The Social and Environmental Consequences of the Twin Energy-Digital Transition

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Abstract

We analyze the employment and environmental effects of US firms' exposure to green and digital technologies between 2010 and 2023. Using establishment-level data on online job postings, we construct a new measure of technological adoption by linking job skill requirements to advances in green and digital patents. We address endogeneity concerns using a shift-share instrumental variables design based on technological progress outside the US, yielding four main findings. First, increases in green technology adoption lead to job creation, with an elasticity of employment to green exposure of 0.4-0.5, though this effect weakened from 2015. Second, the employment impact of green innovation varies across sectors - innovation in information technology and buildings complements labor, while advances in transportation and smart grids substitute for workers. Third, both green and digital innovations raise relative demand for high-skill workers. Fourth, we find no evidence of negative environmental impacts of digital technology at the firm level.

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1 Introduction

Advanced economies face two concurrent technological transformations. The first stems from increasingly binding environmental constraints, which drive investments in green technologies to reduce emissions. The second involves sustained progress in automation – from computer numerical control machinery and industrial robots to artificial intelligence (AI). Both transitions hold the potential to affect labor markets and environmental outcomes, individually or jointly through their interaction.

Policymakers place a large bet on the beneficial social and environmental effects of the so-called twin transition (Muench et al., 2022). For instance, automation can reduce the energy intensity of manufacturing and thus improve competitiveness (Doms and Dunne, 1995; Wang et al., 2022). However, these optimistic claims are, by and large, unsupported by solid and comprehensive empirical research, and critics often point to job destruction and large rebound effects in electricity use. The present paper aims to fill this important evidence gap. We explore the consequences of the twin transition constructing novel measures of establishment-level exposure to green and digital*technologies leveraging information on skills that firms' are acquiring through new hires. Measuring the semantic similarity between the skills content information obtainable from online job postings, on the one hand, and green and digital patents, on the other, we capture firms' propensity to adopt a new vintage of a specific technology by identifying the initial share of workers that are likely to use or develop such technologies. We observe a large sample of US companies over more than a decade (2010-2023), and estimate the effect of green and digital technology adoption on employment, skill composition, wages and GHG emissions, exploiting arguably exogenous technological improvements in other countries than the US. We contrast establishment- and region-level adjustments to gain insights on the composition and general equilibrium effects emerging in the twin transition.

*This version of our paper focus on automation, taking advantage of a well-established classification of automation patents (Hémous et al., 2024) We are expanding this to include further digital patents for the next revision, specifically Artificial Intelligence.

The labor market impacts of various generations of digital technologies have been studied by a voluminous literature (Autor et al., 1998, 2003; Acemoglu and Autor, 2011; Goos et al., 2014; Autor, 2015; Arntz et al., 2017; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019; Atalay et al., 2020; Babina et al., 2024; Bessen et al., 2025). Digital technologies reduce employment in routine-intensive occupations (Goos et al., 2014) and generally depress wage growth (Acemoglu et al., 2022; Autor et al., 2024). The effects of automation appears in line with these general patterns also at the firm-level contributing to explain the decline in the labor share (Hémous et al., 2024). A separate strand of literature quantifies the size of low-carbon employment, but without an explicit focus on the effect of green technologies. Importantly, this research finds that low-carbon employment still accounts for a small share of total employment (1 to 3 percent) in advanced economies (Vona et al., 2019), especially when using granular job vacancy data that are able to identify also jobs in key low-carbon technologies (Saussay et al., 2022). However, ambitious climate policy project significant reallocation of workers across sectors (Hafstead and Williams III, 2018). Green jobs tend to demand more skills compared to similar non-green jobs, especially technical skills (Vona et al., 2018; Popp et al., 2022) and, to a less extent, managerial (Vona et al., 2018) and social skills (Saussay et al., 2022).

Recent research shows the green and digital technologies interact in economically meaningful ways. For instance, clean technologies absorb more spillovers from AI and ICT than dirty technologies (Andres et al., 2022), suggesting complementarity between environmental and digital innovations. On the other hand, increased energy consumption from digital technologies could partially offset emission reductions from green technologies (Bianchini et al., 2023). However, assessment of the environmental effects of green and digital technologies jointly remained descriptive and at a quite aggregated level. The lack of robust evidence on this is problematic because nderstanding the extent to which green and digital skills overlaps is also essential to train the workers for the twin transition.[†] The general tenet of economic

[†]Vona et al. (2018) find limited overlapping between the classical skill categories used for digital technologies (e.g., routine vs. abstract) and what they identify as green skills. More recently, Santoalha et al.

geography literature that regions with higher technological capabilities better absorb both types of innovation (Carlo Corradini and Vecciolini, 2021) is partially confirmed by recent research on green jobs showing that local job multiplier effects from green investments increase with initial high-tech employment (Vona et al., 2019) and green skills (Popp et al., 2022). Still, more research is needed to assess the performance of regions exposed to both rather than to just one technological transition. We fill this gap by studying the joint social and environmental impacts of the twin transition at both the firm and regional level.

We make several contributions to the literature at the intersection between labor, innovation and environmental economics. First, we make a significant improvement in the new literature linking technological innovations and the occupational skills they complement or substitute (Montobbio et al., 2021; Kogan et al., 2021; Autor et al., 2024; Rughi et al., 2023), by build an intuitive and granular skill-based measure of potential adoption of innovation in very specific technological domains.[‡] We do this by developing a new measure of establishment-level exposure to technological change based on advanced semantic similarity techniques recently used in the labor literature on the impacts of digital technologies (Autor et al., 2024), combining comprehensive data on skill requirements in online job postings (from Lightcast) and detailed patent measures of green and digital innovation (from Google Patents Public Data). Importantly, we go beyond the focus on labor-saving and automation technologies looking at the labor content of green innovations, and we are able to study the overlapping of green and digital technologies shedding new light on the relatedness of the sets of digital and green skills. Although our measure takes inspiration from the seminal work of Acemoglu et al. (2022) on the labor market impact of AI, our measure, being based on patents, is time-varying and thus allows to better assess the effects of technological change.

(2021) find that digital skills favour green technological specialization in Eu regions.

[‡]Both capital-skill complementarities (Krusell et al., 2000) and an induced skill-bias technical change argument (Acemoglu, 1998) give theoretical grounds to our measure. The simple intuition is that a company with the right skill portfolio for a specific technology is more likely to adopt such technology. This claim is supported by empirical research showing that the availability of skilled workers is a good predictor for the adoption of digital technology at the firm- (Doms et al., 1997; Harrigan et al., 2021a) or regional-level (Beaudry et al., 2010) as well as being a critical mediating factor for the role of green subsidies (Popp et al., 2022).

Second, we provide new and much-needed evidence on whether green innovation primarily augments or substitutes for labor. Previous research has predominantly focused on the effects of environmental policy on labor demand (Greenstone, 2002; Kahn and Mansur, 2013; Walker, 2013; Curtis, 2018; Marin et al., 2018; Marin and Vona, 2019; Popp et al., 2022), rather than directly estimating the effect of green or energy-saving technological change on labor. The former approach offers more credible causal identification compared to the latter [§] ; yet the latter is routinely used to interpret the policy effects. To address this issue, we proceed in two steps.

We begin by implementing the approach of Autor et al. (2024) to classify the universe of green patents published from 1980 to 2019 based on their textual similarity to either new occupational titles (labor-augmenting) or existing task descriptions (labor-saving). This analysis reveals that the employment impacts of green innovation are expected to be substantially heterogeneous across green technologies. For example, innovations in the decarbonization of information technology and buildings tend to complement labor, while transportation and smart grid advances tend to substitute for workers.

