin RCA and Employment in Green Occupations, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Employment in green occupations, including jobs with increased demand							
RCA	2.398*	1.358**	1.304**	1.140**	0.972**	0.907*	0.941**
	(1.243)	(0.536)	(0.510)	(0.451)	(0.470)	(0.466)	(0.471)
Individual characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Survey-year FE	No	No	Yes	Yes	Yes	Yes	Yes
Arrival-cohort FE	No	No	Yes	Yes	Yes	Yes	Yes
PUMA FE	No	No	No	Yes	Yes	Yes	Yes
Origin GDP per capita	No	No	No	No	Yes	Yes	Yes
STEM degree field	No	No	No	No	No	No	Yes
Years	2005–2020	2005–2020	2005–2020	2005–2020	2005–2020	2009–2020	2009–2020
Observations	2,676,853	2,676,853	2,676,853	2,676,853	2,676,853	2,075,303	2,075,303

Notes: Each column reports the coefficient on continuous origin RCA for 1996–1999 from a separate person-weighted OLS regression; origin-clustered standard errors are in parentheses. Green occupations are defined by O*NET. The dependent variable equals 100 if a worker is employed in a green occupation and zero otherwise. The RCA coefficient therefore measures the percentage-point change in green employment probability associated with a one-unit increase in origin RCA. The sample includes employed immigrants aged 25–64 from all countries with available RCA and GDP data. Individual characteristics include age FE, sex, and education FE. Controls accumulate across specifications (1)–(5); survey-year and arrival-cohort FE enter together in (3). Specification (6) repeats (5) for 2009–2020; (7) adds STEM degree field on that same sample. Origin GDP per capita is its 1996–1999 mean. PUMA FE are defined by state, PUMA, and boundary vintage (2000 boundaries for 2005–2011; 2010 boundaries for 2012–2020). RCA is defined in Section 3.1; its interquartile range is 1.461. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

by comparing immigrants living in the same residential area. Because degree-field data are available only from 2009 onward, column (6) repeats column (5) for 2009–2020, and column (7) adds a STEM degree-field indicator on the same sample. Regressions use ACS person weights and standard errors clustered by origin.

The positive relationship persists with the inclusion of PUMA fixed effects and origin GDP per capita, and changes little with the addition of STEM degree field. This persistence suggests that immigrants from higher-RCA origins have a greater propensity to work in green occupations even conditional on the "greenness" of their chosen destinations. In the full specification, an interquartile increase in origin RCA is associated with a 1.37 percentage-point higher probability of green employment, approximately 11 percent of the sample mean.[13] This evidence is suggestive of productive capabilities tied to immigrants' origins, but is not causal because migration and occupational choices are endogenous. I therefore turn to the county-level 2SLS analysis.

[13]The results remain positive and statistically significant when the outcome is restricted to *Green New and Emerging* and *Green Enhanced Skills* occupations (Appendix Table A.6).

6.2 Green Innovation

Table 6 reports the county-level 2SLS estimates for the three green patent outcomes, followed by the corresponding first-stage results. In the aggregate 2SLS specification, aggregate immigration has a positive and statistically significant effect on broad green and renewable patenting, while its estimate for green energy patenting is positive but statistically insignificant.

In the main 2SLS specification, which includes green and nongreen immigrants together, the green immigrant coefficients are positive and statistically significant across all three outcomes. Controlling for nongreen immigrants, an additional 1,000 green immigrants increases broad green patenting by 0.404 patents per 100,000 residents over five years, or about 9.9 percent of the sample mean. The corresponding increases are 0.049 for green energy patents (5.8 percent of the mean) and 0.025 for renewable patents (7.7 percent of the mean). By contrast, the nongreen immigrant coefficients are statistically insignificant for all three outcomes. Relative to the OLS estimates in Table 2 (a), the 2SLS coefficient for green immigrants is larger (0.404 versus 0.031 for broad green patents), whereas the nongreen coefficient falls from a positive and significant 0.182 to a negative and insignificant estimate. These differences are consistent with the settlement patterns in Appendix Table B.1, where prior green growth is positively associated with subsequent nongreen immigrants and negatively associated with green immigrants.

The bottom panel of Table 6 reports the first-stage estimates for the patent sample. The aggregate instrument positively and significantly predicts the aggregate immigrant stock, and the green and nongreen instruments each positively and significantly predict their corresponding immigrant stocks. The green instrument also positively predicts the nongreen immigrant stock, although this coefficient is smaller in magnitude than its coefficient in the green immigrant equation.

Table 6: Immigration and Green Patenting, 2SLS

Dependent variable	Broad green patents	Green energy patents	Renewable patents
Aggregate 2SLS			
Aggregate immigrant	0.065*	0.011	0.008**
	(0.033)	(0.008)	(0.003)
KP F	34.0	34.0	34.0
Main 2SLS			
Green immigrant	0.404*	0.049**	0.025***
	(0.209)	(0.024)	(0.009)
Nongreen immigrant	−0.329	−0.036	−0.013
	(0.271)	(0.030)	(0.013)
KP F	9.6	9.6	9.6
Observations	18,828	18,828	18,828
County FE	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes

First Stage

	Aggregate	Green and nongreen	
Dependent variable	Aggregate immigrant	Green immigrant	Nongreen immigrant
Aggregate instrument	1.792***		
	(0.307)		
Green instrument		1.246***	0.895***
		(0.253)	(0.141)
Nongreen instrument		−0.771	2.627***
		(0.692)	(0.956)
County FE	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes

Notes: Patent outcomes are five-year patent counts per 100,000 residents, using fixed 1990 Census population, for 1995–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. The controls are the 1990 college share among residents aged 25 or older, the manufacturing share among residents aged 16 or older with civilian industry codes, and 1990 per capita personal income in levels, each interacted with period indicators. Controls enter both stages identically. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6.3 Renewable Electricity Deployment

Table 7 reports the county-level 2SLS estimates for renewable electricity deployment, followed by the corresponding first-stage results. In the aggregate 2SLS specification, an additional 1,000 immigrants increases renewable generation assigned to operator counties by 32,937 MWh per year and installed capacity by 14.1 MW, both statistically significant at the 5 percent level, whereas the plant-county estimates are small and statistically insignificant.

In the main 2SLS specification, controlling for nongreen immigrants, an additional 1,000 green

immigrants increases operator-county renewable generation by 57,113 MWh, or 57.1 GWh, per year. At the 2022 U.S. average of 10,791 kWh of annual electricity purchases per residential electricity customer, this amount is equivalent to the annual electricity purchases of about 5,300 U.S. residential electricity customers (U.S. Energy Information Administration, 2024). The same increase raises operator-county installed capacity by 27.7 MW, equivalent in nameplate capacity to about eight average new U.S. land-based wind turbines, whose average capacity was 3.4 MW in 2023 (U.S. Department of Energy, 2024). By contrast, the nongreen immigrant coefficients are statistically insignificant for both operator-county outcomes. As with patents, the green coefficient rises relative to OLS (from 8,633 to 57,113 MWh for operator-county generation) and the nongreen coefficient falls (from 40,027 to 7,412 MWh), in line with the sorting patterns for operator-county outcomes in Appendix Table B.2.

At plant counties, by contrast, neither immigrant group has a statistically significant effect: the green immigrant estimates are 3,233 MWh for generation and 1.7 MW for capacity, and the nongreen immigrant estimates are also insignificant. This contrast reflects the geographic separation between where operating organizations are based and where power plants are physically sited: as noted in Section 2 (Appendix Table A.3), plants outside the operator county account for 78.6 percent of renewable generation and 84.1 percent of installed capacity attributed to operator counties. Green immigration increases renewable generation and capacity through operators located in receiving counties, even though most of the associated generating facilities are sited elsewhere. This geographic pattern is consistent with the separation of management and production across locations described by Duranton and Puga (2005), and with evidence that local shocks can propagate across regions through firms' internal networks (Giroud and Mueller, 2019).

Table 7: Immigration and Renewable Electricity Deployment, 2SLS

Location	Operator county		Plant county	
Dependent variable	Generation (MWh)	Capacity (MW)	Generation (MWh)	Capacity (MW)
Aggregate 2SLS				
Aggregate immigrant	32,937**	14.1**	137	0.4
	(13,145)	(5.7)	(1,409)	(0.6)
KP F	17.7	17.7	17.7	17.7
Main 2SLS				
Green immigrant	57,113*	27.7**	3,233	1.7
	(30,424)	(13.2)	(4,248)	(2.2)
Nongreen immigrant	7,412	0.4	−2,696	−1.0
	(21,213)	(11.0)	(2,511)	(1.1)
KP F	12.2	12.2	12.2	12.2
Observations	15,695	15,695	15,695	15,695
County FE	Yes	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes	Yes

First Stage			
Specification	Aggregate	Green and nongreen	
Dependent variable	Aggregate immigrant	Green immigrant	Nongreen immigrant
Aggregate instrument	1.268***		
	(0.302)		
Green instrument		0.794***	0.693***
		(0.213)	(0.237)
Nongreen instrument		−0.432	2.309**
		(0.726)	(0.946)
County FE	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes

Notes: Energy outcomes are average annual nonhydro renewable generation in MWh and end-period installed nonhydro nameplate capacity in MW, for 2000–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. The controls are the 1990 college share among residents aged 25 or older, the manufacturing share among residents aged 16 or older with civilian industry codes, and 1990 per capita personal income in levels, each interacted with period indicators. Controls enter both stages identically. The first stages use the same controls and sample as the corresponding 2SLS specifications. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6.4 Renewable Deployment Beyond Immigrant-Receiving Counties

Because the operator-county outcomes in Table 7 combine plants located within and outside the operator's county, the positive estimates could in principle be driven by plants within the county receiving immigrants. To test whether the response extends beyond the receiving county, Panel A of Table 8 restricts the outcomes to generation and installed capacity at plants physically located

outside the operator's county. Both green immigrant coefficients remain positive and statistically significant at the 10 percent level, and their magnitudes—55,867 MWh for generation and 26.7 MW for capacity—are very close to the estimates for all linked plants in Table 7 (57,113 MWh and 27.7 MW). The nongreen immigrant coefficients remain statistically insignificant. These results show that the increase in renewable electricity generation and capacity extends to facilities physically located outside the communities where immigrants settle.

