Green Firms Hiring: Evidence on Technology-Related Structural Change in the Automotive Labor Market

Thomas A. Fackler* Oliver Falck† Moritz Goldbeck‡ Fabian Hans§ Annina T. Hering¶

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Abstract

Workforce adjustments are a crucial dimension of technology-related structural change, yet relying on occupational taxonomies neglects the embedding of jobs in a product context. We introduce a labor demand index based on the near-universe of online job postings that leverages firms' patent portfolios. Our patent-based approach considers the product context of jobs and intra-industry variation in technological specialization, while online job postings enable timely detection of firms' employment adjustments. We demonstrate the applicability of our approach by examining the shift to green propulsion technologies in the German automotive industry. Specifically, we compare labor demand of automotive firms specializing in green propulsion technology and those with a focus on combustion engines during the industry's crisis since 2019. We find that green firms' overall labor demand is significantly and persistently higher, a gap that widens over time. While green firms hire more across all occupations, they systematically shift labor demand towards production and information technology jobs, for which environmental impact depends critically on the product context.

Keywords: technological change; firm employment decisions; low-carbon technology; electric vehicles

JEL: C55; J23; J63; M51; O14; O33

*Surrey Business School, University of Surrey, ifo Institute, and CESifo.
†ifo Institute, University of Munich, and CESifo.
‡Corresponding author: goldbeck@ifo.de. ifo Institute at the University of Munich.
§Indeed Hiring Lab.
¶Indeed Hiring Lab.

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1 Introduction

Technological innovation is not only the main engine of economic growth but also a key lever for addressing societal challenges such as global warming. The diffusion of new technologies in the economy typically triggers structural change, and understanding the interaction between technology and the labor market is crucial to shape policies that support both economic adaptation and employment. The dominant approach to assess the relationship between jobs and technologies is directly classifying occupations via task or skill taxonomies. However, this approach fails whenever skills and tasks are not inherently relatable to a technology, resulting in significant ambiguity. For example, engineers and production workers in the automotive industry with similar skills and executing the same tasks can produce cars relying either on low-carbon or combustion technology. This ambiguity calls for alternative approaches to relate jobs and technologies, which capture the embedding of jobs in a product context.

In this paper, we introduce a labor demand index based on online job postings that leverages firms' patent portfolios to identify the technological context of jobs. Patent portfolios capture technological specialization of firms, which reflects product innovation and development while allowing for firm-level linkage to job postings. As a result, each job posting is observed in its specific product context, which avoids reliance on broad industry classifications or task- or skill-based occupational taxonomies. Our patent-based approach enables comprehensive assessment of both aggregate technology-related hiring trends and their occupational disaggregation in near real-time and is inherently forward-looking. We demonstrate the applicability of our index for the study of technology-related structural change by investigating the shift to low-carbon propulsion technology in the German automotive industry.

Specifically, we track firm-level labor demand in the German automotive industry from January 2018 through April 2024 and differentiate between firms specializing in green or brown propulsion technology. Green propulsion technology refers mainly to battery-electric vehicles but also includes hybrid and fuel-cell technologies, and brown technology to internal combustion engine vehicles. To measure technological specialization, we analyze each firm's patent portfolio and define firms with above (below)-median share of green technology-related patents among its powertrain patents as green (brown). We observe firm-level labor demand in near real-time by using online job postings (OJP) data by *Indeed* that capture the near-universe of the industry's job postings. By combining OJP and patent data at the firm level, we derive a labor demand index that enables us to look beyond the industry level and assess differences between green and brown firms' hiring during the industry's crisis since 2019. Our index is consistent with traditional industry-level measures based on surveys or administrative data while incorporating the firm-specific product and technology context of jobs.

Our results reveal significant intra-industry differences in the dynamics of overall job postings as well as occupational composition depending on the technological context of jobs. In particular, we observe a divergence in the volume of job postings between firms specializing in green and brown propulsion technol-

ogy, starting early 2019, when the industry experienced several unexpected negative political and economic shocks. On average, our labor demand index is 44.8 to 50.4 percentage points higher for green compared to brown firms. This gap widens over time, from about 20 percentage points in mid-2019 to up to almost 60 percentage points by the end of 2023. Since then, the gap narrows again to around 35 percentage points in April 2024. Our result is not driven by differences in firms' size or specialization in powertrain technology, nor by unobserved firm heterogeneity. The occupational breakdown of our labor demand index shows adjustments in hiring differ structurally between green and brown firms. Green firms' hiring increases particularly strongly in information technology and production and less in technical and engineering fields. Overall, our findings suggest a persistently higher labor demand of green relative to brown firms and large differences in occupational hiring trends.

Related literature Our contribution is twofold.

First, we advance the measurement of labor demand using OJA data. Webb (2019) links patent with occupational task content to measure job exposure to technologies and Papoutsoglou et al. (2022) analyze OJAs selected using the keyword "electric vehicle" to learn about the skill demand of EV jobs. We are able to explore heterogeneities in labor demand across firms by combining OJA with patent data, which also allows us to study differences between job categories. A key advantage of OJA-based assessment is their real-time capability (Colombo et al., 2019; Mezzanzanica and Mercorio, 2019; Kässi and Lehdonvirta, 2018), and since labor demand is a highly reactive margin that firms scale flexibly (Hamermesh, 1989), OJAs are a suitable leading indicator for overall labor market performance.

Second, we contribute to the literature on the labor market effects of technological change more broadly (Autor, 2022; Deming et al., 2025) and the green transformation more specifically. The majority of existing works in this field deals with changes in skill demand by using a task-based approach (cf. Acemoglu and Restrepo, 2019; Acemoglu et al., 2025) to identify green occupations (see, e.g., Vona et al., 2015; Consoli et al., 2016). For example, Janser (2018) shows job greenness is positively associated with employment growth in Germany and Curtis et al. (2024) finds increasing transition rates from brown to green jobs in the US. In contrast, we focus on the company perspective by differentiating labor demand of firms that develop green versus brown technology. Thereby, our approach improves upon most survey and administrative time series that only capture industry-level dynamics.

The remainder of this paper is organized as follows. Section 2 introduces our empirical approach and data. Results are presented in Section 3 and Section 4 concludes.

2 Empirical approach

2.1 Labor demand index

Understanding the relationship between the labor market and technological change requires a technology-focused perspective that incorporates the product context and considers intra-industry variation in technological specialization. We propose a simple labor demand index based on firms' patent portfolios to differentiate hiring dynamics by technological specialization.

Suppose an industry with N firms, where each firm $i \in \{1,...,N\}$ specializes in either low-carbon (green) or high-carbon (brown) technology, denoted by $a \in \{G,B\}$. Each time period $t \in \{1,...,T\}$, firms demand a number of workers j_{ikt} in occupation $k \in \{1,...,K\}$. Then, our technology-specific labor demand index is

$$\text{LDI}_{at} = \frac{\sum_{i=1}^{N}\sum_{k=1}^{K} j_{ikt}\,\mathbf{1}\{a(i)=a\}}{\sum_{i=1}^{N}\sum_{k=1}^{K} j_{ik\tau}\,\mathbf{1}\{a(i)=a\}}, \tag{1}$$

normalized to time τ, with an indicator $\mathbf{1}\{a(i)=a\}$ that is one if firm i specializes in technology a and zero otherwise. This results in technology-specific time series LDI_{Gt} and LDI_{Bt} detailing the overall job volume across all occupations for each technology over time. Our index allows to observe intra-industry differences in the evolution of labor demand by technology. In particular, the difference

$$\Delta\text{LDI}_{at} = \text{LDI}_{Gt} - \text{LDI}_{Bt} \tag{2}$$

is a time series that reports the difference in job numbers between firms specializing in technology G and B, normalized to time period τ. Our index LDI_{at} can be broken down by occupation, providing insights into occupation-technology-specific labor demand dynamics LDI_{akt} and differences in occupational labor demand with respect to technological specialization ΔLDI_{akt}.

2.2 The case of low-carbon technology in the German automotive industry

We study the shift to green propulsion technologies in the German automotive industry to demonstrate the usefulness of our labor demand index for the study of technology-related structural change. The automotive industry is a prime example of technology-related structural change and subject of much economics research (see, e.g., Aghion et al., 2016; Dechezleprêtre et al., 2023).

In Germany, the automotive industry is one of the main industries and provides significant employment. In the past decade, societal goals to combat global warming resulted in efforts to transition to low-carbon propulsion technologies. At least since the 'Dieselgate' scandal in 2015 it is clear that combustion engine technology will be discontinued and electric vehicles (EVs) will dominate the automotive industry in the fu-

ture (Bohnsack et al., 2015), so that the transportation sector can meet regulatory emission reduction targets (Ater and Yoseph, 2022; Skeete, 2017). Yet, the diffusion of low-carbon technologies requires disruptive innovation (Christensen et al., 2006; Abernathy et al., 1978), and firms often transition to green technologies only sluggishly (Igami, 2017; Aghion and Howitt, 1990; Arrow, 1962). German carmakers, who maintained global market leadership for several decades by incrementally improving combustion technology, now struggle with the shift to green propulsion technologies (Falck et al., 2023; Aghion et al., 2016; Barbieri, 2016). Automotive firms' strategies differ widely. Especially incumbents face the choice between transitioning to green products to remain competitive in the long term or maximizing short-term profits by selling combustion engine vehicles as long as possible while saving on investments (Igami, 2017; Wesseling et al., 2015). As a result, there is a large intra-industry heterogeneity in technological specialization.