We also find that the overall degree of labor-augmentation by green technologies sharply declines over time. These findings are consistent with life-cycle theories on the impact of innovation on labor demand (Vona and Consoli, 2015) and task-based models augmented for endogenous technological change (Acemoglu and Restrepo, 2019). According to Acemoglu and Restrepo (2019), new tasks initially performed by humans are labor-augmenting, while older tasks are progressively codified, enabling machines to perform them at lower costs. Green innovation follows this trajectory, evolving from its early conception in the 1980s, which was associated with the emergence of new tasks and occupations, to a phase of adoption and deployment from the 2010s onward, where machines increasingly replace human labor. Firm-level evidence further corroborates the positive association between green innovation

[§]Studies on green innovation and employment are usually retrieving interesting association rather than causal effects (Pfeiffer and Rennings, 2001; Rennings et al., 2004; Horbach and Rennings, 2013; Gagliardi et al., 2016; Elliott et al., 2021).

and employment, although it mostly relyies on cross-sectional evidence so far (Horbach and Rennings, 2013; Gagliardi et al., 2016; Elliott et al., 2021).

We then propose a novel approach to estimate the causal effect of both green and digital technological change at both the establishment regional levels. To address endogeneity concerns, we adapt a modern shift-share instrumental variables design to a setup where patent applications are used to predict current changes in our measure of technology exposure (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). In doing so, we combine a measure of initial exposure to patents filed in each technology class using the establishment-level share of workers who are specialized in that class, and the count of patents filed in each technology class *outside* the United States. This identification strategy isolates variation in technology adoption driven by global technological progress rather than local economic conditions or firm-specific factors. Frattini et al. (2024) use a similar identification strategy to study the impact of green reindustialization on employment and productivity at the industry-level in Europe. Our approach is, however, more precise in identifying the specific technologies that an establishment is likely to adopt and in controlling for the large within-sector heterogeneity using establishment-level data.

Our analysis yields four new empirical findings. First, increased adoption of green technologies leads to job creation on average, contrasting with the well-known job destruction effect of digital technologies. The elasticity of employment to green exposure revolves around 0.4 and 0.5 across specifications. However, this positive effect has weakened since 2015, consistent with our patent-level analysis predicting that green innovation has become increasingly labor-saving in recent decades. Second, both green and digital innovations increase the relative demand for high-skill workers, with the share of high-skill job ads increasing by 0.11% per additional unit of technology exposure. Third, while establishments adopting digital technologies reduced the wages they offered, green technology adoption does not appear to impact salaries. Fourth, we find no evidence that digital technology adoption weakens or reinforces emissions reductions associated with the simultaneous adoption with

green technologies.

These results carry important implications for environmental and labor market policy. While green technology adoption increases employment at the establishment level, the gains mostly benefit high-skilled candidates. This suggests that policy support for worker adaptation is warranted, particularly in sectors where green innovation increasingly substitutes for labor. The pronounced skill bias observed in both green and digital transitions underscores the need for targeted education and training programs. On a positive note, the absence of negative interactions between digital technologies and emissions reductions provide some reassurance that pursuing both transitions need not create be at odds.

The remainder of this paper proceeds as follows. Section II develops our conceptual framework for analyzing how different types of innovation affect labor demand, skill composition, and environmental outcomes. Section IV introduces our new skill-based measure of technology adoption, then describes our data sources and details the construction of key variables. Section IV analyses if green innovation is labor-augmenting or -saving. Section V reports our main results on employment, skills, wages, and emissions. Section VI discusses policy implications and concludes.

2 Conceptual framework

This section outlines the conceptual framework we adopt to design our empirical analysis of how different types of technological innovation affect labor markets and environmental outcomes. We start by distinguishing between labor-augmenting and labor-saving innovations and then discuss the potential implications of firm-level adoption of automation and green innovation for skill demand and environmental impacts.

2.1 Technology types and labor market effects

A commonly used taxonomy in the labor economics literature differentiates innovations based on their relationship to worker capabilities (Autor et al., 2024), emphasizing the heterogeneous effects of technological innovation on worker outcomes. Labor-saving technologies directly substitute for human workers in specific tasks, reducing both labor demand and wage growth in affected occupations (Autor et al., 2024). Industrial robots and artificial intelligence applications are prime examples of such technologies, with firm-level evidence suggesting AI deployment can decrease labor demand (Acemoglu et al., 2022). However, the effects of AI remain debated, with some recent contributions finding labor-augmenting effects associated with growth in firm employment, sales, and valuation (Babina et al., 2024).

Labor-augmenting technologies, by contrast, complement worker capabilities and can increase labor productivity in specific tasks. While these innovations often create new occupations and can increase aggregate employment (Autor et al., 2024), their wage effects are theoretically ambiguous and may be negative in some contexts (Kogan et al., 2023). The ultimate impact depends critically on workers' ability to adapt to enhanced productivity requirements.

A priori, it is unclear whether green innovations would manifest either labor-saving or labor-augmenting characteristics – this may depend on their specific application, or the specific type of technology. For example, smart grid systems and automated energy management solutions may primarily save labor, while new installation techniques for renewable infrastructure might complement existing construction skills. Indeed, answering this fundamentally empirical question is one of the key contributions of the present paper. Considering existing low-carbon jobs, recent evidence suggests that while currently comprising only 1-3 percent of employment, they may exhibit a slight skill bias and a moderate degree of spatial concentration (Vona et al., 2019; Saussay et al., 2022). In the medium to long run, significant labor market adjustments are expected under ambitious decarbonization scenarios (Hafstead and Williams III, 2018).

2.2 Skill demand and distributional effects

Automation technologies tend to increase the relative demand for skilled workers. Automation technologies typically reduce middle-skill employment, particularly in routine cognitive tasks (Goos et al., 2014; Harrigan et al., 2021b). This effect is strengthened by the fact that higher low-skill wages tend to accelerate automation innovation (Hémous et al., 2024).

There is empirical evidence in Europe and the United States that existing decarbonization jobs require more STEM and engineering skills (Vona et al., 2018; Popp et al., 2022). They also require enhanced managerial and social skills (Vona et al., 2018; Saussay et al., 2022). While green occupations do not necessarily require more formal education than traditional jobs, they do demand more extensive on-the-job training (Consoli et al., 2016). Notably, although green and brown jobs exhibit similar skill requirements (Vona et al., 2018; Popp et al., 2022; Saussay et al., 2022), transitions between them remain rare in practice (Curtis et al., 2023).

While these studies document the nature of existing green jobs, the long-run labor market effects of decarbonization will depend on the employment impact of green innovation itself just as much as the skill requirements of current environmental occupations. Our analysis addresses this key gap in the literature.

The distributional consequences of these technologies operate through both direct and indirect channels. Direct effects occur within establishments as both types of innovation raise returns to skill. Indirect effects emerge as displaced workers move across sectors or occupations, which can lead to wage penalties. The magnitude of these effects depends on the local availability of appropriate green skills (Popp et al., 2022) and the workers' own capabilities to take advantage of technology (Vona et al., 2019).

2.3 Environmental implications and technological synergies

The environmental impact of automation technologies remains theoretically ambiguous. While automated systems may improve energy efficiency through more precise control, they

could also aim at increasing a firm's productivity - which can ultimately grow total production and energy use faster than the firm can reduce its emission intensity. Further, the digital transition that often accompanies automation may partially offset emission reductions from green innovation due to its own environmental costs (Bianchini et al., 2023).