A related question is whether the capacity response reflects newly built generating equipment rather than local operators acquiring or taking over existing plants elsewhere. Panel B of Table 8 therefore examines new renewable generating capacity that began operating during each five-year period, both for all linked plants and for plants outside the operator's county. In both specifications, the green immigrant coefficients are positive and statistically significant at the 5 percent level: an additional 1,000 green immigrants increases newly operating capacity by 15.5 MW across all linked plants and by 15.0 MW at plants outside the operator's county, whereas the nongreen immigrant coefficients are small and statistically insignificant. Together, the two panels show that green immigration increases renewable deployment beyond the receiving county, including through the addition of new generating capacity.

Table 8: Immigration and Renewable Electricity Deployment: Plants Outside the Operator County and New Capacity, 2SLS

Panel A. Renewable electricity at plants outside the operator county		
Dependent variable	Generation (MWh)	Installed capacity (MW)
Green immigrant	55,867*	26.7*
	(31,346)	(13.5)
Nongreen immigrant	7,102	0.7
	(21,180)	(10.9)
KP F	12.2	12.2
Observations	15,695	15,695
Panel B. New renewable generating capacity		
Plant coverage	All linked plants New capacity	Plants outside the operator county New capacity
Dependent variable	(MW)	(MW)
Green immigrant	15.5**	15.0**
	(6.3)	(6.5)
Nongreen immigrant	1.7	1.9
	(6.6)	(6.5)
KP F	12.2	12.2
Observations	15,695	15,695
County FE	Yes	Yes
State-by-period FE	Yes	Yes

Notes: All outcomes are assigned to operator counties. Panel A includes only plants physically located outside the operator county and measures average annual renewable generation in MWh and end-period installed capacity in MW. Appendix Table A.3 reports the geographic decomposition using the same plant–operator links, allocation weights, and estimation sample as Panel A. Panel B measures generating capacity in MW that began operating during each five-year period, including all linked plants in the first column and only plants outside the operator county in the second. All columns report 2SLS estimates with green and nongreen immigrant stocks included together, in thousands of residents aged 25 or older, for 2000–2020. County and state-by-period fixed effects and 1990 college share, manufacturing share, and per capita personal income interacted with period indicators are included. State-clustered standard errors are in parentheses. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

6.5 Fossil Innovation and Brown Electricity Deployment

I next examine whether the positive effects of green immigration extend to fossil innovation and brown electricity deployment, which serve as comparison outcomes for assessing whether the preceding results simply reflect a broader expansion of local patenting and energy production. I retain the same immigrant stocks, instruments, and county-level specification, replacing the dependent variables with fossil and brown outcomes. Fossil patents follow the classification of Lazkano and Pham (2016) and are measured as five-year patent counts per 100,000 residents, using fixed 1990 Census population. Using the same eGRID and EIA-860 data as in the renewable energy analysis,

Table 9: Immigration, Fossil Patenting, and Brown Electricity Deployment, 2SLS

Outcome group	Fossil innovation	Brown energy deployment			
Location	County	Operator county		Plant county	
Dependent variable	Fossil patents	Generation (MWh)	Capacity (MW)	Generation (MWh)	Capacity (MW)
Green immigrant	−0.016	−39,180	−0.4	47,726	2.3
	(0.031)	(73,937)	(12.8)	(41,261)	(8.5)
Nongreen immigrant	−0.020	40,802	−4.0	12,542	4.6
	(0.021)	(40,772)	(9.3)	(25,962)	(3.2)
KP F	9.6	12.2	12.2	12.2	12.2
Observations	18,828	15,695	15,695	15,695	15,695
County FE	Yes	Yes	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes	Yes	Yes

Notes: Patent outcomes are five-year patent counts per 100,000 residents, using fixed 1990 Census population, for 1995–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. The controls are the 1990 college share among residents aged 25 or older, the manufacturing share among residents aged 16 or older with civilian industry codes, and 1990 per capita personal income in levels, each interacted with period indicators. Fossil patents are the five-year count per 100,000 fixed-1990 residents. Brown energy includes coal, petroleum, natural gas, other fossil fuels, and solid waste. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

I construct brown electricity generation (average annual MWh) and end-period installed capacity (MW) across coal, petroleum, natural gas, other fossil fuels, and solid waste, assigned to either operator or plant counties.

Table 9 reports the 2SLS estimates. Neither green nor nongreen immigration has a statistically significant effect on fossil patenting or on any of the brown generation and capacity outcomes, whether assigned to operator or plant counties. The absence of increases in brown electricity generation and capacity, together with the persistence of the renewable deployment effects at plants outside immigrant-receiving counties, makes it difficult to explain the findings solely by higher local electricity demand. A general increase in electricity demand would not, by itself, account for why the positive effects are confined to renewable energy. Together with the individual-level evidence on green employment and the positive county-level effects on green patenting and renewable deployment, these results are consistent with green immigrants' contributions being concentrated in green activities linked to their origins' comparative advantage.

6.6 Robustness

I conduct several exercises to verify that the main findings are not driven by particular modeling choices, origin-country income differences, sample periods, or a handful of large organizations. First, Appendix Tables E.1 and E.2 vary how the regressions account for counties' initial 1990 characteristics—college share, manufacturing share, per capita income, and population—and their interactions with time, holding the estimation samples and instruments fixed.[14] Across all six specifications, the estimated effects of green immigration on green energy patents, renewable patents, and operator-county installed capacity hold throughout. The estimates for broad green patents and operator-county generation are also similar across specifications, although neither is statistically significant in column (5), which adds 1990 population and interacts all four initial characteristics with linear time trends: the broad green patent estimate is somewhat smaller (0.334 compared with 0.404), and the generation estimate is nearly unchanged (56,856 MWh compared with 57,113 MWh) but less precisely estimated. The nongreen immigrant coefficients remain statistically insignificant across all patent and deployment outcomes and all six specifications.

Second, I test whether the green–nongreen contrast reflects origin-country income rather than comparative advantage in renewable energy goods. Appendix G (Appendix Tables G.1 and G.2) splits both the green and nongreen groups into higher- and lower-income halves and includes all four group-specific instruments in reduced-form regressions. Positive relationships with green patenting and operator-county renewable deployment appear not only for higher-income green origins, but also for origins in the lower half of the green group's income distribution. By contrast, neither higher- nor lower-income nongreen origins show a positive relationship with any patent or deployment outcome; in fact, their coefficients are negative throughout.

Third, restricting the patent sample to 2000–2020 to match the period of the renewable energy analysis yields larger coefficients for green immigration across all three patent outcomes. The green immigrant coefficients remain positive and statistically significant, while the nongreen immigrant coefficients remain statistically insignificant (Appendix Table F.1).

Finally, the findings do not depend solely on a few dominant firms, nor are they driven by operators located at plant sites. Excluding the 10 or 25 largest corporate patent assignees for each

[14] Appendix Tables E.3 and E.4 report the corresponding specifications for aggregate immigration.

patent category and the 10 or 25 largest renewable energy operators leaves the positive effects of green immigration across all three patent outcomes and both operator-county deployment outcomes (Appendix Table D.2). Likewise, excluding operators whose reported address has ever matched a physical plant address leaves the operator-county generation estimate virtually unchanged, at 56,782 MWh compared with 57,113 MWh in the main specification (Appendix Table D.1).

7 Conclusion

This paper examines how immigration from countries with a revealed comparative advantage in renewable energy goods contributes to green innovation and renewable electricity deployment in U.S. counties. To address the endogeneity of immigrant settlement, I construct separate instruments for green and nongreen immigration that exploit variation driven by the historical coincidence between migration waves from each country and periods when a county attracted immigrants more generally. In a 2SLS specification that includes both immigrant groups, I find that green immigration increases broad green, green energy, and renewable patenting, while nongreen immigration has no statistically significant effect. Controlling for the nongreen immigrants, an additional 1,000 green immigrants increases broad green patenting by 9.9 percent of the sample mean. Green immigration also increases renewable generation and installed capacity when these outcomes are assigned to the counties of plant operators: the same increase raises annual nonhydro renewable generation by 57.1 GWh, roughly the annual electricity purchases of 5,300 U.S. residential customers, and installed capacity by 27.7 MW. These effects extend to plants outside the counties receiving immigrants. The positive capacity response also appears for generating equipment that began operating during each five-year period. By contrast, the estimates are statistically insignificant when outcomes are assigned to plant counties. Neither immigrant group has a statistically significant effect on fossil patenting or on brown electricity generation and capacity, consistent with green immigrants' contributions being concentrated in activities related to their origins' comparative advantage. Also, I confirm with a few falsification exercises that pre-period patent and early energy growth does not predict later instrument-generated immigration. Lastly, the green immigrant coefficients remain positive across the specifications with different controls and samples.

Because the green and nongreen groups include countries at similar income levels that differ

in their comparative advantage in renewable energy goods, the findings suggest that immigrants' contributions to green activity are related to their origin-country productive backgrounds. This interpretation suggests a broader way to assess the productive contribution of immigration to the green economy. Education and STEM training describe important dimensions of workers' human capital, but may not fully capture the relevance of their backgrounds to particular economic activities. The individual-level evidence using the ACS microdata highlights the importance of considering workers' origin-country productive backgrounds alongside conventional measures of human capital. The operator-county results point to a parallel consideration on the outcome side: economic activity associated with a destination community need not be physically located within its boundaries. Thus, if immigration is evaluated solely through conventional measures of individual characteristics and outcomes observed within destination counties, important dimensions of both immigrants' backgrounds and their economic contributions may be overlooked.

For policy assessment, these results highlight the importance of both who immigrates and where outcomes are measured. First, evaluating how immigration affects a particular sector requires understanding which dimensions of immigrant composition matter for that sector. OECD (2020) emphasizes that immigration policies can have different consequences across industries even when they do not explicitly target particular sectors. OECD (2022) further suggests examining immigrants' regional economic contributions by country of origin to inform more effective policy design. My findings contribute to this agenda: in the green economy, origin-country comparative advantage captures one such dimension of immigrant composition. Assessments of immigration's sectoral effects can therefore benefit from considering not only the size of the immigrant population but also the productive backgrounds immigrants bring from their origin countries.

Second, policy evaluation can benefit from distinguishing where immigrants settle from where the resulting outcomes are realized. In their review of firms and skilled immigration to the United States, Kerr et al. (2015) point out that large firms operate across multiple local areas, so studies conducted at the local level may not fully capture their responses to immigration. To my knowledge, this paper is the first to provide empirical evidence in the renewable electricity sector that green immigrants' contributions can be reflected in generation and capacity associated with operating organizations in their receiving communities, even when the generating facilities are located elsewhere. As the need

for clean energy grows, the origin composition of immigration may be one of the economic forces sustaining green innovation and renewable electricity production, with effects that reach beyond the communities where immigrants settle.