Public debate often centers around a perceived dilemma between environmental goals and employment, claiming that the green transformation will wipe out many well-paying jobs tied to combustion cars (see, e.g., Financial Times, 2020; DW, 2020). However, from an economic perspective, this reasoning might be flawed as combustion cars will eventually disappear. Avoiding structural change increases the risk of new green competitors establishing dominant market positions on the EV market, ultimately endangering incumbents' survival (Dechezleprêtre et al., 2023; Acemoglu and Cao, 2015). While a combustion-technology focus can be profitable in the short term (Sick et al., 2016), sustaining employment in the long term might only be achieved by following a green strategy (Bohnsack et al., 2014; Christensen, 1997), transitioning to a new business model (Klein et al., 2021; Ceschin and Vezzoli, 2010), developing the necessary (ordinary and dynamic) capabilities (Teece, 2018, 2019) and, in particular, adjusting workforce's skills accordingly (Consoli et al., 2016; Czernich et al., 2021). Labor market data beyond the industry level is often lacking, which prevents comprehensive evidence-based assessments regarding heterogeneous labor market effects with respect to firms' greening strategies.

We use our labor demand index to study the German automotive industry in the period from January 2018 through April 2024. During this time, the industry was not only undergoing a disruptive technological transformation but also faced various unexpected political and economic shocks that accumulated in early 2019 and triggered a sustained crisis. In particular, the launch of Tesla's Model Y in the premium segment at an unexpectedly competitive price and quality surprised German carmakers (The Verge, 2019).[1] At the same time, unexpected escalation of trade tensions caused by imminent no-deal Brexit (New York Times, 2019) and failing negotiations in the global tariff war (Suh, 2019; BBC, 2019a,b; CNBC, 2019) hit German car manufacturers especially hard. On top came announcements of a tightening of environmental regulation (FAZ, 2019), continued economic weakness (Financial Times, 2019), as well as the start of 'Dieselgate'

[1] Note that the fact that Tesla entered the car industry at the high end puts into question whether it is a disruptive innovation in the strict sense of Christensen's work (Harvard Business Review, 2015). In fact, Clayton Christensen did not consider Tesla disruptive, while Elon Musk disagreed in a reply on Twitter in 2018 (https://x.com/elonmusk/status/1075126514851602432; last accessed 08/22/2024.). Nevertheless, for the purposes of our analysis, this distinction is not critical, as Tesla undoubtedly contributed to the challenges facing established carmakers in the poly-crisis.

court proceedings against top management (DW, 2019; SEC, 2019). The crisis of the automotive industry was reinforced by the pandemic with a drop in demand in 2020 and sustained by supply chain disruptions (Karamoozian et al., 2024; Aksoy et al., 2024), and the war of Russia against Ukraine and the resulting energy crisis in 2021 (Hutter and Weber, 2022).

While firms often face challenges regarding employment adjustments, crises are an opportunity to alter employment because pressure to act as well as stakeholder and public acceptance of structural change is higher (Barry et al., 2022; Fabiani et al., 2015; Svalund, 2015). This applies particularly when labor market flexibility is low and unions are strong, as is the case in Germany. Furthermore, firms with higher resilience are more likely to use crisis-driven employment adjustments to realign their workforce with emerging technological requirements and market demands. Indeed, we observe firms reacting with large-scale cost savings and restructuring efforts, including announcements of significant job cuts (Süddeutsche Zeitung, 2019; Manager Magazin, 2019a,b). In this context, the ability to look beyond the industry level and differentiate labor market dynamics by technological focus is invaluable to understand structural change.

We estimate a simple fixed effects model via ordinary least squares to trace differences in labor demand adjustments between green and brown firms after the crisis begins in May 2019:

$$\text{LDI}_{at} = \beta_0 + \beta_1 \left(\text{post}_t * \mathbf{1}\{a = G\}\right) + \beta_2 \mathbf{1}\{a = G\} + \delta_t + \varepsilon_{at}, \tag{3}$$

where post_t indicates months relative to May 2019, an indicator $\mathbf{1}\{a = G\}$ that is one for labor demand of green firms and zero otherwise, and month fixed effects δ_t control for dynamics common to both green and brown firms. ε_{at} is an error term. We use heteroscedasticity-robust Huber-White standard errors. The coefficient β_1 captures the average difference in the number of workers demanded by green relative to brown firms before relative to during May 2019.

2.3 Data

We construct our labor demand index by combining two data sources. In particular, we use patent data to identify patent-active automotive firms and measure their specialization in low-carbon (green) technology, and then link this information to firms' online job postings.

Patent portfolios We source data on patents from the European Patent Office's *Patstat* database, a comprehensive database on worldwide patent (applications) with rich information on each patents' authors, owners, and technology class. Our definition of technology greenness in the automotive industry builds on Aghion et al. (2016), who interview experts to relate patents to technologies using their technology class.[2] In particular, we label technology classes related to battery-electric, hybrid, or fuel-cell propulsion technol-

[2]Clean, gray, and dirty patents include those whose International Patent Classification (IPC) symbols start with B60L, B60K, B60W, H01M, F02, H01G, and H02J.

ogy as *green* and technology classes related to internal combustion technology as *brown*. **??** reports green and brown technology classes. Using this technology class definition, we call patents green whenever they feature at least one green technology class, and brown when they feature no green but at least one brown technology class. We call all patents classified in this way powertrain patents, as opposed to non-classified patents, which do not fall into a green or brown technology class.

This classification comprehensively captures powertrain patents, in contrast to narrower approaches (Dechezleprêtre et al., 2023; Borgstedt et al., 2017) that risk neglecting a significant share of relevant patents (Popp, 2019; Kalthaus, 2017). Since both green and brown technologies are included, it avoids the measurement problems of green taxonomies that only count green patents (Mazzei et al., 2023).

From *Patstat*[3], we extract patent applicants based in Germany that filed powertrain patent applications in the year 2000 or later, and disregard patent applicants who are also inventors to restrict the sample to firms. After merging *Patstat* IDs that refer to the same firm, we are left with a sample of 3,199 firms with significant patenting activity in powertrain technologies.[4] These firms filed a total of 346,950 patents during the observation period, out of which 50,756 (14.6%) are assigned the automotive industry code (NACE 29.1). Remaining patents are assigned mainly other manufacturing industry codes or chemical industry codes.[5] With our method, we are able to classify 18,138 powertrain patents that are specific to green or brown technology, which amounts to 35.7% of automotive patents. 29.3% of powertrain patents in our sample are related to green technology.

For this sample of patent-active automotive firms, we compute multiple metrics. First, we use the size of their entire patent portfolio, i.e., all patents (classified and non-classified) filed during the observation period, as a proxy for firm size. This proxy of firm size is consistent with the average number of monthly job postings, an alternative size proxy (see Figure A.1). Second, we calculate the share of powertrain patents in the patent portfolio as a measure of specialization in the automotive powertrain field. Finally, we compute the share of green patents with respect to powertrain patents as firm-level greenness measure that captures the specialization on green versus brown technology.

Online job postings Our second data source are online job postings (OJP) by *Indeed*, whose database captures the near-universe of OJP in real time. *Indeed* is a leading online job platform that covers more than 60 countries and has more than 350 million unique visitors per month globally (Indeed, Q4 2023 and Q1 2024), with 4.5 million in Germany (Comscore, January 2024). On average the *Indeed* data contains 880,000 new postings per month for the German labor market (Indeed, Q1 2024). We observe monthly job

[3] 2022 Autumn Edition

[4] Note that this approach allows us to capture relevant firms beyond traditional industry classifications in administrative data. During our observation period, there are only 914 firms active in the automotive sector (WZ29), on average. This highlights that many firms active in the automotive industry do not feature this sector as main industry in administrative classifications and would, therefore, be missed when using the official WZ classification.

[5] For example, other frequently occurring industry codes are NACE Rev. 2 20.1, 21, 26.1, 26.5, or 28.1.

postings from January 2018 through April 2024. Adrjan and Lydon (2023) demonstrate the *Indeed* data is representative for major labor markets, including Germany. Job postings originate from both internet sources, such as companies' career sites and applicant tracking systems, as well as from employers directly posting on the platform. *Indeed* de-duplicates postings for the same job on multiple sources, prioritizing versions posted directly by the employer. From each posting, *Indeed* extracts relevant information such as job title, posting date, company, location, and occupational category to structure the data. Low-quality or non-job postings are excluded, as well as postings that do not adhere to the companies minimum standards[6]. For example, generic postings are not allowed.