Green technologies directly reduce emissions by design, but their effectiveness can be enhanced or diminished through interaction with automation. Evidence suggests that clean patents draw on digital patents two to three times more frequently than dirty patents (Andres et al., 2022), indicating potential complementarities. These technological synergies manifest across multiple sectors. In energy systems, smart grids integrate automation for improved efficiency. In manufacturing, automation technologies enable better monitoring, forecasting, and process control, offering potential reductions in material and energy use. The built environment benefits from smart building systems and energy management, while transport systems can leverage smart mobility and traffic management solutions.

The joint impact of green and digital innovations thus depends crucially on their complementarities and the joint capacity of workers and firms to adapt to changing skill requirements. At the local level, labor markets with appropriate skill bases may be better positioned to capture the benefits of these technological transitions while minimizing their potential negative distributional consequences.

3 A novel measure of technological adoption

The relationship between technological innovation and economic outcomes requires measuring the extent to which firms effectively adopt technological advances. This has generally proven challenging to operationalize empirically. While innovation metrics like patent counts or R&D expenditure capture the creation of new technologies, they do not measure their adoption. This distinction matters: the economic impact of a technology stems from its implementation rather than its sole invention.

We introduce a novel measure of technology adoption that tracks innovation adoption at the establishment-level. Our measure leverages two key insights. First, the implementation of any technology requires workers to operate it, creating demand for specific skills. Second, these skill requirements appear in job postings, providing a window into the technologies each establishment uses in its production process.

By connecting skills to the patents they enable and tracking these skills in job postings, we construct an establishment-level measure of technology adoption. This approach builds on recent work using job postings to measure adoption of specific technologies like artificial intelligence (Acemoglu et al., 2022) and automation (Autor et al., 2024). We would like to highlight that the implementation we describe in the following – and thereby our adoption measure – is general and can be applied to any technology class, even though we will focus on the green and digital cases in our empirical application.

3.1 Linking patents to skills

The core challenge in constructing our measure is connecting innovations, as captured by patents, to the skills that are most closely associated with their implementation. We accomplish this by measuring the semantic similarity between patent technology classifications and skill descriptions from job postings.

Patents are classified using Cooperative Patent Classification (CPC) codes, which organize technologies into hierarchical categories. Each CPC code has an associated text description of the technology it covers. For example, code Y02A10/26 describes technologies for "Adaptation to climate change in agriculture, forestry, livestock or agroalimentary production.". Further, they provide a title and an extensive abstract describing the invention being patented.

We measure the semantic proximity between the body of text describing the patent (CPC code descriptions, title and abstract) and standardized skill descriptions from job postings using Sentence Transformers (Reimers, 2019). This method embeds text strings into high-

dimensional vectors such that similar concepts are represented by vectors which are close topologically. As a result, the similarity between two texts can then be measured by the cosine similarity (Apallius de Vos et al., 2021) of their embedding vectors.

The highly specialized vocabulary often encountered in patents raises an additional difficulty, as Sentence Transformers cannot generate vector representations of words or phrases that the model has not encountered in its training set. To ensure accurate representation of technical patent language, we use PaECTER (**?**), a transformer model specifically fine-tuned for patent classification on the entire USPTO corpus. This model builds on Google's BERT for Patents and incorporates domain-specific vocabulary and context.

At this stage, we obtain a matrix of semantic similarity scores between each of the 32,000 skills and 1.6 million patents in our dataset (see Section XX).

3.2 Measuring technology adoption

We then aggregate the patent dimension of this very large matrix to the CPC 4-digit technology class and compute for each CPC4-skill pair a similarity score between 0 and 1. Higher scores indicate the skill is more relevant for implementing the technology class. For instance, storm drain technologies (Y02A) have strong connections to infrastructure skills, while computer numerical control patents (B25J) link to manufacturing automation skills.

We classify skills as "marker skills" for a technology if their average similarity to patents in that technology class exceeds the 95^{th} percentile of all patent-skill similarities. Examples include "Storm Drains" for climate adaptation patents and "Computer Numerical Control" for automation patents.

For each establishment i and technology type K, we then calculate exposure as:

$$S_{iK,t} = \sum_{k \in K} s^{ads}_{ik,t} \quad \text{where} \quad s^{ads}_{ik,t} = \frac{\sum_{a \in \mathbb{A}_{i,t}} \mathbb{1}^k_a}{|\mathbb{A}_{i,t}|} \tag{1}$$

Here, k indexes specific technology classes within type K, $\mathbb{A}_{i,t}$ represents the set of job

ads posted by establishment i in period t, and $\mathbb{1}_a^k$ indicates whether ad a requires at least one marker skill for technology k. In effect, the exposure of establishment i to technology class k in period t is the share of job ads posted by i during t that contain at least one of the marker skills for technology k. In the remainder of this paper, we will focus on $K \in \{\text{green}, \text{automation}\}$.

We now turn to the data we collect to operationalize this novel metric. The rest of this section describes our data sources and details the construction of key variables.

3.3 Job postings data

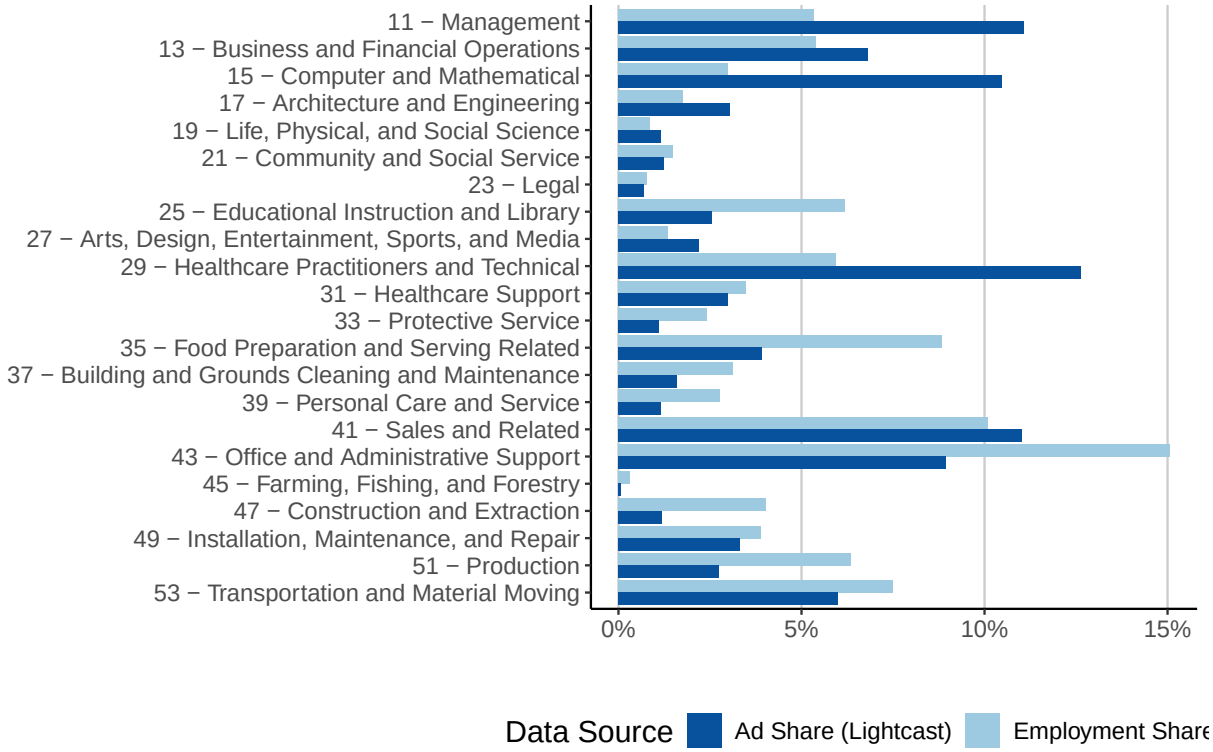
The primary dataset comes from Lightcast's database of online job vacancy postings, which covers the near-universe of U.S. online job advertisements from 2010-2024. Lightcast collects these data through systematic web scraping of over 50,000 sources, including both job boards and company websites. The resulting dataset contains approximately 330 million unique job postings.