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A Data and Measurement Details

A.1 Renewable Energy Export Goods

Table A.1: Renewable Energy Products Used to Construct Export RCA

HS96 code	BACI HS96 product category	CLEG HS2007 source code
392510	Plastics: builders' ware, reservoirs, tanks, vats and similar containers of a capacity exceeding 300 litres	392510
700991	Glass mirrors: unframed, excluding rear-view mirrors for vehicles	700991
700992	Glass mirrors: framed, excluding rear-view mirrors for vehicles	700992
730820	Iron or steel: structures and parts thereof, towers and lattice masts	730820
730890	Iron or steel: structures and parts thereof, n.e.s. in heading no. 7308	730890
732111	Cooking appliances and plate warmers: for gas fuel or for both gas and other fuels, of iron or steel	732119
732183	Domestic appliances: non-electric, other than cookers and plate warmers, for solid fuel, of iron or steel	732189
761090	Aluminium: structures and parts of structures, n.e.s. in heading no. 7610, including plates, rods, profiles, tubes, and similar items	761090
761100	Aluminium reservoirs, tanks, vats, and similar containers exceeding 300 litres, not fitted with mechanical or thermal equipment	761100
830630	Photograph, picture, or similar frames and mirrors of base metal	830630
840681	Steam and other vapour turbines, other than for marine propulsion, of an output exceeding 40 MW	840681
840682	Steam and other vapour turbines, other than for marine propulsion, of an output not exceeding 40 MW	840682
840690	Parts of steam and other vapour turbines	840690
841011	Hydraulic turbines and water wheels of a power not exceeding 1,000 kW	841011
841012	Hydraulic turbines and water wheels of a power exceeding 1,000 kW but not exceeding 10,000 kW	841012
841013	Hydraulic turbines and water wheels of a power exceeding 10,000 kW	841013
841090	Parts of hydraulic turbines and water wheels, including regulators	841090

Continued on next page

Appendix Table A.1 continued

HS96 code	BACI HS96 product category	CLEG HS2007 source code
841181	Gas turbines, excluding turbo-jets and turbo-propellers, of a power not exceeding 5,000 kW	841181
841182	Gas turbines, excluding turbo-jets and turbo-propellers, of a power exceeding 5,000 kW	841182
841199	Parts of gas turbines, excluding turbo-jets and turbo-propellers	841199
841280	Pneumatic power engines and motors, n.e.s. in heading no. 8412	841280
841290	Parts for engines and motors of heading no. 8412	841290
841581	Air-conditioning machines incorporating a refrigerating unit and a valve for reversal of the cooling or heat cycle	841581
841861	Compression-type refrigerating or freezing units whose condensers are heat exchangers	841861
841869	Heat pumps other than compression-type units whose condensers are heat exchangers	841869
841919	Instantaneous or storage water heaters, non-electric, other than gas	841919
841990	Parts of machinery, plant, and laboratory equipment for treating materials through a change in temperature	841990
848340	Gears and gearing, ball or roller screws, gear boxes, and other speed changers, including torque converters	848340
848360	Clutches and shaft couplings, including universal joints	848360
850161	AC generators and alternators of an output not exceeding 75 kVA	850161
850162	AC generators and alternators of an output exceeding 75 kVA but not exceeding 375 kVA	850162
850163	AC generators and alternators of an output exceeding 375 kVA but not exceeding 750 kVA	850163
850164	AC generators and alternators of an output exceeding 750 kVA	850164
850231	Wind-powered electric generating sets	850231
850239	Electric generating sets other than wind-powered sets and sets with spark-ignition or compression-ignition internal-combustion piston engines	850239
850300	Parts suitable for use solely or principally with electric motors and generators of headings 8501 or 8502	850300
850421	Liquid dielectric transformers with a power-handling capacity not exceeding 650 kVA	850421
850422	Liquid dielectric transformers with a power-handling capacity exceeding 650 kVA but not exceeding 10,000 kVA	850422
850423	Liquid dielectric transformers with a power-handling capacity exceeding 10,000 kVA	850423

Continued on next page

Appendix Table A.1 continued

HS96 code	BACI HS96 product category	CLEG HS2007 source code
850431	Other electrical transformers with a power-handling capacity not exceeding 1 kVA	850431
850432	Other electrical transformers with a power-handling capacity exceeding 1 kVA but not exceeding 16 kVA	850432
850433	Other electrical transformers with a power-handling capacity exceeding 16 kVA but not exceeding 500 kVA	850433
850434	Other electrical transformers with a power-handling capacity exceeding 500 kVA	850434
850440	Electrical static converters	850440
850490	Parts of electrical transformers, static converters, and inductors	850490
850720	Lead-acid electric accumulators other than those used for starting piston engines	850720
853710	Boards, panels, consoles, desks, and other bases for electric control or electricity distribution, for a voltage not exceeding 1,000 volts	853710
853720	Boards, panels, consoles, desks, and other bases for electric control or electricity distribution, for a voltage exceeding 1,000 volts	853720
854140	Photosensitive semiconductor devices, including photovoltaic cells whether or not assembled in modules or panels, and light-emitting diodes	854140
900190	Unmounted lenses, prisms, mirrors, and other optical elements, excluding elements of glass not optically worked	900190
900290	Mounted lenses, prisms, mirrors, and other optical elements used as parts or fittings for instruments or apparatus	900290
901380	Optical devices, appliances, and instruments, n.e.s. in heading no. 9013, including liquid-crystal devices	901380
901390	Parts and accessories for optical appliances and instruments of heading no. 9013	901390
903289	Automatic regulating or controlling instruments and apparatus other than hydraulic or pneumatic instruments	903289

Notes: All 54 HS96 codes enter the RCA numerator.

A.2 Patent Outcome Taxonomy

Table A.2: Patent Outcome Classifications

Outcome	Technology coverage
Broad green patents	All technologies matched to the WIPO IPC Green Inventory of Environmentally Sound Technologies
Green energy patents	Solar, wind, geothermal, biofuels, energy from manmade waste, fuel cells, use of waste heat, and natural heat
Renewable patents	Solar, wind, geothermal, and energy from manmade waste

Notes: A patent qualifies when at least one IPC code matches the corresponding WIPO Green Inventory category. All three outcomes are five-year county-period counts per 100,000 fixed-1990 residents.

A.3 Geographic Relationship Between Plants and Operators

Table A.3: Geographic Relationship Between Plants and Operators

	Share (%)		
Outcome	Same county	Same state, different county	Different state
Generation	21.4	26.9	51.6
Installed capacity	15.9	26.2	57.9

Notes: Shares decompose operator-county outcomes using the same plant–operator links, county allocation weights, and 15,695 county–period observations as Panel A of Table 8. Each weighted plant contribution is classified by the plant's physical location relative to the operator county. Generation is average annual nonhydro MWh, using the same observed years within each five-year period as the full operator-county outcome; capacity is installed nonhydro nameplate MW at the period endpoints, 2000, 2005, 2010, 2015, and 2020. Each share divides the category's outcome summed across counties and periods by the corresponding total. Allocation weights are retained when separating geographic categories. Same-state/different-county and different-state contributions together equal the outside-county outcome in Panel A. Combined shares use unrounded values. Rounding may prevent shares from summing to 100.

A.4 Origin Classification

Table A.4: Classification of Origin Countries

Green countries: Austria (AUT), China (CHN), Czechoslovakia (CSK), Denmark (DNK), Finland (FIN), Germany (DEU), Hungary (HUN), Italy (ITA), Japan (JPN), Mexico (MEX), Philippines (PHL), Poland (POL), Republic of Korea (KOR), Socialist Yugoslav (YUG), Sweden (SWE), Switzerland (CHE), Thailand (THA), and United Kingdom of Great Britain and Northern Ireland (GBR).

Nongreen countries: Algeria (DZA), Angola (AGO), Argentina (ARG), Australia (AUS), Bahamas (BHS), Bahrain (BHR), Bangladesh (BGD), Belgium–Luxembourg (BEL/LUX), Brazil

(BRA), Brunei Darussalam (BRN), Bulgaria (BGR), Canada (CAN), Chile (CHL), Colombia (COL), Costa Rica (CRI), Côte d'Ivoire (CIV), Cyprus (CYP), Dominican Republic (DOM), Ecuador (ECU), Egypt (EGY), El Salvador (SLV), France (FRA), Gabon (GAB), Greece (GRC), Guatemala (GTM), Honduras (HND), Iceland (ISL), India (IND), Indonesia (IDN), Iran (IRN), Ireland (IRL), Israel (ISR), Jordan (JOR), Kenya (KEN), Kuwait (KWT), Lebanon (LBN), Libya (LBY), Malaysia (MYS), Malta (MLT), Morocco (MAR), Netherlands (NLD), Netherlands Antilles (ANT), New Zealand (NZL), Nicaragua (NIC), Nigeria (NGA), Norway (NOR), Oman (OMN), Pakistan (PAK), Panama (PAN), Paraguay (PRY), Peru (PER), Portugal (PRT), Qatar (QAT), Romania (ROU), Saudi Arabia (SAU), Singapore (SGP), Spain (ESP), Sri Lanka (LKA), Trinidad and Tobago (TTO), Tunisia (TUN), Turkey (TUR), United Arab Emirates (ARE), United Republic of Tanzania (TZA), Uruguay (URY), USSR (SUN), Venezuela (VEN), Viet Nam (VNM), and Yemen (YEM).