The data provides a classification of job titles into 60 consistent occupational categories similar to two-digit occupational codes used by statistical agencies (Adrjan and Lydon, 2023). Table A.1 reports the descriptions of all 52 occupational categories that appear in our sample.[7] However, many occupations only account for a small percentage of postings while others occur frequently. The largest occupational categories are displayed in Figure A.2, which shows that the automotive industry advertises predominantly jobs in the categories 'installation & maintenance' (15%), which includes technicians, and 'software development' (11%). Automotive firms also advertise jobs in 'management' (7%), 'sales' (6%), and 'project management' (6%). For our analysis, we select the 19 most frequently occurring occupational categories.

Rarely, there are firm-specific data gaps that arise for technical reasons during the data collection process, e.g., scraping interruptions. For the largest firms that account for most postings, i.e., OEMs and large automotive suppliers[8], we correct for this missing data by detecting sudden drops to a level of less than 10% compared to the moving average (with a large window including 12 months before and after the current month) and interpolate detected gaps. We first apply a linear interpolation to the gap and then smooth the data with moving average (with a narrower window that includes 3 months before and after the current one). This procedure leads to 0.44% of interpolated month-firm observations.

Record linkage To link OJP and patent data at the firm level, we develop a tiered approach for string matching on company names. We use the cleaned and standardized firm names that are provided in *Patstat* and originate from EPO's worldwide bibliographic database *DOCDB*. Prior to matching, we remove common abbreviations for legal forms such as *GmbH* (limited liability company) or *AG* (stock company). In the first matching tier, we apply exact matching to link company names in the OJP and the patent data. In the second tier, we use fuzzy matching, specifically the weighted Jaccard similarity algorithm with a cutoff distance of 0.6. We then manually cross-check the matching results to detect and correct mismatched records and merge names that relate to the same firm with different spellings, typos, or abbreviations. We arrive at

[6] *Indeed* job postings standards: https://indeed.my.site.com/employerSupport1/s/article/115005915763?language=en_US; last accessed 05/27/2024.

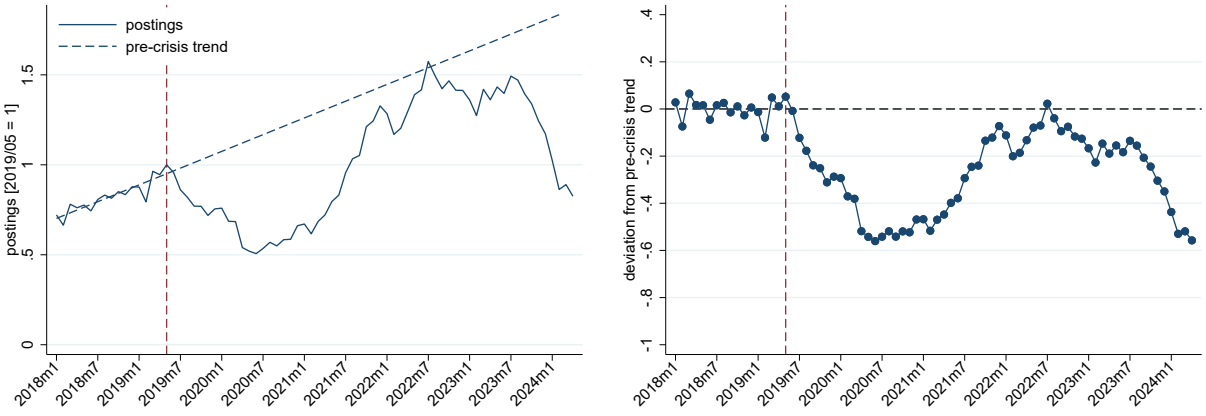
[7] Occupational categories with no observation for automotive firms include, for example, [[...]].

[8] Suppliers are identified using the 2021 *Meyer Industry Research* list of top 100 German automotive suppliers.

a sample of 2,166 firms that are in both the *Indeed* and the *Patstat* data. In total, these firms account for 1,517,654 distinct job postings during the observation period.

Industry-wide labor demand Business decisions triggered by the accumulation of negative shocks are clearly reflected in our data. Figure 1 depicts the development of our labor demand index for the German automotive industry over time. The left panel plots the number of job postings normalized to May 2019, with the dashed line representing the pre-crisis trend. The right panel shows the deviation of the number of job postings to the pre-crisis trend. There is a continued drop in labor demand after May 2019, which reaches its low point at the beginning of 2020. Labor demand remains at just below 50% of the pre-pandemic trend over the entire year 2020 and then slowly recovers to the pre-crisis trend until July 2022. After a brief period of recovery, labor demand drops again, first slowly by about 15% until spring 2023 and then rapidly since summer 2023. In April 2024, labor demand is again 50% lower than the pre-crisis trend.

Figure 1: Automotive industry labor demand



(a) normalized **(b)** trend deviation

Sources: Indeed, Patstat.

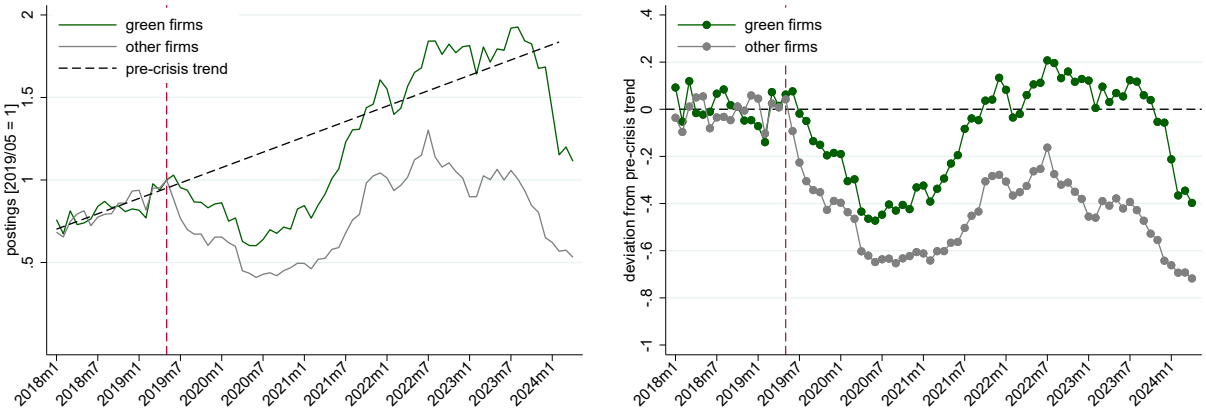
The observed pattern is consistent with industry dynamics. The crisis was most severe during the pandemic, when stay-at-home mandates and supply shortages (Puls et al., 2021), confirmed by the leading business climate survey for Germany (see Figure A.4). After a slow recovery, the German automotive industry experienced weak demand (CNN, 2023; Spiegel, 2023), further fueled by the elimination of purchase subsidies for EVs in fall 2023 (Zeit, 2023). We validate our index using two external data sources in Figure A.3. First, there is a parallel behavior of our index compared to a survey-based employment index, asking businesses in the automotive sector about their employment plans for the next three months (Sauer et al., 2023). Our labor demand index is less volatile compared to the survey-based index. Second, we compare our labor demand index to the number of employees in the automotive sector. Although this is a comparison of a flow (labor demand) and a stock variable (employees), the drop in the number of employees after May 2019 is clearly

visible in the administrative data, as well, although it is lagging the postings data by approximately three months. The recovery of labor demand after the pandemic until end of 2022 is consistent with the number of employees in the automotive sector not declining further. Overall, both general industry dynamics and external data substantiate the effectiveness of our index in capturing labor demand appropriately.

3 Results

Figure 2 plots the dynamics of our labor demand index for green and brown firms. Before the poly-crisis, green and brown firms' labor demand shows a parallel behavior. After May 2019, labor demand of green and brown firms diverges. Specifically, green firms' labor demand is persistently higher. This is true for both the normalized labor demand index (left panel) and deviation from the pre-crisis trend (right panel). The labor demand of brown firms drops significantly lower and does not return to its pre-crisis trajectory while green firms' labor demand recovers until mid-2021 and then follows the pre-crisis trajectory until declining sharply starting end of 2023. In April 2024, green firms' labor demand is about 40 percentage points lower than what the pre-crisis trend suggests, compared to over 65 percentage points for brown firms.

Figure 2: Labor demand and firm greenness



(a) normalized **(b)** trend deviation

Sources: Indeed, Patstat.