Each job posting contains detailed information on position requirements and characteristics. Key variables include standardized occupational codes (SOC), required skills, education levels, offered wages when available, and geographic location. Particularly valuable for our analysis, Lightcast processes job description text to identify and standardize skill requirements. These map to a controlled vocabulary of over 32,000 distinct skills organized in a hierarchical taxonomy.

The dataset's main advantages include its granular measurement of skill demands and broad coverage across sectors and regions. However, several features warrant discussion. First, online postings systematically over-represent certain sectors and occupations. Figure 1 compares the occupational distribution in our data to economy-wide employment shares from the Bureau of Labor Statistics. Technology, business services, and healthcare show particularly high representation, while construction and hospitality appear under-represented.

Second, we observe only the demand side of the labor market through employers' stated

Figure 1: Representativeness of Lightcast Data



requirements. We cannot track which postings resulted in hires or the characteristics of eventual matches. While this limits certain analyses, it suits our focus on measuring firms' desired skill sets.

3.4 Patent data

Our patent data come from Google Patents Public Data covering worldwide patent activity since the 19$^{\text{th}}$ century. To ameliorate the feasibility of the subsequent semantic analysis, we focus on patents which fulfill two common quality criteria: belong to a triadic patent family – *ie* a family of patents filed simultaneously in the US Patents & Trademarks Office (USPTO), the European Patents Office (EPO) and the Japanese Patents Office (JPO) ; and having received at least one citation. This yields a final dataset of more than 1.6 million patents from 1980-2019.

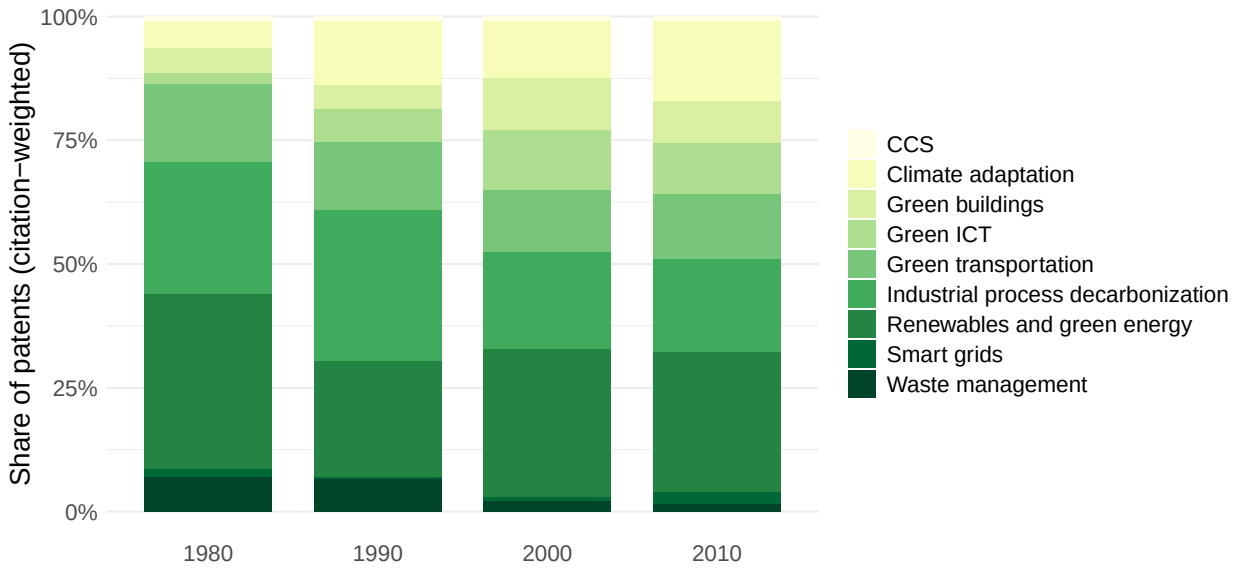
3.4.1 Identifying green innovation

We identify green patents through Cooperative Patent Classification (CPC) codes, focusing on *Climate Change Mitigation Technologies* (Y02) and *Smart Grid Technologies* (Y04S). Specifically, any patent categorized using at least one CPC code belonging to either of these two categories is included in our set of green patents.

These classes encompass innovations ranging from renewable energy generation to energy-efficient buildings and low-carbon transportation. Figure A1 shows that green patents' share has risen substantially, doubling from approximately a citation-weighted share of 5% of triadic patents in 1980 to over 10% by 2020.

The composition of green innovation has evolved markedly (Figure 2). Early patents focused heavily on energy generation and industrial processes. More recent innovation increasingly targets information technology applications and adaptation measures.

Figure 2: Green Technology Composition by Decade

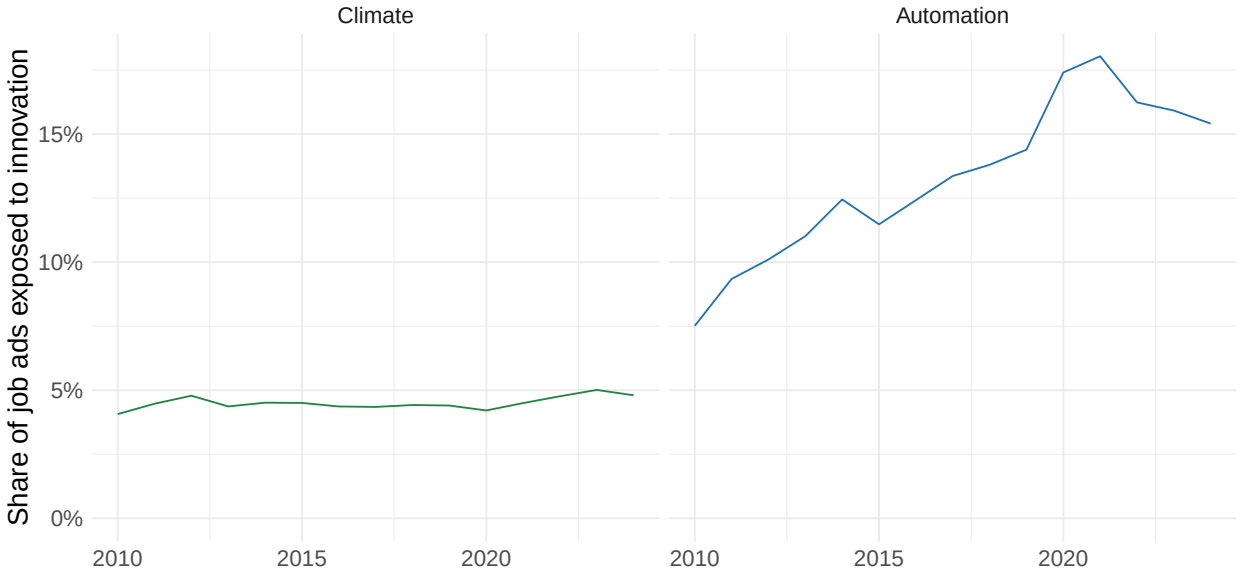


3.4.2 Identifying automation innovation

For automation technologies, we follow Hémous et al. (2024)'s classification approach. They identify automation patents through keyword analysis of machinery-related CPC codes, focusing on innovations that directly substitute for human labor in specific tasks. Figure A2 shows automation patents maintaining a relatively stable 2-3% share of triadic patents, with notable shifts from industrial robotics toward digital automation over time.