Unclassified countries: Afghanistan, Albania, Andorra, Anguilla, Antigua and Barbuda, Aruba, Barbados, Belize, Benin, Bermuda, Bhutan, Bolivia (Plurinational State of), Botswana, British Virgin Islands, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Cayman Islands, Central African Republic, Chad, Comoros, Congo, Cook Islands, Cuba, Democratic Republic of the Congo, Djibouti, Dominica, Equatorial Guinea, Ethiopia, Faeroe Islands, Falkland Islands (Malvinas), Fiji, French Guiana, French Polynesia, Gambia, Ghana, Gibraltar, Greenland, Grenada, Guadeloupe, Guinea, Guinea-Bissau, Guyana, Haiti, Iraq, Jamaica, Kiribati, Lao People's Democratic Republic, Lesotho, Liberia, Liechtenstein, Madagascar, Malawi, Maldives, Mali, Martinique, Mauritania, Mauritius, Monaco, Mongolia, Montserrat, Mozambique, Myanmar, Namibia, Nauru, Nepal, New Caledonia, Niger, Niue, Norfolk Island, Papua New Guinea, Pitcairn, Puerto Rico, Réunion, Rwanda, Saint Helena, Saint Kitts and Nevis, Saint Lucia, Saint Pierre and Miquelon, Saint Vincent and the Grenadines, Samoa, San Marino, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Solomon Islands, Somalia, South Africa, State of Palestine, Sudan, Suriname, Swaziland, Syrian Arab Republic, Timor-Leste, Togo, Tokelau, Tonga, Turks and Caicos Islands, Tuvalu, Uganda, Vanuatu, Wallis and Futuna Islands, Western Sahara, Zambia, and Zimbabwe.

Notes: Green countries have renewable goods RCA ≥ 1, and nongreen countries have RCA < 1, among classified countries. Unclassified countries are used in the instrument construction. South Africa remains unclassified because the 1996–1999 trade data combine its exports with those of other Southern African Customs Union members, so its RCA cannot be calculated separately. As a robustness check, I classify South Africa as nongreen based on the union's RCA and rebuild the instruments. The main results remain similar: green immigration has positive and statistically significant effects on patenting and operator-county renewable electricity outcomes, while the effects of nongreen immigration remain statistically insignificant.

A.5 Green Occupation Employment: Data and Measurement

ACS sample and comparison groups. The occupation analysis pools annual ACS samples from 2005 through 2020 and includes civilian employed workers aged 25–64 (U.S. Census Bureau, 2026). The sample begins in 2005, when the ACS expanded to nationwide implementation, and ends in 2020 to match the endpoint of the main analysis (U.S. Census Bureau, 2024). Workers are pooled nationally because further dividing the sample by county, origin group, and occupation would create

small cells.

The descriptive analysis compares green immigrants, nongreen immigrants, and unclassified immigrants using the origin classification defined in Section 3.2. U.S.-born workers provide a reference group. Because the main county-level analysis uses immigrant stocks, the primary comparison includes immigrants of all arrival durations. I additionally distinguish recent immigrants, who arrived zero to four years before the survey, from immigrants who arrived five or more years earlier. All occupation shares use ACS person weights. Among U.S.-born workers, 6.4 percent are employed in new green occupations or occupations requiring updated skills. The share rises to 12.5 percent when existing occupations with increased demand are also included.

O*NET green occupation definitions. I construct two measures from the O*NET green occupation framework (Dierdorff et al., 2009; National Center for O*NET Development, 2017). The first measure, shown in Panel A of Figure A.1, includes Green New and Emerging occupations and Green Enhanced Skills occupations. Green New and Emerging occupations represent new types of work created by green activities and technologies, such as solar photovoltaic installers. Green Enhanced Skills occupations are existing occupations whose tasks or skill requirements change substantially in response to green activities, such as electrical engineers.

The second measure, used in the main analysis and shown in Panel B, additionally includes Green Increased Demand occupations, such as electricians. For these occupations, green activities increase employment demand without substantially changing tasks or skill requirements. The first measure therefore emphasizes new types of work and changes in job content, while the second also captures increased demand for existing types of work. Neither measure identifies employment devoted exclusively to renewable energy.

Classification version and occupation-code mapping. I use the fixed green occupation list from O*NET version 22.0, released in August 2017 (National Center for O*NET Development, 2017, n.d.). O*NET first presented its green occupation framework in February 2009, and the Green Occupations file was added to the database in version 16.0 in July 2011 (Dierdorff et al., 2009; National Center for O*NET Development, n.d.). I apply the version 22.0 classification consistently across all ACS years. The resulting measures capture employment in a fixed set of occupations rather

than annual changes in occupations' green status.

I link O*NET occupations to Census occupation codes for each survey year. When a parent occupation belongs to the relevant green categories, its detailed occupations inherit that classification. A Census occupation is classified as green only if all its linked detailed occupations satisfy the relevant definition. This rule avoids classifying an entire Census occupation as green when only some of its detailed occupations qualify. It produces a binary employment indicator for each of the two occupation measures.

Regression sample and specification. The OLS analyses in Table 5 and Appendix Tables A.5 and A.6 use continuous origin RCA for 1996–1999. Each dependent variable equals 100 if a worker is employed in an occupation meeting the relevant green definition and zero otherwise. Each RCA coefficient therefore measures the percentage-point change in green occupation employment associated with a one-unit increase in origin RCA. The full specification is

$$y_i = \alpha + \beta RCA_{o(i)} + X_i'\gamma + \lambda_{t(i)} + \kappa_{a(i)} + \mu_{p(i)} + \theta GDP_{o(i)} + \rho STEM_i + \varepsilon_i. \tag{10}$$

Here, $RCA_{o(i)}$ is the RCA of worker i's origin country, and X_i includes age, sex, and education controls. The fixed effects $\lambda_{t(i)}$, $\kappa_{a(i)}$, and $\mu_{p(i)}$ account for survey year, arrival cohort, and residential PUMA, respectively. $GDP_{o(i)}$ is origin GDP per capita, and $STEM_i$ indicates STEM degree field.

The main regression sample includes immigrants from all countries with available RCA and GDP data. U.S.-born workers are excluded from the regressions. Table 5 and Appendix Table A.6 use the same workers within each specification. Appendix Table A.5 uses all three O*NET categories and the same specifications, restricting the sample to immigrants from green and nongreen origins. Regressions use ACS person weights and standard errors clustered by origin.

The first specification includes only RCA. Specification (2) adds individual characteristics, consisting of single-year age fixed effects, sex, and education fixed effects. Specification (3) additionally includes survey-year and arrival-cohort fixed effects, specification (4) adds PUMA fixed effects, and specification (5) adds origin GDP per capita. PUMA fixed effects are defined jointly by state, PUMA, and boundary vintage: 2000 boundaries for 2005–2011 and 2010 boundaries for 2012–2020. Origin GDP per capita is the 1996–1999 average of real GDP per capita in constant 2015 U.S. dollars from

the World Development Indicators (World Bank, n.d.) and enters in levels. Because degree-field data are available beginning in 2009, I first repeat the specification including education, PUMA fixed effects, and origin GDP per capita for 2009–2020 and then add a STEM degree-field indicator on that same sample. This separates the effect of adding the STEM control from the effect of changing the sample period.

Additional employment evidence. Figure A.1 reports employment shares for all arrival durations, arrivals within the past five years, and arrivals five or more years earlier. Green immigrants have the highest share among the immigrant groups under both occupation definitions in each duration category. These comparisons describe differences across workers rather than changes in individuals' occupations over time. Table A.6 reports the individual-level OLS estimates using only Green New and Emerging and Green Enhanced Skills occupations. The coefficients remain positive and statistically significant across specifications. In the full specification, an interquartile increase in origin RCA is associated with a 1.24 percentage-point higher employment probability, approximately 17 percent of the sample mean.

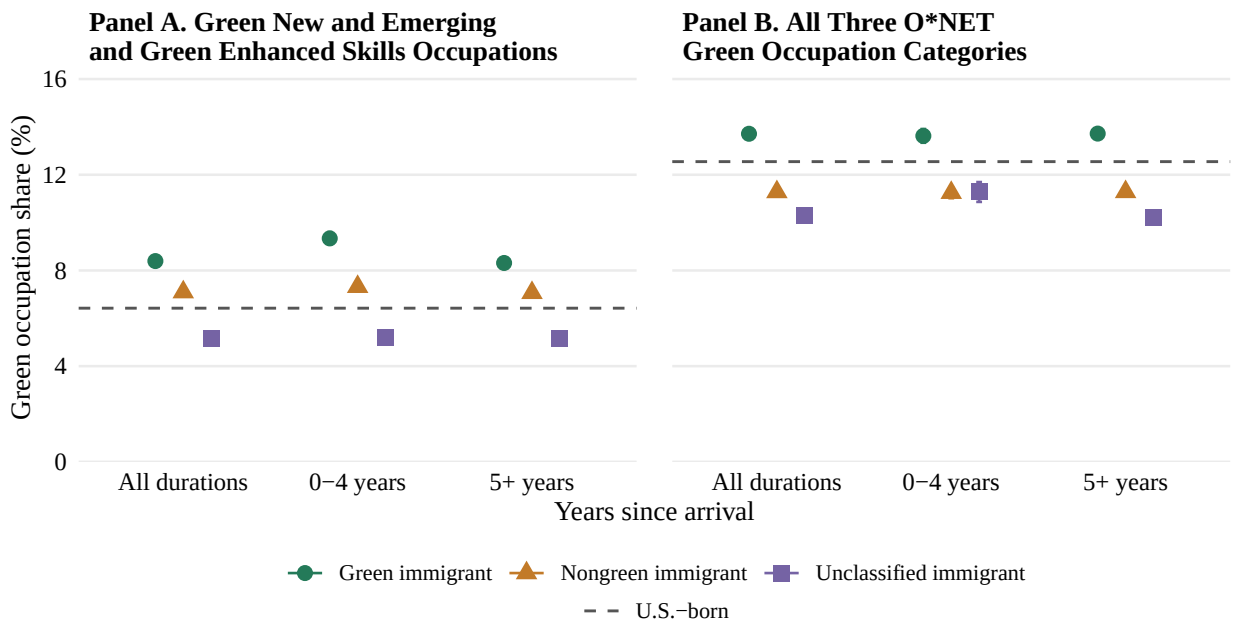


Figure A.1: Share of Workers Employed in O*NET-Defined Green Occupations, by Immigrant Group

Notes: Annual ACS, 2005–2020; civilian employed workers aged 25–64. Shares use person weights. Panel A includes O*NET Green New and Emerging and Green Enhanced Skills occupations. Panel B additionally includes Green Increased Demand occupations, for which green activities raise labor demand without substantially changing tasks or skill requirements. A Census occupation qualifies only if all linked detailed occupations meet the definition, after applying the parent-occupation rule described in Appendix A.5. The dashed line is the U.S.-born share under each definition.