Results of the difference-in-differences regression reported in Table 1 confirm these findings. Column (1) shows the results of a model without year × month fixed effects and suggests green firms' normalized labor demand index is on average 44.8 percentage points higher than the labor demand of brown firms, relative to May 2019. Adding month fixed effects in column (2) accounts for dynamics common to both green and brown firms and yields similar results, with an estimate that indicates an increase in green versus brown firms' labor demand of 50.4 percentage points compared to May 2019. Note that the number of postings generally increases over time and it is unknown to what extent this is due to an increase in the share of job

ads posted online, improvements of data collection, or actual increase in job ads, respectively. Although the indexed *Indeed* data is consistent with steadily increasing labor shortages in Germany (see, e.g., Hering, 2024) and administrative data on vacancies[9], we use the deviation from the pre-crisis trend as outcome in column (3) to estimate a lower bound of the effect. This specification finds labor demand of green firms to be 33.6 percentage points higher compared to brown firms during the poly-crisis compared to the pre-crisis trend. In column (4), we estimate a firm-level count data model via Poisson pseudo-maximum likelihood (PPML), which allows us to add firm fixed effects that account for unobserved differences across firms. With naturally larger confidence intervals, the point estimate of this specification suggests that green versus brown firms' labor demand is, on average, 48.7 percentage points higher after May 2019. Overall, these results suggest green firms' labor demand during the poly-crisis is, on average, 36 to 53 percentage points higher than brown firms' labor demand.

Table 1: Difference-in-differences

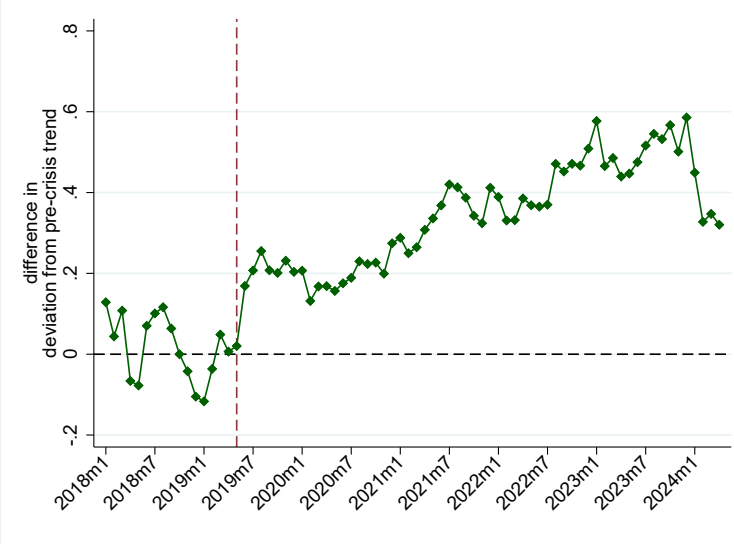
	(1) norm. LDI	(2) norm. LDI	(3) trend deviation	(4) firm-level PPML
Post × green	0.448***	0.504***	0.336***	0.487*
	(0.062)	(0.037)	(0.025)	(0.258)
Green firms	0.038	-0.005	-0.004	
	(0.033)	(0.015)	(0.019)	
Year × month FE		×	×	×
Firm FE				×
Observations	152	152	152	164,115
Adj. R-squared	0.351	0.919	0.947	
Pseudo R-squared				0.873

Notes: Robust standard errors in parentheses and clustered at the firm level in column (4). *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. *Sources:* Indeed, Patstat.

Since the average effect estimated in Table 1 neglects potential dynamics already apparent in Figure 2, we plot the evolution of the effect from the conservative specification using the deviation from the pre-crisis trend in Figure 3. Before the poly-crisis, the difference between green and brown firms hovers around zero. After May 2019, the difference in the deviation from pre-crisis trend of labor demand jumps to around 20 percentage points and remains at this level until the end of 2020. Starting 2021, the difference further increases as green firms' labor demand recovers more strongly than brown firms' labor demand. The gap between green and brown firms continuously widens until the end of 2022, when it reaches a maximum of just below 60 percentage points. During 2023, the gap stays roughly constant before it drops to about 35 percentage points at the end of 2023 and remains at this level until April 2024. The generally widening gap between green and brown firms implies that green firms were able to expand their advantage over brown

[9]IAB-Stellenerhebung: https://iab.de/das-iab/befragungen/iab-stellenerhebung/aktuelle-ergebnisse/; last accessed 05/29/2024.

Figure 3: Dynamic difference between green and brown firms



Note: Graph plots the difference in the deviation to the pre-crisis trend in the labor demand index between green and brown firms. *Sources:* Indeed, Patstat.

firms. Even with the recent setbacks to EVs and a resulting narrowing of the gap, brown firms are unable to catch up to green firms.

Green and brown firms potentially differ in aspects other than greenness. Our firm-level estimation in column (4) of Table 1, which includes firm fixed effects, already mitigates potential concerns regarding unobserved firm heterogeneity.[10] Nevertheless, we present additional tests. Two channels seem particularly salient: differences in firms size and the exposure to powertrain-related business, the core area of the green transformation in the automotive industry. Generally, the volume of postings between green and brown firms prior to the poly-crisis is virtually the same (see Figure A.5). Still, in Figure A.7 we assess if similar differences arise from a specification using our proxy of firm size. We do not find any signs of differences in firm size systematically driving our effect.[11] Similarly, the left panel of Figure A.7 plots the difference with respect to powertrain specialization, using the share of powertrain patents in total patents instead of the share of green patents in powertrain patents. The groups show similar behavior, mitigating concerns that our effect is driven by differences in firms' specialization in powertrain technology. Consequently, differences in labor demand dynamics indeed seem to be driven by firm greenness.

We explore structural differences in labor demand by leveraging information on occupational categories. Table 2 shows the results of the trend deviation model specification for each of the 19 occupational categories, with additional details reported in Table A.2 in the Appendix. Note that there are significant differences in

[10] Figure A.6 plots a dynamic version of model (4) in Table 1.

[11] Note that the median-split by size results in vastly different volumes of job postings in each category and therefore more volatility in the data for small firms.

green and brown firms' labor demand with respect to the occupational categories advertised even before the poly-crisis hit the industry as shown by the coefficient estimates on the green firms indicator. For example, green firms post significantly more jobs in the area of sales (+12.4 percentage points), software engineering (+11.6 p.p.) or industrial engineering (+11.1 p.p.) while brown firms seek more employees in logistic support (-25.6 p.p.) or installation and maintenance (-14.8 p.p.). This is consistent with a complementarity between the green and digital transformation, higher production complexity of combustion engines compared to battery-electric vehicles, and higher sales efforts needed to establish EVs as a new product.

Table 2: Green Firm Hiring Differences by Occupation

Occupation	(1) **Green Firm**	(2) **Post × Green**
All jobs	-0.004	0.336***
Installation & maintenance	-0.148***	0.195***
Software development	0.116***	0.308***
Management	-0.019	0.284***
Project management	-0.007	0.308***
Sales	0.124***	0.123***
IT operations & helpdesk	-0.083***	0.404***
Production & manufacturing	-0.028*	0.386***
Administrative assistance	0.014	0.260***
Marketing	-0.158***	0.299***
Loading & stocking	0.075***	0.359***
Construction	-0.283***	0.308***
Mechanical engineering	-0.033	0.191***
Information design	-0.052	0.298***
Accounting	-0.016	0.324***
Industrial engineering	0.111***	0.320***
Human resources	-0.062***	0.218***
Logistic support	-0.256***	0.029
Retail	-0.051	1.102***
Scientific R&D	-0.067***	0.246***

Notes: The table shows the coefficients for the green jobs indicator in Column (1) and for its interaction with a post dummy in Column (2). See Table A.2 in the Appendix for more details. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. *Sources:* Indeed, Patstat.

Importantly, during the poly-crisis green firms increase postings across the board compared to the pre-crisis trend relative to brown firms. We observe especially high increases in the occupational categories retail (+110.2 percentage points), IT operations and helpdesk (+40.4 p.p.), production and manufacturing (+38.6 p.p.), and loading and stocking (+35.9 p.p.). In contrast, we estimate below-average increases for roles in logistic support (+2.9 p.p.), sales (+12.3 p.p.), mechanical engineering (+19.1 p.p.), and installation and maintenance (+19.4 p.p.). Note that compositional effects for logistic support both before and after the poly-crisis are especially weak in line with a lower supply chain complexity of EV production. An alternative specification using the normalized LDI as outcome is reported in Table A.3 and yields qualitatively similar results. Overall, these findings point to significant structural differences in labor demand of green versus brown firms that are reinforced by the poly-crisis. While green firms' labor demand is higher across the board, it is below-average for traditional engineers and technicians and especially high for IT professionals and production personnel.