Figure 3 shows the resulting distribution of technology exposure across establishments over time. The share of job ads requiring green technology skills remained relatively stable around 5% through our sample period. In contrast, automation exposure rose from about 8% to 15% of ads between 2010 and 2023.

Figure 3: Share of Job Ads Exposed to Innovation



4 Is green innovation labor-augmenting or labor-saving?

4.1 Measurement approach

We adapt the empirical framework developed by Autor et al. (2024) to classify green innovations as labor-augmenting or labor-saving. This approach leverages and furthers the linkages between patent content to occupational skill and task content that we developed in the previous section.

First, following Autor et al. (2024), we define labor-saving innovations as those that replace tasks currently performed by workers – in effect acting as a *substitute* for some subset of workers' tasks. To identify these, we measure the semantic similarity between patent text and descriptions of existing occupational tasks. Patents whose content aligns more closely with existing task descriptions are classified as labor-saving, as they are more likely to automate or streamline established workflows. For example, a patent detailing a robotic assembly line system for a given product would exhibit high semantic similarity to tasks associated with the manufacturing of said product.

Second, labor-augmenting innovations are defined as those that *complement* workers' outputs by introducing new tools, specializations, or services. Here, we assess semantic similarity between patent text and descriptions of *new occupational titles* recorded in the Census Bureau's Alphabetical Index of Occupations (CAI). For example, titles such as "Cybersecurity Analyst" (added in 2018) reflect emerging expertise driven by technological change. Patents whose language aligns with these new titles signal innovations that expand the scope of work rather than displacing it.

To implement this, we use our corpus of 1.6 million U.S. patents published from 1980 to 2020. We then employ the same Sentence Transformer-based techniques to compute semantic similarity scores between patent text and two reference textual sets: (1) task descriptions from 1977 Dictionary of Occupational Titles and (2) new occupational micro-titles in each decade from the CAI, as identified by Autor et al. (2024). Just as before, patents are assigned

to technology classes using the Cooperative Patent Classification (CPC) system.

The use of Sentence Transformers in this step represents a significant improvement over the earlier word embedding approach that was employed in Autor et al. (2024). Unlike word-level embeddings, Sentence Transformers do not require the removal of stop words, which sometime carry semantically useful meaning at the phrase level – *e.g.* consider "Power on demand" vs "Power demand". Further, aggregating word-level embeddings across an entire document requires averaging thousands of embedding vectors, incurring a significant reversal to the mean penalty. By contrast, Sentence Transformers deliver vector representations of several paragraphs at a time, thereby better capturing semantic context (Reimers, 2019).

This yields four matrices of semantic similarity scores between patents and the new CAI occupation titles we observe in each of the four decades from 1980 to 2018, and symmetrically four matrices between patents and DoT tasks. We then count the number of cells scoring above the 85^{th} percentile of semantic similarity in each matrix, which we aggregate to the CPC 4-digits technology class level (weighting by citation count). This allows us to calculate the citation-weighted ratio of labor-augmenting to labor-saving patents at the technology class level.

4.2 Results

Figure 5 documents the recent decline in the labor-augmenting share of green patents, falling from a peak of nearly 70% in the 1990s to close to 20% in the 2010s. This trend mirrors successive phases in the life cycle of green innovation. During the 1980s and 1990s, early-stage technologies such as renewable energy systems and pollution control devices required novel expertise, spurring demand for new specialized roles like environmental engineers or solar technicians. Correspondingly in our empirical approach, these innovations exhibited high semantic alignment with new occupational titles, reflecting their labor-augmenting nature.

The 2000s marked a transitional phase as green technologies began scaling. Innovations shifted toward optimizing production processes (e.g., advanced battery manufacturing) and

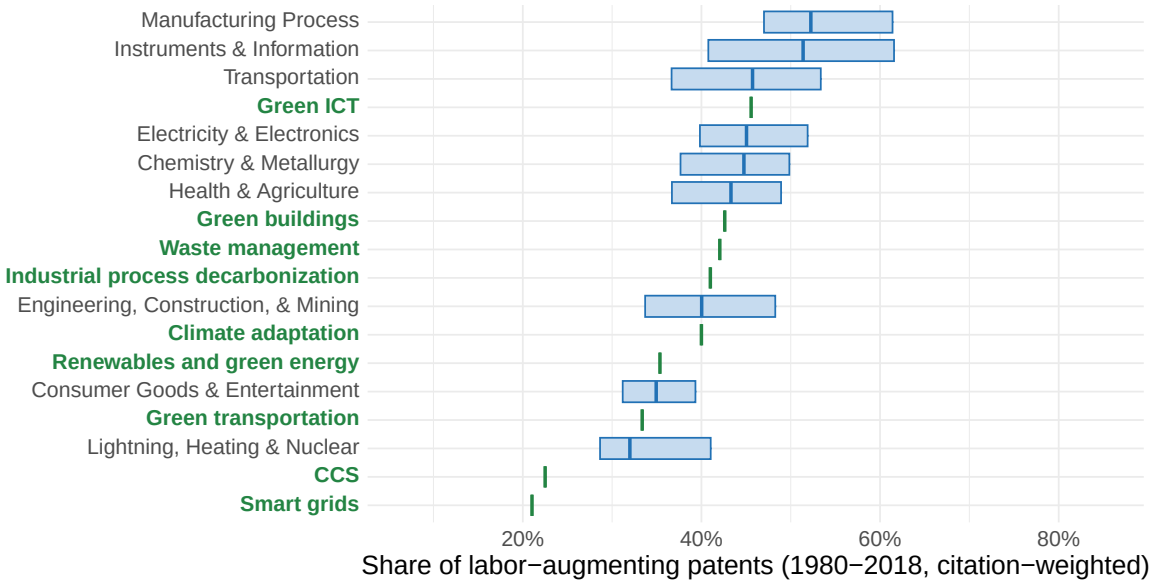


Figure 4: Share of Labor-Augmenting Patents Across Green Technology Classes, 1980–2018 (citation-weighted)

integrating existing systems (e.g., smart grids). These developments rely less on blue-sky innovation and more on optimizing workflows, leading to a rise in labor-saving patents. By the 2010s, green technologies had reached a certain maturity and policy-driven pressures for accelerated deployment and cost reduction could explain a novel emphasis on labor-saving innovation.

The steepest decline occurred post-2010, coinciding with global commitments to faster decarbonization. Competitive markets and standardized regulatory frameworks incentivized firms to adopt scalable solutions. The 40-year trajectory of green innovation from predominantly labor-augmenting to labor-saving underscores a central trade-off in the green transition: accelerating deployment and lowering the cost of the energy transition could be at odds with inclusive job creation.

These findings highlight the empirical nature dual role of green innovation: while it can create new opportunities in emerging sectors, its labor market impacts depend critically on the balance between augmentation and automation across technology classes and over time.



Figure 5: Declining Share of Labor-Augmenting Green Patents by Decade, 1980–2020

5 Establishment-level analysis

This section presents our empirical approach for estimating the causal effects of technology adoption on establishment outcomes. We begin by discussing identification challenges, then detail our instrumental variables strategy.

5.1 Baseline specification

Our goal is to estimate how exposure to green and digital technologies affects establishment-level outcomes. For each establishment i and outcome y, we examine long differences between a baseline period t_0 (2010-2014) and outcome period t_1 (2021-2023):

$$\Delta \log y_{i,t} = \alpha_{t_1} + \beta_G \Delta S_{iG,t} + \beta_A \Delta S_{iA,t} + X'_{i,t_0}\gamma + \varepsilon_i$$

where $\Delta S_{iK,t}$ measures the change in exposure to technology type K (green or automation), and X_{i,t_0} contains baseline establishment characteristics including size, age, and industry. The coefficients of interest, β_G and β_A, capture the elasticity of outcomes to technology exposure.