Table A.5: Origin RCA and Employment in Green Occupations: Green and Nongreen Origins, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Employment in green occupations, including jobs with increased demand							
RCA	2.491*	1.306**	1.248**	1.107**	0.968*	0.875*	0.931*
	(1.366)	(0.602)	(0.573)	(0.505)	(0.510)	(0.504)	(0.510)
Individual characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Survey-year FE	No	No	Yes	Yes	Yes	Yes	Yes
Arrival-cohort FE	No	No	Yes	Yes	Yes	Yes	Yes
PUMA FE	No	No	No	Yes	Yes	Yes	Yes
Origin GDP per capita	No	No	No	No	Yes	Yes	Yes
STEM degree field	No	No	No	No	No	No	Yes
Years	2005–2020	2005–2020	2005–2020	2005–2020	2005–2020	2009–2020	2009–2020
Observations	2,371,363	2,371,363	2,371,363	2,371,363	2,371,363	1,835,051	1,835,051

Notes: Each column reports the coefficient on continuous origin RCA for 1996–1999 from a separate person-weighted OLS regression; origin-clustered standard errors are in parentheses. The outcome equals 100 times the occupation indicator. The definition includes O*NET Green New and Emerging, Green Enhanced Skills, and Green Increased Demand occupations. The sample includes employed immigrants aged 25–64 from green and nongreen countries with available RCA and GDP data, pooling all arrival durations. Individual characteristics include single-year age FE, sex, and education FE. Controls accumulate across specifications (1)–(5); survey-year and arrival-cohort FE enter together in (3). Specification (6) repeats (5) for 2009–2020; (7) adds STEM degree field on that same sample. Origin GDP per capita is its 1996–1999 mean. PUMA FE are defined by state, PUMA, and boundary vintage (2000 boundaries for 2005–2011; 2010 boundaries for 2012–2020). RCA is defined in Section 3.1. Unclassified origins are excluded. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.6: Origin RCA and Employment in Green Occupations: Excluding Green Increased Demand Occupations, OLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: Employment in new green jobs and jobs requiring updated skills							
RCA	1.639**	0.930**	0.921**	1.019**	0.862*	0.816*	0.847*
	(0.800)	(0.387)	(0.385)	(0.419)	(0.437)	(0.440)	(0.444)
Individual characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes
Survey-year FE	No	No	Yes	Yes	Yes	Yes	Yes
Arrival-cohort FE	No	No	Yes	Yes	Yes	Yes	Yes
PUMA FE	No	No	No	Yes	Yes	Yes	Yes
Origin GDP per capita	No	No	No	No	Yes	Yes	Yes
STEM degree field	No	No	No	No	No	No	Yes
Years	2005–2020	2005–2020	2005–2020	2005–2020	2005–2020	2009–2020	2009–2020
Observations	2,676,853	2,676,853	2,676,853	2,676,853	2,676,853	2,075,303	2,075,303

Notes: Each column reports the coefficient on continuous origin RCA for 1996–1999 from a separate person-weighted OLS regression; origin-clustered standard errors are in parentheses. The outcome equals 100 times the occupation indicator. The two-category definition includes O*NET Green New and Emerging and Green Enhanced Skills occupations. The sample includes employed immigrants aged 25–64 from all countries with available RCA and GDP data, pooling all arrival durations. Individual characteristics include single-year age FE, sex, and education FE. Controls accumulate across specifications (1)–(5); survey-year and arrival-cohort FE enter together in (3). Specification (6) repeats (5) for 2009–2020; (7) adds STEM degree field on that same sample. Origin GDP per capita is its 1996–1999 mean. PUMA FE are defined by state, PUMA, and boundary vintage (2000 boundaries for 2005–2011; 2010 boundaries for 2012–2020). RCA is defined in Section 3.1; its interquartile range is 1.461. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

B Immigrant Sorting and Prior Green Activity

Table B.1: Prior Green Patenting Growth and Subsequent Immigration, OLS

Dependent variable	Change in green immigrant		Change in nongreen immigrant	
	(1)	(2)	(3)	(4)
Panel A. Broad green patents				
Lagged change in broad green patents	-0.010	-0.017**	0.029***	0.014***
	(0.011)	(0.008)	(0.010)	(0.005)
Panel B. Green energy patents				
Lagged change in green energy patents	-0.017	-0.032	0.040	0.019*
	(0.022)	(0.020)	(0.026)	(0.011)
Panel C. Renewable patents				
Lagged change in renewable patents	-0.025	-0.050	0.077	0.037*
	(0.042)	(0.037)	(0.047)	(0.021)
County FE	No	Yes	No	Yes
State-by-period FE	Yes	Yes	Yes	Yes
Observations	15,690	15,690	15,690	15,690

Notes: Each column within each panel reports a separate OLS regression of the five-year change in the immigrant stock named above the columns on the lagged change indicated in that panel. Immigrant stocks are observed residents aged 25 or older, in thousands. For immigrant changes from $t-5$ to t, predictors are changes from $t-10$ to $t-5$; the two intervals are adjacent and do not overlap. Every regression controls for the opposite group's immigrant change over the same subsequent interval, state-by-period fixed effects, and the 1990 college share, manufacturing share, and per capita personal income, each interacted with period indicators. Columns (2) and (4) additionally include county fixed effects, absorbing persistent county-specific growth components. Patent changes run from 1990–1995 through 2010–2015; subsequent immigrant changes run from 1995–2000 through 2015–2020, covering 3,138 counties. Patent measures are five-year counts per 100,000 residents using fixed 1990 Census population. State-clustered standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.2: Prior Renewable Electricity Growth and Subsequent Immigration, OLS

Dependent variable	Change in green immigrant		Change in nongreen immigrant	
	(1)	(2)	(3)	(4)
Panel A. Operator generation				
Lagged change in operator generation (per 100 GWh)	-0.059	-0.192**	0.226**	0.071**
	(0.044)	(0.089)	(0.091)	(0.034)
Panel B. Operator capacity				
Lagged change in operator capacity (per 100 MW)	-0.123	-0.630**	0.637***	0.308**
	(0.131)	(0.290)	(0.202)	(0.125)
Panel C. Plant generation				
Lagged change in plant generation (per 100 GWh)	0.045***	-0.075***	-0.018***	-0.028***
	(0.011)	(0.010)	(0.004)	(0.004)
Panel D. Plant capacity				
Lagged change in plant capacity (per 100 MW)	0.130*	-0.307***	-0.065***	-0.090***
	(0.066)	(0.110)	(0.016)	(0.029)
County FE	No	Yes	No	Yes
State-by-period FE	Yes	Yes	Yes	Yes
Observations	9,417	9,417	9,417	9,417

Notes: Each column within each panel reports a separate OLS regression of the five-year change in the immigrant stock named above the columns on the lagged change indicated in that panel. Immigrant stocks are observed residents aged 25 or older, in thousands. For immigrant changes from $t-5$ to t, predictors are changes from $t-10$ to $t-5$; the two intervals are adjacent and do not overlap. Every regression controls for the opposite group's immigrant change over the same subsequent interval, state-by-period fixed effects, and the 1990 college share, manufacturing share, and per capita personal income, each interacted with period indicators. Columns (2) and (4) additionally include county fixed effects, absorbing persistent county-specific growth components. Energy changes run from 2000–2005 through 2010–2015; subsequent immigrant changes run from 2005–2010 through 2015–2020, covering 3,139 counties. Generation is average annual nonhydro renewable output, with changes measured per 100 GWh (100,000 MWh); capacity is end-period nonhydro nameplate capacity, with changes measured per 100 MW. Operator and plant measures assign activity to the respective counties. State-clustered standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C Additional Details on the Immigration Instruments

C.1 Census-Division Geography

Throughout the instrument construction, $r(d)$ denotes the Census division containing county d. The analysis uses the nine Census divisions listed in Table C.1.

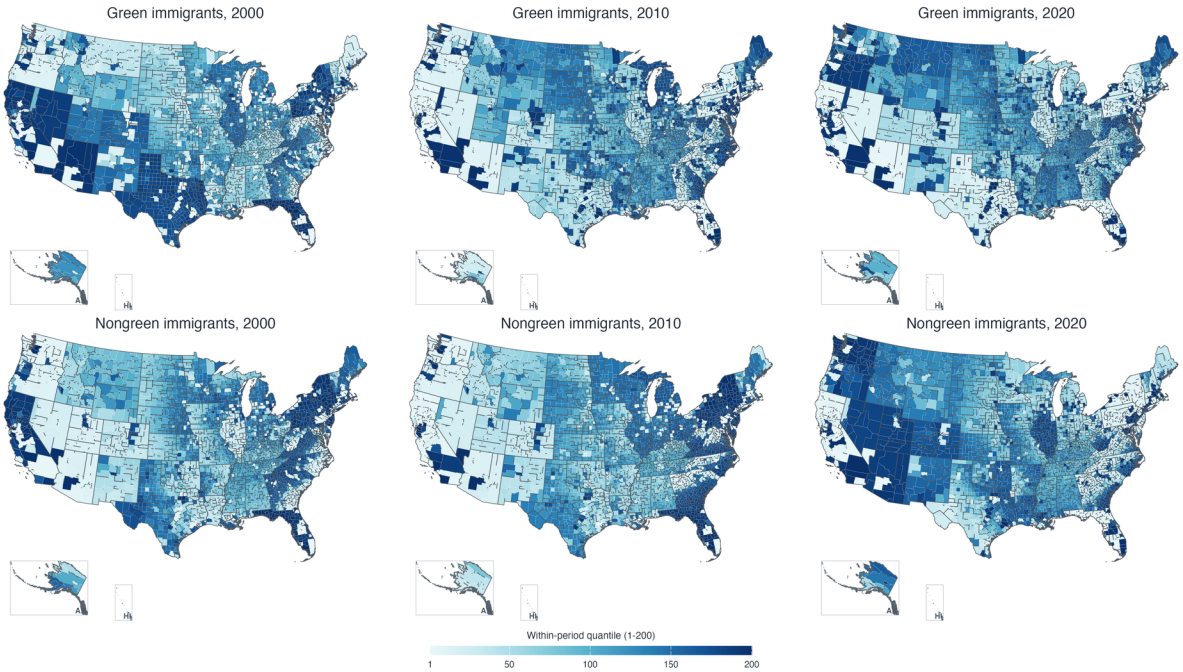
Table C.1: Census Divisions Used to Construct the Immigration Instruments

Code	Census division	Census region	States and District of Columbia	Harmonized 1990 counties
1	New England	Northeast	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont	67
2	Middle Atlantic	Northeast	New Jersey, New York, and Pennsylvania	150
3	East North Central	Midwest	Illinois, Indiana, Michigan, Ohio, and Wisconsin	437
4	West North Central	Midwest	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota	618
5	South Atlantic	South	Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia	591
6	East South Central	South	Alabama, Kentucky, Mississippi, and Tennessee	364
7	West South Central	South	Arkansas, Louisiana, Oklahoma, and Texas	470
8	Mountain	West	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming	281
9	Pacific	West	Alaska, California, Hawaii, Oregon, and Washington	163
			Total	**3,141**

Notes: The table reports the Census division classification used in the instrument construction. The county counts are calculated from the 3,141 harmonized 1990 county units. All leave-out calculations are performed at the 9 division level.