4 Conclusion

Technological transitions should be accompanied by responsive, evidence-based policies to foster growth and mitigate negative consequences. Yet empirical assessments are difficult because up-to-date, real-time labor market data beyond the industry level is scarce. Understanding technology-related structural change within an industry is particularly relevant in the automotive industry, where the current transformation is centered on the shift to green technologies. As with previous disruptive technological changes, effects on employment are the most contentious topic in the public and policy debate. We demonstrate how to trace within-industry employment shifts linked to the technological transformation by combining online job postings and patent data at the firm level. Measuring labor demand of automotive firms in Germany by greenness and in real time, we find that green firms' labor demand is significantly and persistently higher compared to brown firms' labor demand as the crisis triggered firms to restructure their business. In addition, there are structural differences in firms' labor demand response, with green firms advertising more production and information technology jobs. As a result, the green transformation systematically benefits some jobs while others face declining demand.

This study has limitations. We measure greenness of patent-active firms in the area of powertrain technology, which is at the core of the green transformation in the automotive industry. Still, this excludes, e.g., efforts with respect to circularity in production or raw material efficiency. We also do not capture green activity upstream, e.g., in battery production, or downstream, e.g., in charging infrastructure, as well as non-patent related greenness. With respect to labor market outcomes, we focus on labor demand as a highly reactive decision parameter of firms at the extensive margin of employment, but do not observe employees leaving or intensive-margin workforce adjustments through continuing education and retraining efforts. Lastly, while our analysis for the German automotive industry shows that green firms outperform brown firms in terms of generating employment opportunities, our analysis does not inform about the overall employment effects of the industry's green transformation. More generally, even though our fine-grained data offers a unique perspective on the relationship between jobs and the green transition, future research should aim to complement our insights with internal firm data to identify the causal relationships between strategic decisions and firm behavior over time.

Our results have several policy implications. Importantly, we observe no evidence of a trade-off between environmental goals and employment. In fact, the opposite is true in the past years as green firms' labor demand is significantly higher compared to brown firms. It is therefore important to distinguish the effects of firm strategies in the green transformation on the labor market from effects on (short-term) profitability. Policies supporting the green transition could have more favorable and lasting employment effects compared to policies that try to protect employment related to combustion technology. Although the potential for brown firms to become greener remains unclear, understanding skill requirements for future tasks can guide reskilling and training efforts to help workers transition to growing fields. Still, a transition to a

green job might not be feasible for everyone, requiring mitigation measures. To the extent that firms' profitability and employment incentives are misaligned, policies aimed at reducing risk and uncertainty about future green business models promise to achieve both environmental and employment goals. More broadly, our methodological contribution provides policymakers with a forward-looking tool to monitor firm-level labor demand in real time, helping them design responsive interventions during periods of technological transition.

References

Abernathy, William J., James M. Utterback et al., "Patterns of Industrial Innovation," *Technology Review*, 1978, *80* (7), 40–47.

Acemoglu, Daron and Dan Cao, "Innovation by Entrants and Incumbents," *Journal of Economic Theory*, 2015, *157*, 255–294.

_ and Pascual Restrepo, "Automation and new tasks: How technology displaces and reinstates labor," *Journal of economic perspectives*, 2019, *33* (2), 3–30.

_ , Fredric Kong, and Pascual Restrepo, "Tasks At Work: Comparative Advantage, Technology and Labor Demand," *Handbook Chapter*, 2025.

Adrjan, Pawel and Reamonn Lydon, "What do wages in online job postings tell us about wage growth?," *Available at SSRN 4451751*, 2023.

Aghion, Philippe and Peter Howitt, "A Model of Growth Through Creative Destruction," *Econometrica*, 1990.

_ , Antoine Dechezleprêtre, David Hemous, Ralf Martin, and John Van Reenen, "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry," *Journal of Political Economy*, 2016, *124* (1), 1–51.

Aksoy, Cevat Giray, Andreas Baur, Lisandra Flach, and Beata Javorcik, "Reactions to Supply Chain Disruptions: Evidence from German Firms," *EconPol Policy Brief*, 2024.

Arrow, Kenneth J., "The Economic Implications of Learning by Doing," *The Review of Economic Studies*, 1962, *29* (3), 155–173.

Ater, Itai and Nir S. Yoseph, "The Impact of Environmental Fraud on the Used Car Market: Evidence from Dieselgate," *The Journal of Industrial Economics*, 2022, *70* (2), 463–491.

Autor, David, "The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty," Technical Report, National Bureau of Economic Research 2022.

Barbieri, Nicolò, "Fuel Prices and the Invention Crowding Out Effect: Releasing the Automotive Industry from its Dependence on Fossil Fuel," *Technological Forecasting and Social Change*, 2016, *111*, 222–234.

Barry, John W, Murillo Campello, John R Graham, and Yueran Ma, "Corporate flexibility in a time of crisis," *Journal of Financial Economics*, 2022, *144* (3), 780–806.

BBC, "China's tariff hikes on US goods come into force," *BBC*, 2019.

_ , "Trump threatens to raise tariffs on $200bn of Chinese goods," *BBC*, 2019.

Bohnsack, René, Ans Kolk, and Jonatan Pinkse, "Catching recurring waves: Low-emission vehicles, international policy developments and firm innovation strategies," *Technological Forecasting and Social Change*, 2015, *98*, 71–87.

_ , Jonatan Pinkse, and Ans Kolk, "Business models for sustainable technologies: Exploring business model evolution in the case of electric vehicles," *Research policy*, 2014, *43* (2), 284–300.

Borgstedt, Philipp, Bastian Neyer, and Gerhard Schewe, "Paving the Road to Electric Vehicles: A Patent Analysis of the Automotive Supply Industry," *Journal of Cleaner Production*, 2017, *167*, 75–87.

Cattaneo, Matias D., Richard K. Crump, Max H. Farrell, and Yingjie Feng, "On Binscatter," *American Economic Review*, 2024.

Ceschin, Fabrizio and Carlo Vezzoli, "The role of public policy in stimulating radical environmental impact reduction in the automotive sector: the need to focus on product-service system innovation," *International Journal of Automotive Technology and Management*, 2010, *10* (2-3), 321–341.

Christensen, Clayton M., *The innovator's dilemma: when new technologies cause great firms to fail*, Harvard Business Review Press, 1997.

Christensen, Clayton M, Heiner Baumann, Rudy Ruggles, and Thomas M Sadtler, "Disruptive innovation for social change," *Harvard Business Review*, 2006, *84* (12), 94.

CNBC, "German auto sector could drop as much as 12% if Trump announces tariffs, analyst says," *CNBC*, 2019.

CNN, "Germany risks falling back into recession as car industry sputters," *CNN*, 2023.

Colombo, Emilio, Fabio Mercorio, and Mario Mezzanzanica, "AI meets labor market: Exploring the link between automation and skills," *Information Economics and Policy*, 2019, *47*, 27–37.

Consoli, Davide, Giovanni Marin, Alberto Marzucchi, and Francesco Vona, "Do green jobs differ from non-green jobs in terms of skills and human capital?," *Research Policy*, 2016, *45* (5), 1046–1060.

Curtis, E Mark, Layla O'Kane, and R Jisung Park, "Workers and the green-energy transition: Evidence from 300 million job transitions," *Environmental and Energy Policy and the Economy*, 2024, *5* (1), 127–161.

Czernich, Nina, Oliver Falck, Murat Erer, Kristin Keveloh, and Sein Ó Muineacháin, "Transformation in der Automobilindustrie–welche Kompetenzen sind gefragt?," *ifo Schnelldienst Digital*, 2021, *2* (12), 1–5.

Dechezleprêtre, Antoine, Luis Díaz, Milenko Fadic, and Guy Lalanne, "How the Green and Digital Transitions are Reshaping the Automotive Ecosystem," *OECD Science, Technology and Industry Policy Papers*, 2023.

Deming, David J, Christopher Ong, and Lawrence H Summers, "Technological disruption in the labor market," Technical Report, National Bureau of Economic Research 2025.

DW, "Anklage gegen Ex-VW-Chef Winterkorn," *DW*, 2019.

_ , "Could 400,000 German car industry jobs go?," *DW*, 2020.

Fabiani, Silvia, Ana Lamo, Julián Messina, and Tairi Rõõm, "European firm adjustment during times of economic crisis," *IZA Journal of Labor Policy*, 2015, *4*, 1–28.

Falck, Oliver, Moritz Goldbeck, and Tim Lixfeld, "Die Grüne Transformation der deutschen Automobilindustrie: Eine Patentdatenanalyse," *ifo Studie*, 2023.

FAZ, "Jetzt kommt das Klimakabinett," *FAZ*, 2019.

Financial Times, "German factory orders post biggest slump in two years," *Financial Times*, 2019.

_ , "Continental warns of price to livelihoods of electric car transition," *Financial Times*, 2020.

Hamermesh, Daniel S, "Labor Demand and the Structure of Adjustment Costs," *American Economic Review*, 1989, *79* (4), 674–689.

Harvard Business Review, "Tesla's Not as Disruptive as You Might Think," *Harvard Business Review*, May 2015, p. 22–23.

Hering, Annina, "Zwischen wirtschaftlicher Unsicherheit und Arbeitskräftemangel: Chancen des aktuellen Arbeitsmarktes," *Indeed Report*, 2024.