We examine four main outcomes: (1) employment, measured through job posting counts; (2) skill composition, captured by the share of high-skill occupations; (3) wages, from posted salary information; and (4) emissions, from EPA facility data. Changes in these outcomes between periods reflect establishments' responses to increased technology exposure.

5.2 Identification challenges

Several factors complicate causal identification in this setting. First, establishments select into technology adoption based partly on unobserved characteristics that may correlate with outcomes. More productive establishments might simultaneously adopt new technologies and expand employment for reasons unrelated to the technology itself. Addressing this concern drives our choice of a within-establishment empirical design.

Second, local economic conditions could drive both technology adoption and outcomes. Areas experiencing positive economic shocks might see both increased technology investment and employment growth. Conversely, negative shocks could accelerate automation while reducing overall labor demand. This is partially mitigated by our long-difference within-establishment design, which controls for local, firm and establishment unobserved heterogeneity.

Third, measurement error in technology exposure could attenuate estimated effects. Our skill-based exposure measure captures adoption with noise, as not all technology-related skills appear in job postings. Such measurement error would bias coefficients toward zero.

5.3 Shift-Share instrumental variable

We address these identification challenges through a shift-share instrumental variables strategy following Borusyak et al. (2022). For each broad technology type $K = green, automation$, we construct an instrument:

$$z_{iK,t} = \sum_{k \in K} s^{ads}_{ik,t_0} \ln \left(\sum_{p \in \mathbb{P}_{k,t-\tau}} cw_p \right)$$

where k indexes CPC technology classes belonging to the broad category K. The logic follows that of a standard shift-share instrument combining the establishments' initial share of workers with skills complementary to CPC class k (s^{ads}_{ik,t_0}, the shares) and subsequent technological advances in those CPC classes (measured through the flow of citation-weighted patents $\mathbb{P}_{k,t-\tau}$, the shifts). The economic intuition is that establishments having more tech-specific workers at baseline are more likely to adopt subsequent innovations of that technology and thus further increase their share of tech-specific workers.

5.4 Identification Assumptions

To increase the plausibility that innovations are as-good-as randomly assigned (Borusyak et al., 2022), we restrict $\mathbb{P}_{k,t-\tau}$ to include only patents filed outside the United States. More specifically, we use only dyadic patents, filed jointly in the EPO and JPO when constructing the instrument. This isolates variation driven by global technological progress rather than local economic conditions or establishment-specific factors.

The shift-share IV strategy relies on two key identifying assumptions. The first is instrument relevance. Figure A3 shows that dyadic and triadic patent flows correlate strongly across technology classes, supporting the instrument's relevance. Table **??** confirms strong first-stage relationships, with F-statistics well above conventional thresholds.

The second is the exclusion restriction that establishment outcomes are uncorrelated with global technological improvements, conditional on the set of controls included. Restricting to foreign patents increases the plausibility of this assumption - individual U.S. establishments likely have minimal influence on worldwide innovation outside their country, that, however, remains untestable. As now standard in shift-share IV design (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020), we conduct supplementary empirical analyses to

increase the plausibility of this assumption, such as adding industry-by-period fixed effects or conducting placebo tests using technology classes unrelated to green or automation innovation. Particularly important, we investigate whether establishments with different initial skill compositions are on different trends for other reasons (the so-called parallel trends assumption). We provide supportive evidence through pre-trend analysis showing similar outcome trajectories before 2010.

5.4.1 Sample Construction

We construct our analysis sample in several steps. First, we take advantage of Lightcast's standardized firm names to identify the company advertising a given position. For example, Lightcast's firm name extraction and standardization algorithm guarantees that a job ad listing 'Amazon.com', 'Amazon Ltd' or 'Amazon Corp.' will all be correctly allocated to a unique 'Amazon' identifier. We have obtained the latest revision of the Lightcast dataset, which benefits from a significantly improved coverage compared with earlier version - in effect, we observe firm name in more than 80% of job ads over the whole duration of our sample. This very high coverage is essential in enabling our empirical design.

We also observe the geographical location where the position advertised in a job ad would be performed. It is important to note that is – in general – distinct from the company's headquarters' location, and is job ad-specific. This location is observed at the county-level.[¶] We then allocate each job ad to a corresponding ERS 2000 Commuting Zone.[‖] Following Acemoglu et al. (2022), we then define an establishment as a firm-commuting zone pair.

Second, we restrict attention to establishments posting at least 10 ads per year in both our baseline (2010-2014) and outcome periods (2021-2023). This ensures that we observe sufficient data to measure technology exposure. Third, we ensure that establishments remain in a consistent industry classification between the two periods to avoid confounding the

[¶] As identified by the county's 5-digit FIPS code.

[‖] This commuting zones classification was established by the U.S. Department of Agriculture's Economic Research Service (ERS) for the baseline year 2000.

impact of innovation exposure with shifts in business focus. The resulting sample covers 79,678 establishments.

This empirical approach allows us to estimate the causal effects of technology exposure while addressing the main threats to identification. The next section presents our findings.

6 Labor market-level analysis

This section will be included in a future revision of the paper.

7 Results

This section presents our empirical findings on how technology adoption affects establishment outcomes. We examine in turn overall employment effects, then impacts on skill composition, wages, and emissions.

7.1 Employment effects

Table 1 presents our main results on establishment-level employment. Column (1) shows the impact of green technology exposure alone. The point estimate of 0.39 indicates that a one percentage point increase in the share of jobs exposed to green technology increases total job ads by 0.39%. Column (2) shows the negative effect of increased automation adoption on establishment-level job creations, with a coefficient of -0.88 indicating substantial job displacement. Column (3) includes both measures simultaneously - the green technology coefficient strengthens to 0.56 while the automation effect remains stable at -0.91.

These baseline estimates remain robust across various specifications. Appendix Table B1 shows similar results with commuting-zone specific time trends to account for the heterogeneity of labor market conditions across the US over our period of observation. Table B2 adds detailed industry-specific time trends, at the NAICS 4-digits level, better accounting

Table 1: Impact on employment (IV estimates)

	(1)	(2)	(3)
Δexp.^{green}	0.390**		0.560***
	(0.162)		(0.168)
Δexp.^{auto}		-0.878***	-0.914***
		(0.093)	(0.093)
Observations	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
K-P F-stat (green)	690***		391***
K-P F-stat (auto)		2,201***	1,127***

* p < 0.1, ** p < 0.05, *** p < 0.01

for sector-specific technological trends. The impact of green technology exposure on job ads creation remains consistently positive and statistically significant across all specifications, including when we simultaneously control for CZ-specific and industry-specific time trends. The magnitude of the effect ranges from 0.26 to 0.39. Meanwhile, the impact of automation technology exposure is consistently negative, but varies from -0.71 to -0.39.

The opposing employment effects align with the distinct nature of these technologies. Most green technologies require new installation and maintenance work to be deployed, creating jobs even as production processes change. By contrast, automation technologies explicitly target labor replacement in existing tasks.

However, the employment impact of green technology has evolved over time. Table 2 splits the sample into early (2010-2014 vs 2016-2018) and late (2017-2019 vs 2021-2023) periods. The green technology coefficient declines from 0.555 in the early period to -0.322 in the late period, suggesting increasingly labor-saving characteristics.

This is well-aligned with the results of our patent-level analysis: the latter period in the table 2 corresponds to the innovation phase the (2010s) where we expected green innovation to become predominantly labor-saving, by contrast with earlier green patents in the 1990s and 2000s.