C.2 Geographic Variation in the Immigration Instruments

Figure C.1: Geographic Variation in Immigration Instruments after Removing Fixed Effects



Notes: This figure maps the green and nongreen immigration instruments after removing county and state-by-period fixed effects. Using the 1995–2020 patent estimation sample, I regress each instrument on these fixed effects and calculate the residuals. The top row shows the green instrument and the bottom row the nongreen instrument for 2000, 2010, and 2020. Colors indicate 200 quantiles of the residuals across counties within each instrument and period, with darker colors indicating higher quantiles. Colors show relative ranks rather than instrument magnitudes.

D Organizational Geography and Concentration

The following tables examine address overlap and concentration across organizations. Table D.1 excludes operators reporting an address that exactly matches a plant address. Table D.2 excludes the largest patent assignees and operators. Section 6.4 presents the results for plants outside the operator county and for new generating capacity.

Table D.1: Immigration and Renewable Electricity Generation: Excluding Operators Located at Plant Sites, 2SLS

	Including all operators	Excluding operators located at plant sites
Green immigrant	57,113*	56,782*
	(30,424)	(30,560)
Nongreen immigrant	7,412	7,180
	(21,213)	(21,273)
KP F	12.2	12.2
Observations	15,695	15,695
County FE	Yes	Yes
State-by-period FE	Yes	Yes

Notes: The outcome is operator-county average annual nonhydro renewable generation in MWh, for 2000–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. The controls are the 1990 college share among residents aged 25 or older, the manufacturing share among residents aged 16 or older with civilian industry codes, and 1990 per capita personal income in levels, each interacted with period indicators. Column (2) excludes every operator whose full street address, city, state, and ZIP code ever exactly match a plant address. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table D.2: Immigration and Green Outcomes: Excluding the Largest Patent Assignees and Plant Operators, 2SLS

Concentration across patent assignees and operators					
Location	Corporate-assignee county			Operator county	
Dependent variable	Broad green patents	Green energy patents	Renewable patents	Generation (MWh)	Capacity (MW)
Panel A. Main specification					
Green immigrant	0.404*	0.049**	0.025***	57,113*	27.7**
	(0.209)	(0.024)	(0.009)	(30,424)	(13.2)
Nongreen immigrant	-0.329	-0.036	-0.013	7,412	0.4
	(0.271)	(0.030)	(0.013)	(21,213)	(11.0)
Outcome mean	4.098	0.843	0.323	60,368	23.5
Panel B. Excluding the top 10 assignees or operators					
Green immigrant	0.274***	0.039**	0.025**	36,269***	16.8***
	(0.100)	(0.019)	(0.010)	(9,684)	(4.5)
Nongreen immigrant	-0.179	-0.026	-0.014	13,444	5.9
	(0.149)	(0.024)	(0.013)	(18,706)	(7.7)
Outcome mean	3.861	0.780	0.303	47,455	18.6
Panel C. Excluding the top 25 assignees or operators					
Green immigrant	0.233***	0.039**	0.021**	28,860***	16.0***
	(0.086)	(0.018)	(0.008)	(8,738)	(4.7)
Nongreen immigrant	-0.151	-0.028	-0.010	14,670	6.5
	(0.130)	(0.025)	(0.011)	(15,213)	(7.5)
Outcome mean	3.701	0.732	0.293	40,622	16.3
KP F	9.6	9.6	9.6	12.2	12.2
Observations	18,828	18,828	18,828	15,695	15,695
Periods	1995–2020	1995–2020	1995–2020	2000–2020	2000–2020
County FE	Yes	Yes	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes	Yes	Yes

Notes: All columns report 2SLS estimates with green and nongreen immigrant stocks included together, in thousands of residents aged 25 or older. County and state-by-period fixed effects and 1990 college share, manufacturing share, and per capita personal income interacted with period indicators are included. State-clustered standard errors are in parentheses. Panels B and C exclude the 10 or 25 largest corporate assignees or plant operators while retaining the county sample. Assignees are ranked separately for each patent outcome by total patent counts; operators are ranked by total nonhydro renewable generation, with the same exclusions applied to capacity. Patent outcomes are five-year counts per 100,000 residents using fixed 1990 Census population. Generation is average annual output, and capacity is measured at period end. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

E Robustness to Alternative Controls

Tables E.1 and E.2 include green and nongreen immigration together; Tables E.3 and E.4 pool the two groups.

Table E.1: Immigration and Green Patenting: Alternative Controls, 2SLS

Initial controls	None	Education and manufacturing	Education, manufacturing and income		Education, manufacturing, income and population	
Time interactions	—	Period indicators	Linear trends	Period indicators	Linear trends	Period indicators
	(1)	(2)	(3)	(4) Main	(5)	(6)
Dependent variable: broad green patents						
Green immigrant	0.543**	0.396*	0.392*	0.404*	0.334	0.468*
	(0.223)	(0.203)	(0.210)	(0.209)	(0.217)	(0.276)
Nongreen immigrant	−0.268	−0.292	−0.320	−0.329	−0.426	−0.432
	(0.298)	(0.266)	(0.273)	(0.271)	(0.334)	(0.315)
KP F	9.2	9.8	9.7	9.6	6.1	8.2
Observations	18,828	18,828	18,828	18,828	18,828	18,828
Dependent variable: green energy patents						
Green immigrant	0.066***	0.048**	0.052**	0.049**	0.052**	0.063*
	(0.023)	(0.022)	(0.024)	(0.024)	(0.026)	(0.036)
Nongreen immigrant	−0.032	−0.033	−0.038	−0.036	−0.037	−0.037
	(0.035)	(0.029)	(0.032)	(0.030)	(0.036)	(0.033)
KP F	9.2	9.8	9.7	9.6	6.1	8.2
Observations	18,828	18,828	18,828	18,828	18,828	18,828
Dependent variable: renewable patents						
Green immigrant	0.035***	0.025***	0.026***	0.025***	0.028***	0.039***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.013)
Nongreen immigrant	−0.011	−0.012	−0.013	−0.013	−0.009	−0.009
	(0.015)	(0.012)	(0.013)	(0.013)	(0.015)	(0.014)
KP F	9.2	9.8	9.7	9.6	6.1	8.2
Observations	18,828	18,828	18,828	18,828	18,828	18,828
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Patent outcomes are five-year patent counts per 100,000 residents, using fixed 1990 Census population, for 1995–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. Column (1) includes fixed effects only. Column (2) adds the 1990 college and manufacturing shares interacted with period indicators. Columns (3) and (4) include these shares and 1990 per capita personal income in levels, interacted with a linear trend and period indicators, respectively. Column (4) reproduces the main specification. Columns (5) and (6) additionally include 1990 population in levels, with all four characteristics interacted with a linear trend and period indicators, respectively. Within each outcome, all columns use the same estimation sample and instruments as the main specification, with identical controls in both stages. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table E.2: Immigration and Operator-County Renewable Electricity Deployment: Alternative Controls, 2SLS

Initial controls	None	Education and manufacturing	Education, manufacturing and income		Education, manufacturing, income and population	
Time interactions	—	Period indicators	Linear trends	Period indicators	Linear trends	Period indicators
	(1)	(2)	(3)	(4) Main	(5)	(6)
Operator generation (MWh)						
Green immigrant	56,379*	56,704*	55,267*	57,113*	56,856	79,344**
	(28,825)	(30,035)	(30,567)	(30,424)	(33,930)	(37,129)
Nongreen immigrant	10,322	8,641	8,761	7,412	13,680	10,425
	(20,001)	(20,731)	(20,618)	(21,213)	(34,171)	(36,069)
KP F	11.1	12.3	12.4	12.2	12.4	5.8
Observations	15,695	15,695	15,695	15,695	15,695	15,695
Operator capacity (MW)						
Green immigrant	27.6**	27.5**	26.9**	27.7**	26.8*	36.5**
	(12.4)	(12.9)	(13.2)	(13.2)	(13.8)	(14.6)
Nongreen immigrant	1.9	1.1	1.1	0.4	0.8	−0.9
	(10.4)	(10.8)	(10.7)	(11.0)	(16.6)	(17.5)
KP F	11.1	12.3	12.4	12.2	12.4	5.8
Observations	15,695	15,695	15,695	15,695	15,695	15,695
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Energy outcomes are average annual nonhydro renewable generation in MWh and end-period installed nonhydro nameplate capacity in MW, for 2000–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. Column (1) includes fixed effects only. Column (2) adds the 1990 college and manufacturing shares interacted with period indicators. Columns (3) and (4) include these shares and 1990 per capita personal income in levels, interacted with a linear trend and period indicators, respectively. Column (4) reproduces the main specification. Columns (5) and (6) additionally include 1990 population in levels, with all four characteristics interacted with a linear trend and period indicators, respectively. Within each outcome, all columns use the same estimation sample and instruments as the main specification, with identical controls in both stages. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table E.3: Aggregate Immigration and Green Patenting: Alternative Controls, 2SLS