Hutter, Christian and Enzo Weber, "Russia-Ukraine war: Short-run production and labour market effects of the energy crisis," *IAB Discussion Paper*, 2022.

Igami, Mitsuru, "Estimating the Innovator's Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 1981–1998," *Journal of Political Economy*, 2017, *125* (3), 798–847.

Janser, Markus, "The Greening of Jobs in Germany: First Evidence from a Text Mining based Index and Employment Register Data," Technical Report, IAB Discussion Paper 2018.

Kalthaus, Martin, "Identifying Technological Sub-trajectories in Photovoltaic Patents," *Working Paper*, 2017.

Karamoozian, Aminreza, Chin An Tan, Desheng Wu, Amirhossein Karamoozian, and Saied Pirasteh, "COVID-19 automotive supply chain risks: A manufacturer-supplier development approach," *Journal of Industrial Information Integration*, 2024, *38*, 100576.

Kässi, Otto and Vili Lehdonvirta, "Online labour index: Measuring the online gig economy for policy and research," *Technological forecasting and social change*, 2018, *137*, 241–248.

Klein, Sascha P, Patrick Spieth, and Sven Heidenreich, "Facilitating business model innovation: The influence of sustainability and the mediating role of strategic orientations," *Journal of Product Innovation Management*, 2021, *38* (2), 271–288.

Manager Magazin, "20.000 wollen Antworten vom Volkswagen-Chef," *Manager Magazin*, 2019.

_ , "Zetsche schätzt Kosten für Daimler-Umbau auf 700 Millionen," *Manager Magazin*, 2019.

Mazzei, Julia, Tommaso Rughi, and Maria Enrica Virgillito, "Knowing Brown and Inventing Green? Incremental and Radical Innovative Activities in the Automotive Sector," *Industry and Innovation*, 2023, *30* (7), 824–863.

Mezzanzanica, Mario and Fabio Mercorio, "Big data for labour market intelligence: An introductory guide," *European Training Foundation*, 2019, pp. 2019–06.

New York Times, "Where Europe Would Be Hurt Most by a No-Deal Brexit," *New York Times*, 2019.

Papoutsoglou, Maria, Emmanouil S Rigas, Georgia M Kapitsaki, Lefteris Angelis, and Johannes Wachs, "Online labour market analytics for the green economy: The case of electric vehicles," *Technological Forecasting and Social Change*, 2022, *177*, 121517.

Popp, David, "Environmental Policy and Innovation: A Decade of Research," *NBER Working Paper*, 2019.

Puls, Thomas, Werner Olle, Heike Proff, Oliver Falck, Nina Czernich, Johannes Koenen, Florian Herrmann, Wolfgang Beinhauer, Stefan Reindl, Alexander Wottge et al., "Strukturwandel in der Automobilindustrie–wirkt die Pandemie als Beschleuniger?," *ifo Schnelldienst*, 2021, *74* (05), 03–35.

Sauer, Stefan, Moritz Schasching, and Klaus Wohlrabe, "Handbook of ifo Surveys," *ifo Beiträge zur Wirtschaftsforschung*, 2023.

SEC, "SEC Charges Volkswagen, Former CEO With Defrauding Bond Investors During "Clean Diesel" Emissions Fraud," *SEC*, 2019.

Sick, Nathalie, Ann-Marie Nienaber, Bernd Liesenkötter, Nicole vom Stein, Gerhard Schewe, and Jens Leker, "The Legend About Sailing Ship Effects: Is It True or False? The Example of Cleaner Propulsion Technologies Diffusion in the Automotive Industry," *Journal of Cleaner Production*, 2016, *137*, 405–413.

Skeete, Jean-Paul, "Examining the Role of Policy Design and Policy Interaction in EU Automotive Emissions Performance Gaps," *Energy Policy*, 2017, *104*, 373–381.

Spiegel, "Konkurrenz aus China: Den deutschen Autoherstellern stehen schwere Zeiten bevor," *Spiegel*, 2023.

Suh, Jin Kyo, "US–China Trade Conflict and the Changing Multilateral Trading System: Korea's Perspective," *Asian Economic Papers*, 2019, *18* (3), 142–160.

Svalund, Jørgen, "Adjusting labour through crisis: A three industry comparison," *Economic and Industrial Democracy*, 2015, *36* (1), 99–121.

Süddeutsche Zeitung, "Wo VW jetzt Milliarden sparen muss," *Süddeutsche Zeitung*, 2019.

Teece, David J, "Tesla and the reshaping of the auto industry," *Management and Organization Review*, 2018, *14* (3), 501–512.

_ , "China and the reshaping of the auto industry: A dynamic capabilities perspective," *Management and Organization Review*, 2019, *15* (1), 177–199.

The Verge, "Tesla Model Y announced," *The Verge*, 2019.

Vona, Francesco, Giovanni Marin, Davide Consoli, and David Popp, "Green skills," *NBER Working Paper*, 2015.

Webb, Michael, "The impact of artificial intelligence on the labor market," *Available at SSRN 3482150*, 2019.

Wesseling, Joeri H., Eva Niesten, Jan Faber, and Marko P. Hekkert, "Business Strategies of Incumbents in the Market for Electric Vehicles: Opportunities and Incentives for Sustainable Innovation," *Business Strategy and the Environment*, 2015, *24* (6), 518–531.

Zeit, "Förderstopp für Elektroautos: Das sollten Käufer von E-Autos jetzt beachten," *Zeit*, 2023.

A Appendix

A.1 Tables

Table A.1: Normalized job categories

	Label	German	English
1	accounting	Buchhaltung	Accounting
2	admin	Büro und Verwaltung	Administrative Assistance
3	agriculture	Land- & Forstwirtschaft	Agriculture & Forestry
4	arch	Architektur	Architecture
5	arts	Kunst & Kultur	Arts & Entertainment
6	care	Pflege- & Gesundheitswesen	Personal Care & Home Health
7	childcare	Kinderbetreuung	Childcare
8	construction	Bauwesen	Construction
9	customer	Kundendienst	Customer Service
10	driver	Fahrdienst	Driving
11	education	Erziehung & Bildung	Education & Instruction
12	engchem	Chemieingenieurwesen	Chemical Engineering
13	engcivil	Bauingenieurwesen	Civil Engineering
14	engelectric	Elektrotechnik	Electrical Engineering
15	engid	Wirtschaftsingenieurwesen	Industrial Engineering
16	engmech	Maschinenbau	Mechanical Engineering
17	finance	Bank- & Finanzwesen	Banking & Finance
18	food	Lebensmittelzubereitung & -dienstleistung	Food Preparation & Service
19	hospitality	Hotelgewerbe & Tourismus	Hospitality & Tourism
20	hr	Personalwirtschaft	Human Resources
21	install	Technik & Mechanik	Installation & Maintenance
22	insurance	Versicherungswesen	Insurance
23	legal	Rechtswesen	Legal
24	management	Management	Management
25	manufacturing	Produktion & Fertigung	Production & Manufacturing
26	marketing	Marketing	Marketing
27	math	Mathematik	Mathematics
28	meddental	Zahnmedizin	Dental
29	meddr	Arztberufe	Physicians & Surgeons
30	media	Medien & Kommunikation	Media & Communications
31	medinfo	Verwaltung im Gesundheitswesen	Medical Information
32	mednurse	Gesundheits- & Krankenpflege	Nursing
33	medtech	Medizintechnik	Medical Technician
34	personal	Beauty & Wellness	Beauty & Wellness
35	pharmacy	Pharmazie	Pharmacy
36	project	Project Management	Project Management
37	protective	Private und öffentliche Sicherheit	Security & Public Safety
38	realestate	Immobilienbranche	Real Estate
39	retail	Einzelhandel	Retail
40	sales	Vertrieb	Sales
41	sanitation	Reinigungsdienste, Gebäude- und Grundstückspflege	Cleaning & Sanitation
42	science	Wissenschaftliche Forschung & Entwicklung	Scientific Research & Development
43	service	Sozialdienst und Sozialarbeit	Community & Social Service
44	socialscience	Sozialwissenschaften	Social Science
45	sports	Sport	Sports
46	techhelp	IT Support	IT Operations & Helpdesk
47	techinfo	Informationsdesign & Dokumentation	Information Design & Documentation
48	techsoftware	Software-Entwicklung	Software Development
49	therapy	Therapie	Therapy
50	transport	Logistik	Logistic Support
51	veterinary	Veterinärmedizin	Veterinary
52	warehouse	Lagerhaltung	Loading & Stocking

Notes: Out of 60 normalized job categories in the *Indeed* data, 52 appear in our sample. Not all job postings can be categorized, e.g., generic titles. Typical examples of jobs for each category are listed at https://github.com/hiring-lab/job_postings_tracker/blob/master/occ%20sector%20job%20title%20examples.csv. *Sources:* Indeed.