Table 2: Employment Effects Over Time: IV Estimates

	2010-14 vs 2016-18		2017-19 vs 2021-23	
	(1)	(2)	(3)	(4)
Δexp.^{green}	0.555***	0.573***	-0.322***	-0.273***
	(0.110)	(0.110)	(0.091)	(0.091)
Δexp.^{auto}		-0.084		-0.272***
		(0.068)		(0.036)
Observations	83,383	83,383	112,101	112,101
Establishment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
CZ $\times$ Period FE	Yes	Yes	Yes	Yes
NAICS 4-digit $\times$ Period FE	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

7.2 Skill composition effects

Both technology types substantially alter establishments' skill composition. Table 3 examines changes in the share of high-skill job ads offered at the establishment-level, defined as positions classified in occupations belonging to SOC codes 11 through 29. Column (3) shows that an increase of one point in green and automation exposure raises the share of high-skill positions offered by 0.10 and 0.11 percentage points respectively.

Table 3: Impact on Skill Composition: IV Estimates

	(1)	(2)	(3)
Δexp.^{green}	0.126***		0.105***
	(0.018)		(0.019)
Δexp.^{auto}		0.117***	0.110***
		(0.011)	(0.011)
Observations	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
K-P F-stat (green)	690***		391***
K-P F-stat (auto)		2,201***	1,127***

* p < 0.1, ** p < 0.05, *** p < 0.01

This skill bias can manifest through multiple channels. For green technologies, previous

analyses of green jobs revealed that they require an increased number of engineering and technical skills, which could drive the shift. Further, many environmental innovations require specialized knowledge in fields like materials science or electrical systems. Automation creates skill bias both by eliminating routine jobs and by increasing demand for qualified workers who can install and maintain automated systems.

7.3 Wage effects

Table 4 examines how technology exposure affects posted wages. Both types of innovation reduce average wages, with elasticities of -0.23 for green technology and -0.29 for automation. However this is only marginally significant at the 10% level in the case of green technology.

Table 4: Impact on Posted Wages: IV Estimates

	(1)	(2)	(3)
Δexp.^{green}	-0.230*		-0.156
	(0.133)		(0.135)
Δexp.^{auto}		-0.289***	-0.274***
		(0.085)	(0.086)
Observations	21,173	21,173	21,173
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
K-P F-stat (green)	149***		95***
K-P F-stat (auto)		591***	314***

* p < 0.1, ** p < 0.05, *** p < 0.01

Appendix Table B3 shows effects on the ratio of low-skill to high-skill wages within establishments. We do not find statistically significant evidence of an impact of green technology exposure on the relative compensation of low and high-skilled workers. By contrast, in line with previous contributions, we find that automation technology exposure affects low-skilled workers' wages very negatively. Combined with the employment and skill share results, this suggests that both technologies increase inequality through two channels: direct displacement of lower-skill workers; and in the case of automation, rising relative returns to skill

among remaining workers.

7.4 Environmental Effects

In this section, we supplement our main dataset with establishment-level emissions data from the EPA's Greenhouse Gas Reporting Program from 2010 to 2023, which collects GHG emissions data from large emitting facilities, suppliers of fossil fuels and industrial gases that result in GHG emissions when used, and facilities that inject carbon dioxide underground. Each facility is identified by its name, the name(s) of its corporate owner(s), its 6-digits NAICS sector and its geographical location.

We take advantage of this information to perform a merge with the job ads at the same location by the same firm, where observed, in our Lightcast dataset. While we manage to match close to 2,500 establishments, once combined with our other establishment inclusion criteria to construct the innovation exposure metrics, we obtain a final subset of 949 establishments where we jointly observe baseline technology exposure, employment outcomes and emissions over time.

Table 5 presents results for establishment-level GHG emissions. As expected, green technology adoption reduces emissions, with an elasticity of -0.370. Importantly, we find no evidence that automation adoption significantly affects emissions when observed independently or simultaneously – the point estimates are close to zero and not statistically significant in both cases.

This pattern suggests that automation neither substantially helps nor hinders emissions reduction efforts. The emissions reductions from green technology adoption persist regardless of establishments' automation exposure. This result lends support to the possibility of achieving "green growth", understood as a decoupling between productivity improvements and emissions reduction.

Table 5: Impact on GHG Emissions: IV Estimates

	(1)	(2)	(3)
Δexp.^{green}	-0.370***		-0.366***
	(0.113)		(0.112)
Δexp.^{auto}		0.024	-0.053
		(0.116)	(0.134)
Observations	949	949	949
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
K-P F-stat (green)	160***		87***
K-P F-stat (auto)		100***	51***

* p < 0.1, ** p < 0.05, *** p < 0.01

8 Conclusion

This paper examines how exposure to green and digital technologies affects labor markets and environmental outcomes. Using novel establishment-level data on job postings matched to patent measures of technological innovation, we document several empirical patterns.

First, green technology adoption increases employment on average, with an elasticity of 0.4-0.5. However, this effect has weakened since 2015 as green innovation has become increasingly labor-saving. The employment impact varies systematically across technology types - information technology and building-related innovations tend to complement labor, while transportation and smart grid technologies more often substitute for workers.

Second, both green and digital innovations raise relative demand for skilled workers. Skill premia increase by 0.11-0.13 log points per unit of technology exposure. This skill bias operates through both direct displacement of lower-skill workers and rising returns to skill among remaining workers.

Third, automation reduces both employment and wages, with elasticities of -0.9 and -0.3 respectively. These effects concentrate in routine-intensive occupations and establishments, consistent with automation primarily displacing standardized tasks.

Fourth, we find no evidence that automation adoption weakens the emissions reductions

from green technologies. Green innovation reduces emissions with an elasticity of -0.37, while automation shows no significant effect on environmental outcomes.

These results inform several policy debates. First, they suggest that green technology adoption need not reduce aggregate employment, at least in the medium term. However, the gains concentrate among skilled workers and certain sectors. Policy support for worker adaptation appears warranted, particularly in areas where green innovation increasingly substitutes for labor.

Second, the pronounced skill bias in both transitions indicates a key role for education and training programs. The positive interaction between skill levels and technology adoption suggests that expanding access to training could help spread the benefits of these transitions more broadly.

Third, our findings on automation and emissions provide some reassurance about pursuing both transitions simultaneously. While automation substantially affects labor markets, it does not appear to create environmental conflicts.

Several questions merit further research. First, examining longer-run effects could reveal whether displaced workers eventually transition to new roles. Second, the geographic distribution of impacts warrants investigation, particularly in areas with weaker labor markets. Third, understanding which policies most effectively support worker adaptation could inform program design.

The green technology transition represents a major economic transformation. Our results suggest that this shift can support both environmental and employment goals, but not without distributional consequences. Policy responses that address these distributional effects while maintaining technology adoption incentives will prove important for managing this transition.