Initial controls	None	Education and manufacturing	Education, manufacturing and income		Education, manufacturing, income and population	
Time interactions	—	Period indicators	Linear trends	Period indicators	Linear trends	Period indicators
	(1)	(2)	(3)	(4) Main	(5)	(6)
Panel A. Broad green patents						
Aggregate immigrant	0.167***	0.077**	0.065*	0.065*	0.029	0.040
	(0.042)	(0.032)	(0.034)	(0.033)	(0.073)	(0.087)
KP F	37.7	35.6	34.0	34.0	17.9	10.8
Observations	18,828	18,828	18,828	18,828	18,828	18,828
Panel B. Green energy patents						
Aggregate immigrant	0.021**	0.012	0.011	0.011	0.018	0.018
	(0.008)	(0.008)	(0.008)	(0.008)	(0.014)	(0.017)
KP F	37.7	35.6	34.0	34.0	17.9	10.8
Observations	18,828	18,828	18,828	18,828	18,828	18,828
Panel C. Renewable patents						
Aggregate immigrant	0.015***	0.009**	0.008**	0.008**	0.014**	0.017**
	(0.004)	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)
KP F	37.7	35.6	34.0	34.0	17.9	10.8
Observations	18,828	18,828	18,828	18,828	18,828	18,828
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Patent outcomes are five-year patent counts per 100,000 residents, using fixed 1990 Census population, for 1995–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. Column (1) includes fixed effects only. Column (2) adds the 1990 college and manufacturing shares interacted with period indicators. Columns (3) and (4) include these shares and 1990 per capita personal income in levels, interacted with a linear trend and period indicators, respectively. Column (4) reproduces the main aggregate specification in Table 6. Columns (5) and (6) additionally include 1990 population in levels, with all four characteristics interacted with a linear trend and period indicators, respectively. Within each outcome, all columns use the same estimation sample and instruments as the main aggregate specification, with identical controls in both stages. Aggregate immigration is the sum of green and nongreen immigrant stocks. The aggregate specification uses the separately pooled aggregate instrument. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table E.4: Aggregate Immigration and Operator-County Renewable Electricity Deployment: Alternative Controls, 2SLS

Initial controls	None	Education and manufacturing	Education, manufacturing and income		Education, manufacturing, income and population	
Time interactions	—	Period indicators	Linear trends	Period indicators	Linear trends	Period indicators
	(1)	(2)	(3)	(4) Main	(5)	(6)
Panel A. Operator generation (MWh)						
Aggregate immigrant	33,740***	33,314**	32,995**	32,937**	39,767*	42,357**
	(11,606)	(12,881)	(13,251)	(13,145)	(22,300)	(20,782)
KP F	20.1	18.7	17.7	17.7	8.0	6.3
Observations	15,695	15,695	15,695	15,695	15,695	15,695
Panel B. Operator capacity (MW)						
Aggregate immigrant	14.6***	14.3**	14.1**	14.1**	15.5	16.3*
	(5.0)	(5.6)	(5.7)	(5.7)	(9.4)	(8.5)
KP F	20.1	18.7	17.7	17.7	8.0	6.3
Observations	15,695	15,695	15,695	15,695	15,695	15,695
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Energy outcomes are average annual nonhydro renewable generation in MWh and end-period installed nonhydro nameplate capacity in MW, for 2000–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. Column (1) includes fixed effects only. Column (2) adds the 1990 college and manufacturing shares interacted with period indicators. Columns (3) and (4) include these shares and 1990 per capita personal income in levels, interacted with a linear trend and period indicators, respectively. Column (4) reproduces the main aggregate specification in Table 7. Columns (5) and (6) additionally include 1990 population in levels, with all four characteristics interacted with a linear trend and period indicators, respectively. Within each outcome, all columns use the same estimation sample and instruments as the main aggregate specification, with identical controls in both stages. Aggregate immigration is the sum of green and nongreen immigrant stocks. The aggregate specification uses the separately pooled aggregate instrument. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

F Patent Robustness to Sample Restriction

Table F.1: Immigration and Green Patenting: Sample Restriction, 2SLS

	Main (1)	2000–2020 sample (2)
Dependent variable: Broad green patents		
Green immigrant	0.404*	0.590**
	(0.209)	(0.288)
Nongreen immigrant	−0.329	−0.373
	(0.271)	(0.313)
KP F	9.6	12.2
Observations	18,828	15,690
Dependent variable: Green energy patents		
Green immigrant	0.049**	0.077**
	(0.024)	(0.035)
Nongreen immigrant	−0.036	−0.034
	(0.030)	(0.034)
KP F	9.6	12.2
Observations	18,828	15,690
Dependent variable: Renewable patents		
Green immigrant	0.025***	0.044***
	(0.009)	(0.014)
Nongreen immigrant	−0.013	−0.015
	(0.013)	(0.016)
KP F	9.6	12.2
Observations	18,828	15,690
County FE	Yes	Yes
State-by-period FE	Yes	Yes

Notes: Patent outcomes are five-year patent counts per 100,000 residents, using fixed 1990 Census population. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. The controls are the 1990 college share among residents aged 25 or older, the manufacturing share among residents aged 16 or older with civilian industry codes, and 1990 per capita personal income in levels, each interacted with period indicators. Column (1) reproduces the main joint specification in Table 6. Column (2) excludes the 1995 period to align the analysis period with the 2000–2020 energy sample, while retaining the patent county sample and outcome construction used in the main specification. KP F denotes the Kleibergen–Paap rk Wald F statistic. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

G Origin Income, Green Innovation, and Renewable Deployment

I divide green and nongreen origins separately into higher- and lower-income halves, ranking countries within each RCA group by average real GDP per capita in 1996–1999 from the World Development Indicators (World Bank, n.d.). This yields 9 higher-income and 9 lower-income green origins, and 34 higher-income and 34 lower-income nongreen origins. Higher and lower income refer to relative positions within each RCA group. The higher-income green origins are Austria, Denmark, Finland, Germany, Italy, Japan, Sweden, Switzerland, and the United Kingdom.

For each group, I sum county-level immigrant stocks aged 25 or older. I retain the predicted ancestry construction in Section 5, and re-estimate the contemporary origin-level stock-prediction equation separately within each group. Summing the fitted interaction contributions within each group produces its instrument.

The purpose of this exercise is to examine whether the positive relationships associated with green-origin immigration are confined to higher-income origins. I report reduced-form estimates to examine how innovation and deployment relate directly to the instruments constructed for the four origin groups. Estimating separate 2SLS effects would additionally require sufficient independent first-stage variation to distinguish the effects of the four immigrant stocks. The reduced-form analysis addresses the narrower question of whether positive relationships also appear for the instrument constructed from lower-income green origins.

Each reduced-form regression includes all four instruments jointly, the same initial-characteristic controls as the main specification interacted with period indicators, and county and state-by-period fixed effects. Standard errors are clustered by state.

Table G.1 shows positive green-instrument coefficients in both income groups for all three patent outcomes. The higher-income green instrument is significantly associated with green energy and renewable patents, while the lower-income green instrument is significantly associated with broad green and renewable patents. Both nongreen instruments have negative coefficients throughout; the higher-income nongreen coefficients are significant for all three outcomes, and the lower-income nongreen coefficient is significant only for broad green patents.

For renewable deployment, Table G.2 shows positive and significant relationships between the lower-income green instrument and both operator-county generation and capacity. The higher-income green coefficients are positive but statistically insignificant, and neither nongreen instrument is significantly associated with either operator-county outcome. At plant counties, both green coefficients are insignificant; the higher-income nongreen instrument has negative coefficients significant at the 10 percent level for generation and capacity, while the lower-income nongreen coefficients are insignificant.

These results show that positive green-instrument relationships extend to origins in the lower half of the green group's income distribution.

Table G.1: Immigration Instruments and Green Patenting: By Origin Income Group, Reduced-Form OLS

Instrument	Broad green patents (1)	Green energy patents (2)	Renewable patents (3)
Green, higher-income	1.029	0.432^{**}	0.223^{***}
	(0.798)	(0.198)	(0.073)
Green, lower-income	0.198^{**}	0.017	0.014^{**}
	(0.075)	(0.015)	(0.006)
Nongreen, higher-income	-13.007^{**}	-2.402^{**}	-1.489^{**}
	(5.436)	(1.014)	(0.645)
Nongreen, lower-income	-0.880^{*}	−0.029	−0.020
	(0.484)	(0.043)	(0.016)
Observations	18,828	18,828	18,828
County FE	Yes	Yes	Yes
State-by-period FE	Yes	Yes	Yes

Notes: Patent outcomes are five-year patent counts per 100,000 residents, using fixed 1990 Census population, for 1995–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. The controls are the 1990 college share among residents aged 25 or older, the manufacturing share among residents aged 16 or older with civilian industry codes, and 1990 per capita personal income in levels, each interacted with period indicators. Regressions are unweighted. The sample contains 3,138 counties observed in six periods, 1995–2020. All four group-specific instruments enter jointly. Row labels identify the corresponding instruments. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table G.2: Immigration Instruments and Renewable Electricity Deployment: By Origin Income Group, Reduced-Form OLS

Instrument	Generation (MWh) (1)	Capacity (MW) (2)
Panel A. Operator county		
Green, higher-income	275,148	54.2
	(264,856)	(111.8)
Green, lower-income	48,917**	23.7**
	(21,480)	(9.4)
Nongreen, higher-income	−2,017,347	−715.2
	(1,634,838)	(679.1)
Nongreen, lower-income	−27,830	−22.6
	(40,684)	(21.0)
Panel B. Plant county		
Green, higher-income	19,522	19.4
	(31,482)	(17.2)
Green, lower-income	616	0.4
	(2,280)	(1.1)
Nongreen, higher-income	−676,928*	−294.3*
	(381,158)	(175.4)
Nongreen, lower-income	−13,430	−5.2
	(8,275)	(3.3)
Observations	15,695	15,695
County FE	Yes	Yes
State-by-period FE	Yes	Yes

Notes: Energy outcomes are average annual nonhydro renewable generation in MWh and end-period installed nonhydro nameplate capacity in MW, for 2000–2020. All regressions include county and state-by-period fixed effects. State-clustered standard errors are in parentheses. Immigrants are measured in thousands of residents aged 25 or older. The controls are the 1990 college share among residents aged 25 or older, the manufacturing share among residents aged 16 or older with civilian industry codes, and 1990 per capita personal income in levels, each interacted with period indicators. Regressions are unweighted. Outcomes are assigned to operator counties in Panel A and plant counties in Panel B. Each regression uses 3,139 counties observed in five periods, 2000–2020. All four group-specific instruments enter jointly. Row labels identify the corresponding instruments. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

H Additional Falsification Exercises

Table H.1: Reduced-Form Falsification Tests
Future Instruments and Prior Green Activity, OLS

Panel A. Pre-period patent growth (instrument changes, 1995–2020)