Table A.2: Difference-in-differences by occupational category

	(1) **all jobs**	(2) installation & maintanance	(3) software development	(4) management	(5) project management	(6) sales	(7) IT operations & helpdesk	(8) production & manufacturing	(9) administrative assistance	(10) marketing
Post × green	0.336***	0.195***	0.308***	0.284***	0.308***	0.123***	0.404***	0.386***	0.260***	0.299***
	(0.025)	(0.030)	(0.035)	(0.027)	(0.031)	(0.029)	(0.021)	(0.026)	(0.022)	(0.028)
Green firms	-0.004	-0.148***	0.116***	-0.019	-0.007	0.124***	-0.083***	-0.028*	0.014	-0.158***
	(0.019)	(0.028)	(0.033)	(0.017)	(0.026)	(0.021)	(0.019)	(0.016)	(0.014)	(0.023)
Year × month FE	×	×	×	×	×	×	×	×	×	×
Observations	152	152	152	152	152	152	152	152	152	152
Adj. R-squared	0.947	0.946	0.967	0.931	0.952	0.921	0.980	0.921	0.933	0.941

	(11) loading & stocking	(12) construction	(13) mechanical engineering	(14) information design & documentation	(15) accounting	(16) industrial engineering	(17) human resources	(18) logistic support	(19) retail	(20) scientific research & development
Post × green	0.359***	0.308***	0.191***	0.298***	0.324***	0.320***	0.218***	0.029	1.102***	0.246***
	(0.023)	(0.048)	(0.028)	(0.038)	(0.037)	(0.043)	(0.039)	(0.077)	(0.111)	(0.038)
Green firms	0.075***	-0.283***	-0.033	-0.052	-0.016	0.111***	-0.062***	-0.256***	-0.051	-0.067***
	(0.016)	(0.045)	(0.023)	(0.032)	(0.016)	(0.026)	(0.020)	(0.071)	(0.053)	(0.022)
Year × month FE	×	×	×	×	×	×	×	×	×	×
Observations	152	152	152	152	152	152	152	152	152	152
Adj. R-squared	0.963	0.902	0.925	0.904	0.817	0.874	0.800	0.818	0.808	0.747

Notes: Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. *Sources:* Indeed, Patstat.

Table A.3: Difference-in-differences by job category: normalized LDI

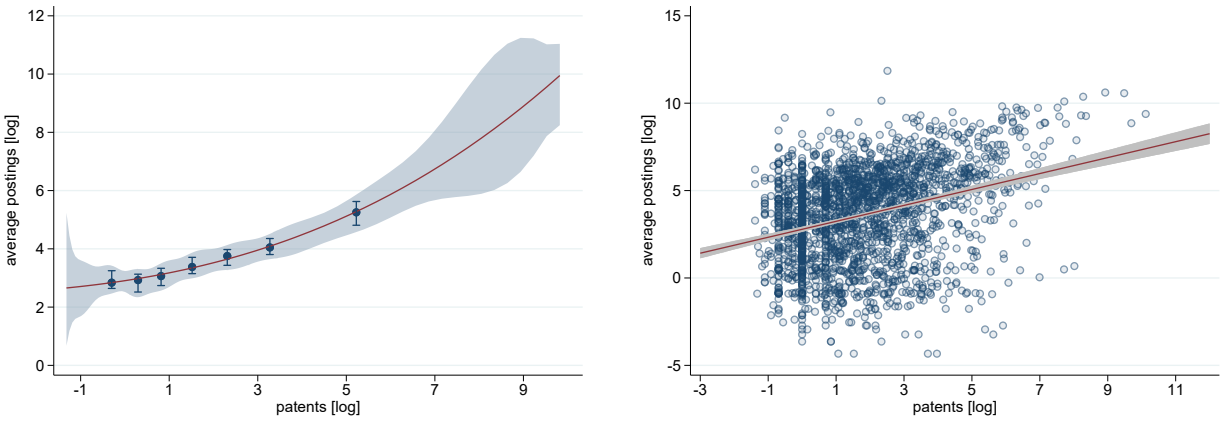
	(1) **all jobs**	(2) installation & maintanance	(3) software development	(4) management	(5) project management	(6) sales	(7) IT operations & helpdesk	(8) production & manufacturing	(9) administrative assistance	(10) marketing
Post × green	0.504***	0.213***	0.628***	0.330***	0.423***	0.193***	0.641***	0.554***	0.487***	0.339***
	(0.037)	(0.031)	(0.043)	(0.030)	(0.038)	(0.030)	(0.033)	(0.040)	(0.039)	(0.030)
Green firms	-0.005	-0.120***	0.080***	-0.018	-0.010	0.107***	-0.060***	-0.026*	0.010	-0.130***
	(0.015)	(0.023)	(0.023)	(0.015)	(0.024)	(0.017)	(0.013)	(0.015)	(0.011)	(0.019)
Year × month FE	×	×	×	×	×	×	×	×	×	×
Observations	152	152	152	152	152	152	152	152	152	152
Adj. R-squared	0.919	0.972	0.929	0.931	0.942	0.954	0.946	0.914	0.923	0.905

	(11) loading & stocking	(12) construction	(13) mechanical engineering	(14) information design & documentation	(15) accounting	(16) industrial engineering	(17) human resources	(18) logistic support	(19) retail	(20) scientific research & development
Post × green	0.522***	0.238***	0.267***	0.439***	0.394***	0.485***	0.306***	-0.104	1.331***	0.373***
	(0.032)	(0.042)	(0.034)	(0.048)	(0.044)	(0.055)	(0.049)	(0.067)	(0.133)	(0.056)
Green firms	0.072***	-0.211***	-0.026	-0.048*	-0.014	0.095***	-0.050***	-0.195***	-0.045	-0.060***
	(0.015)	(0.033)	(0.019)	(0.028)	(0.013)	(0.022)	(0.015)	(0.053)	(0.050)	(0.019)
Year × month FE	×	×	×	×	×	×	×	×	×	×
Observations	152	152	152	152	152	152	152	152	152	152
Adj. R-squared	0.967	0.895	0.919	0.889	0.836	0.876	0.788	0.812	0.820	0.779

Notes: Robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. *Sources:* Indeed, Patstat.

A.2 Figures

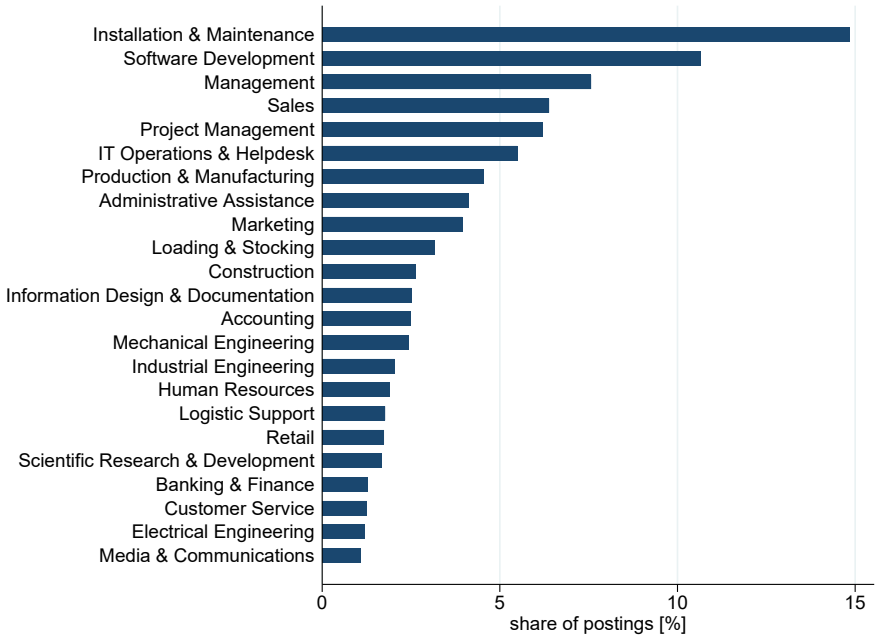
Figure A.1: Firm size: patents and postings



(a) binscatter **(b)** scatterplot

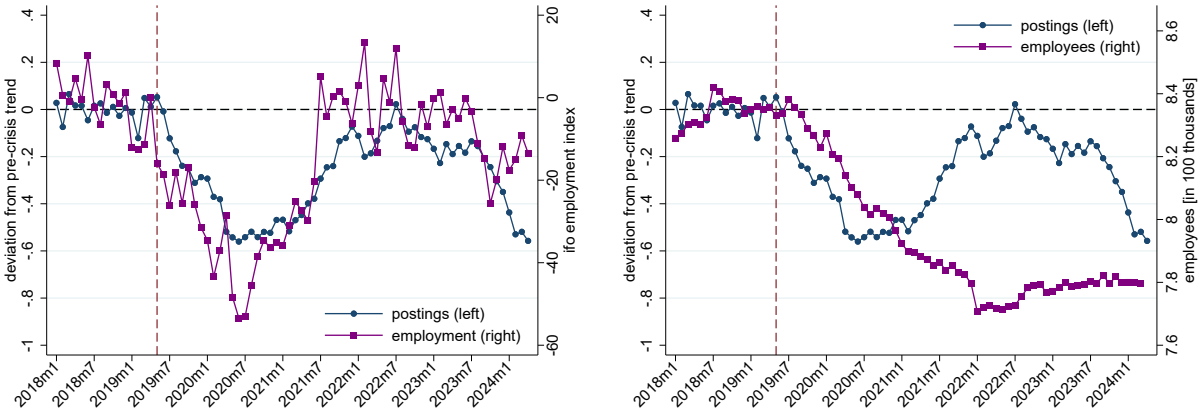
Note: The left panel shows a binscatter representation by Cattaneo et al. (2024) with 95% confidence intervals and a third-order polynomial fit. The right panel shows the raw data in a scatterplot with a linear fit and 95% conficence interval. *Sources:* Indeed, Patstat.