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A Patent-level analyses

Figure A1: Share of Green Patents over time

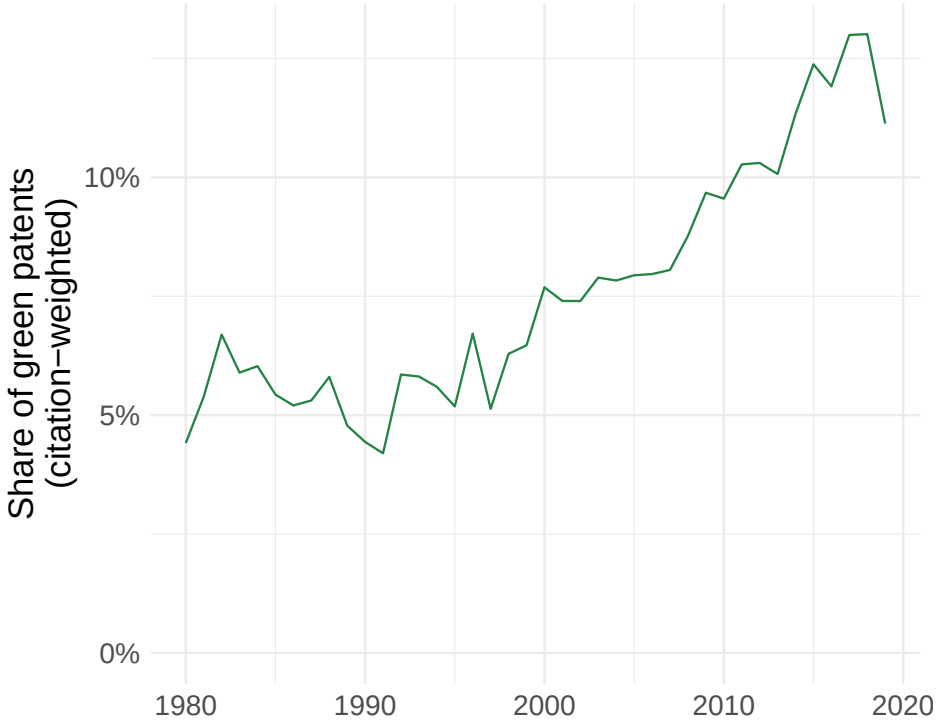


Figure A2: Share of Automation Patents over time

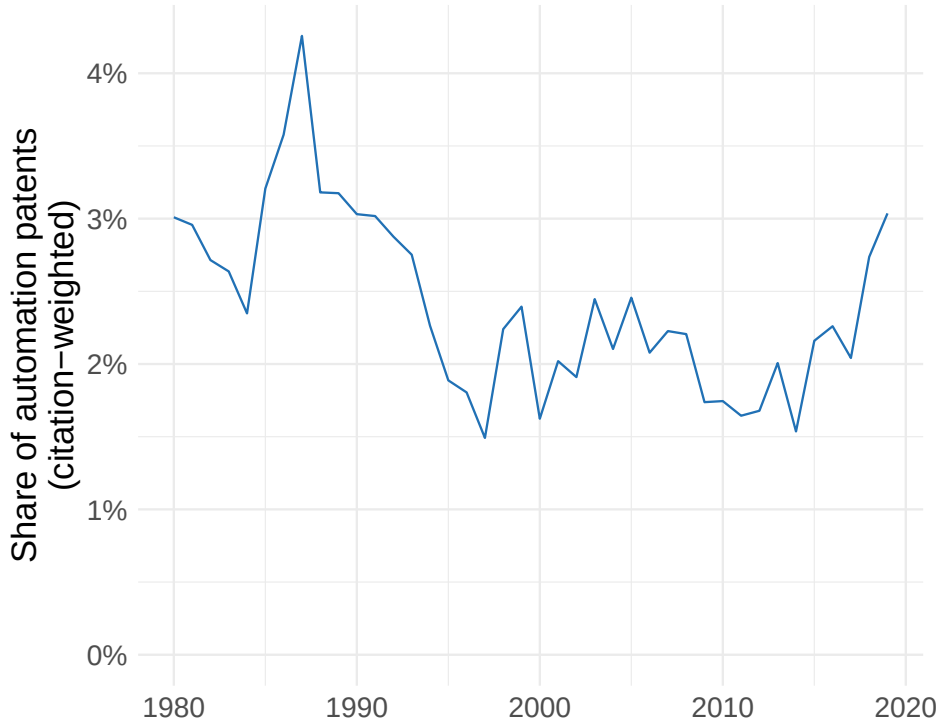
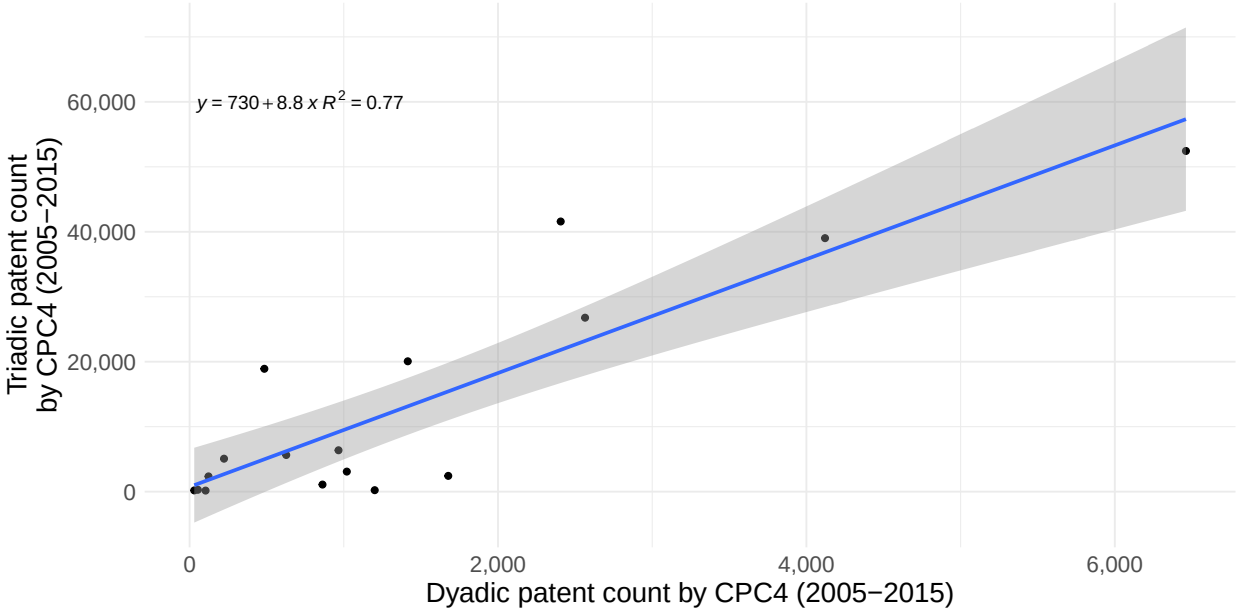


Figure A3: Correlation between triadic and dyadic patent flows



B Establishment-level robustness checks

Table B1: IV: establishment-level ad count, CZ × Period FE (weighted)

	(1)	(2)	(3)
Δexp.^{green}	0.320**		0.451***
	(0.154)		(0.157)
Δexp.^{auto}		-0.681***	-0.710***
		(0.078)	(0.078)
Observations	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
CZ × Period FE	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Table B2: IV: establishment-level ad count, NAICS4 × Period FE (weighted)

	(1)	(2)	(3)	(4)	(5)	(6)
Δexp.^{green}	0.203		0.275**	0.200		0.260**
	(0.137)		(0.139)	(0.131)		(0.132)
Δexp.^{auto}		-0.452***	-0.464***		-0.376***	-0.387***
		(0.076)	(0.076)		(0.067)	(0.067)
Observations	79,678	79,678	79,678	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ × Period FE				Yes	Yes	Yes
NAICS 4-digit × Period FE	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Table B3: IV: establishment-level salary ratio (weighted)

	(1)	(2)	(3)
Δexp.^{green}	-0.216		0.221
	(1.159)		(1.176)
Δexp.^{auto}		-2.070***	-2.085***
		(0.557)	(0.544)
Observations	5,139	5,139	5,139
K-P F-stat (green)	39***		20***
K-P F-stat (auto)		136***	69***

* p < 0.1, ** p < 0.05, *** p < 0.01