Dependent variable	Change in Broad green patents (1985–1990)	Change in Green energy patents (1985–1990)	Change in Renewable patents (1985–1990)
	(1)	(2)	(3)
Change in green instrument	−0.00306	0.00198	0.00071
	(0.00329)	(0.00122)	(0.00072)
Change in nongreen instrument	0.00013	−0.00426	−0.00267
	(0.01925)	(0.00927)	(0.00484)
Observations	3,138	3,138	3,138
State FE	Yes	Yes	Yes

Panel B. Early renewable energy growth (instrument changes, 2005–2020)

Dependent variable	Change in renewable generation (1999–2000, MWh)	Change in renewable capacity (1999–2000, MW)
	(1)	(2)
Change in green instrument	121.6	0.182
	(286.2)	(0.198)
Change in nongreen instrument	3,041.7	0.325
	(2,650.9)	(0.493)
Observations	3,139	3,139
State FE	Yes	Yes

Notes: Each column reports a separate reduced-form OLS regression including changes in both the green and nongreen instruments. Instruments are measured in thousands of predicted immigrants aged 25 or older. Samples, outcomes, and controls match the corresponding specifications in Table 4. Panel A relates 1985–1990 changes in five-year patent counts per 100,000 residents, using fixed 1990 Census population, to instrument changes over 1995–2020. Panel B relates 1999–2000 changes in operator-county nonhydro renewable generation (MWh) or capacity (MW) to instrument changes over 2005–2020. All regressions include state fixed effects and the 1990 college share, manufacturing share, and BEA per capita personal income (in thousands of 1990 dollars). Standard errors clustered by state (50 clusters) are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

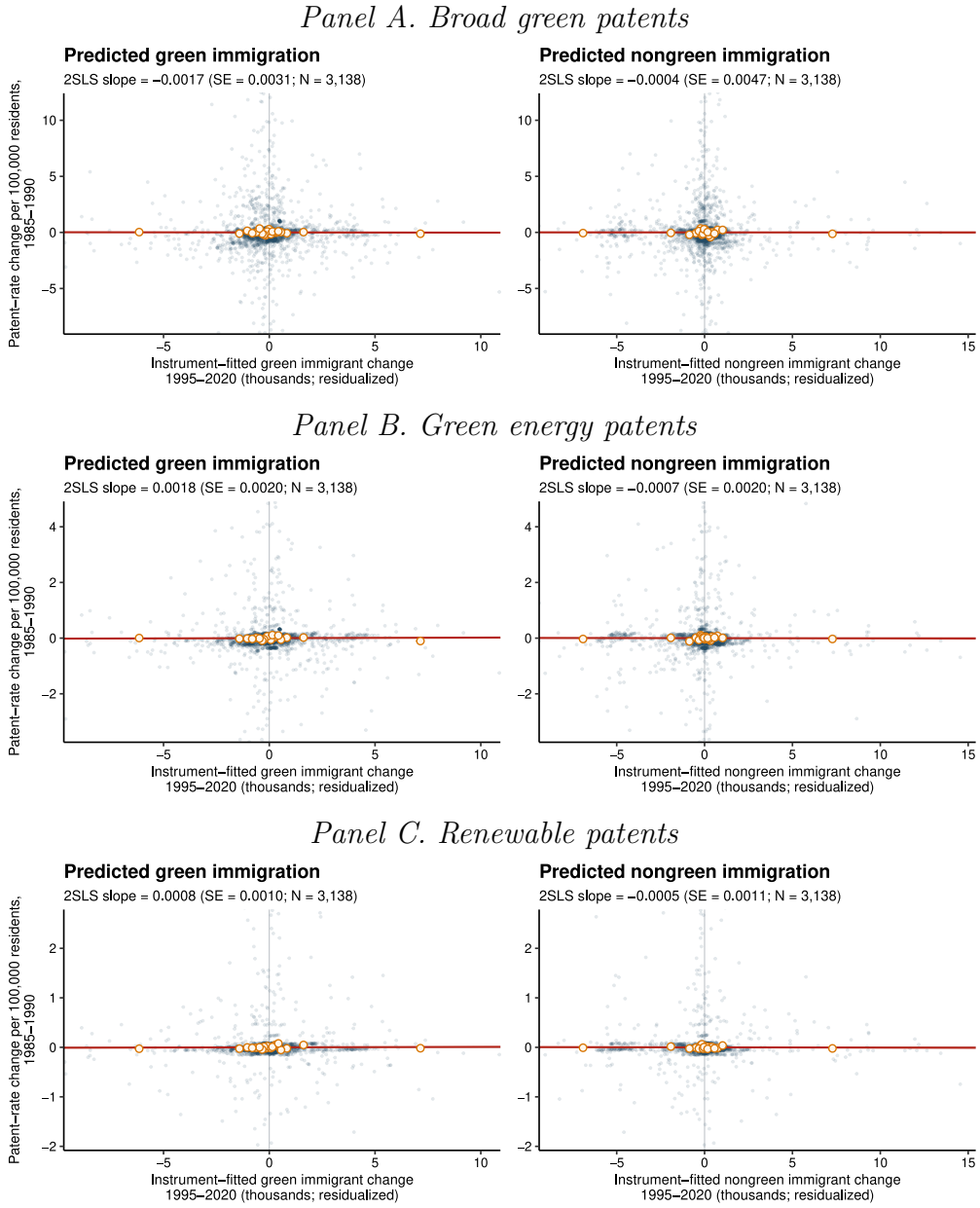


Figure H.1: Predicted Immigration and Pre-Period Patent Growth

Notes: The panels visualize Panel A of Table 4 for 1995–2020 immigrant changes: 1985–1990 changes in five-year patent counts per 100,000 residents, using fixed 1990 Census population, and instrument-fitted 1995–2020 changes in green (left) and nongreen (right) immigrant stocks, in thousands. The 2SLS specification includes state fixed effects and 1990 college share, manufacturing share, and BEA per capita personal income (in thousands of 1990 dollars) in levels, without a separate population control. Both axes partial out these controls and the other group's fitted immigrant change. Lines use the 2SLS coefficients; shaded regions use their state-clustered 95% confidence bands. Orange circles show 20 equal-count bin means. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

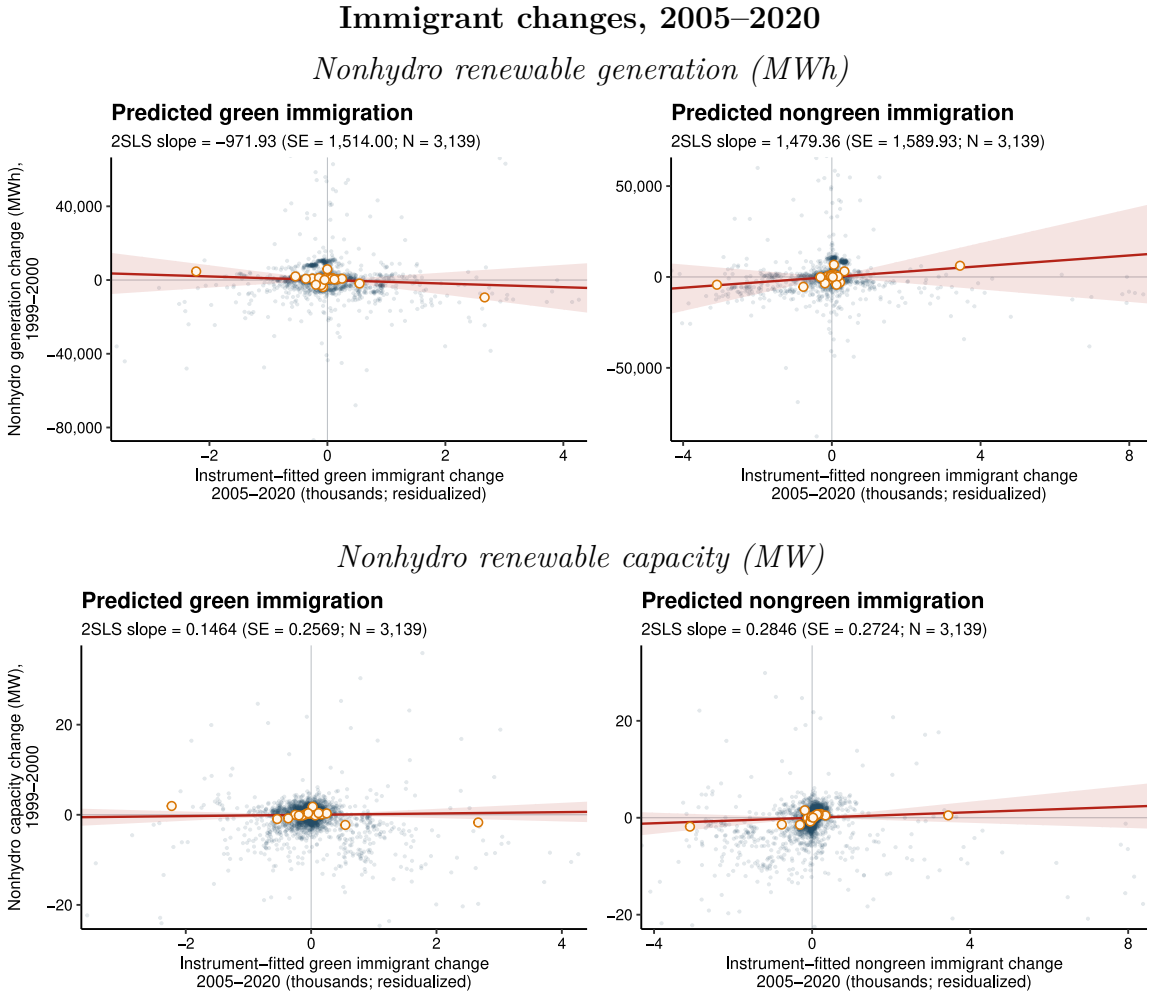


Figure H.2: Early Operator County Renewable Generation and Capacity Growth and Future Predicted Immigration

Notes: This page visualizes Panel B of Table 4 for 2005–2020 immigrant changes. Outcomes are 1999–2000 operator-county nonhydro renewable generation changes in MWh (top) and capacity changes in MW (bottom). Horizontal axes show instrument-fitted 2005–2020 changes in green (left) and nongreen (right) immigrant stocks, in thousands. Both axes partial out state fixed effects, 1990 population, college share, manufacturing share, BEA per capita personal income (in thousands of 1990 dollars), and the other group's fitted immigrant change. Lines and shaded bands use 2SLS coefficients and state-clustered 95% confidence intervals. Orange circles show 20 equal-count bin means. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.