Figure A.2: Job categories



Note: Plot shows job categories with a share in overall postings in our sample above 1%. *Sources:* Indeed.

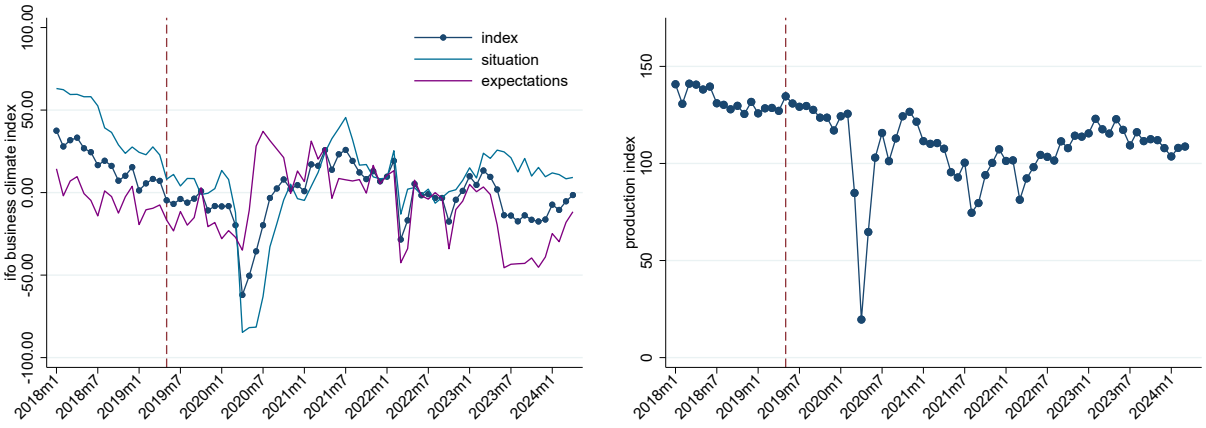
Figure A.3: Job postings and employment



(a) employment survey **(b)** employees

Note: The ifo employment index for the automotive sector (C290000: "Manufacture of motor vehicles trailers and semi-trailers") is seasonally adjusted and based on a survey question regarding employment plans for the next three months. The number of employees from the statistical office reflects employees in the automotive sector (WZ29: "Manufacture of motor vehicles and vehicle parts"). During the observation period, on average, 941 firms are in that sector. *Sources:* Indeed, Patstat, ifo Business Climate Survey, Destatis.

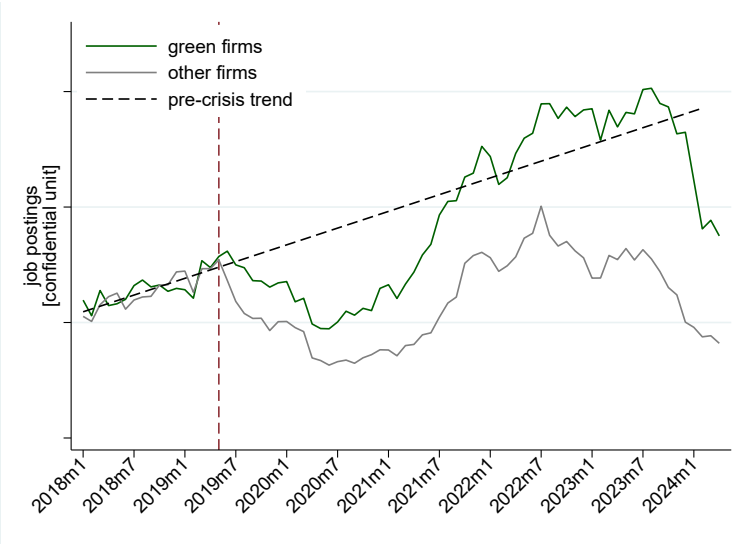
Figure A.4: Business climate indicators



(a) business climate survey **(b)** production index

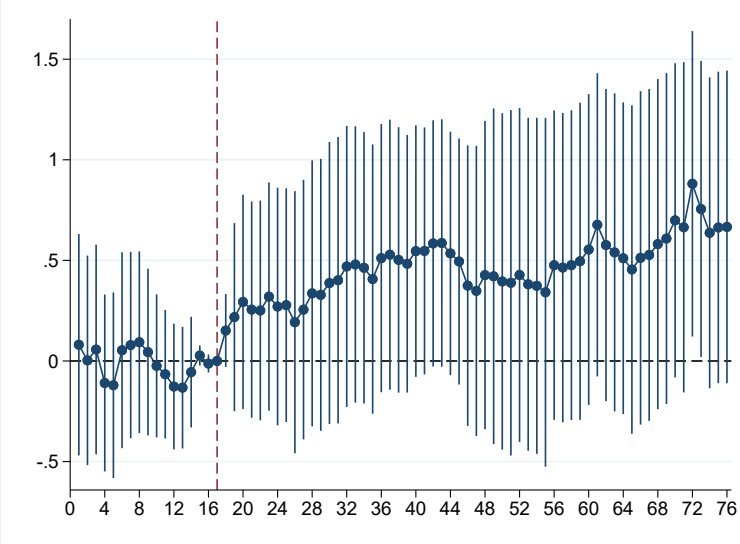
Note: The left panel shows the three components of the ifo Business Climate Index for the automotive sector (C290000: "Manufacture of motor vehicles trailers and semi-trailers"). Firms are asked to assess their current business situation as well as their expectations for their future business situation. The index averages the two questions. Values are seasonally adjusted. The right panel shows the official production index for the automotive sector (WZ29: "Manufacture of motor vehicles and vehicle parts"). *Sources:* ifo Business Climate Survey, Destatis.

Figure A.5: Job postings: levels



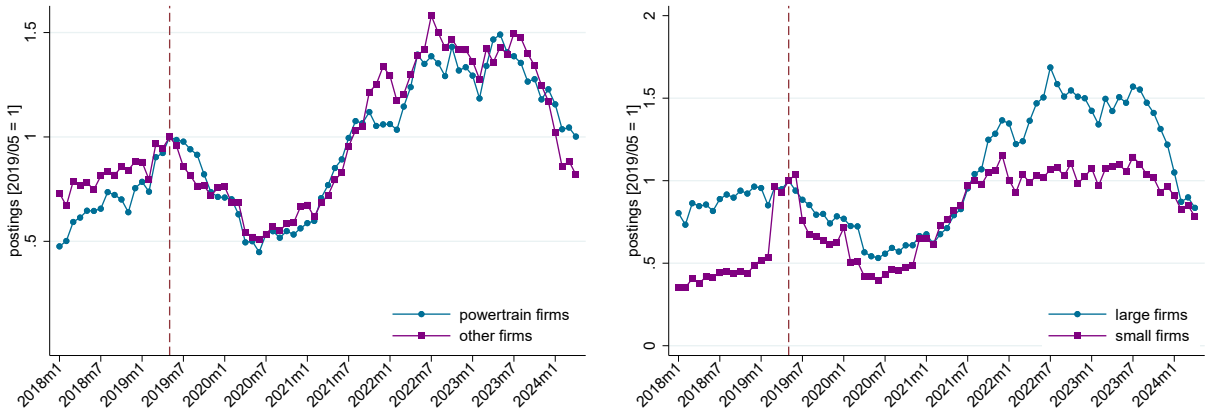
Note: The number of postings is multiplied by a constant for confidentiality. *Sources:* Indeed, Patstat.

Figure A.6: Dynamic firm-level difference-in-differences



Note: Graph plots coefficients from a dynamic version of specification (4) in Table 1, which is a PPML count data model with firm fixed effects. Bars represent 95% confidence intervals. *Sources:* Indeed, Patstat.

Figure A.7: Powertrain and firm size placebos



(a) powertrain exposure **(b)** firm size

Note: Graphs plot the normalized labor demand index split by powertrain exposure (left) and firm size (right). *Sources:* Indeed, Patstat.