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

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Abstract

Technological transitions reshape labor markets, yet conventional occupational taxonomies overlook how jobs are embedded in firms' product and technology contexts. We develop an index that combines firms' patent portfolios with their online job postings, linking technological specialization to hiring behavior in real time. Using 1.52 million postings by 2,166 patent-active German automotive firms between 2018 and 2024, we demonstrate the approach by comparing companies specializing in green propulsion technologies with those focused on combustion engines during the sector's post-2019 crisis. We find that green firms' labor demand is 35–50 percentage points higher than that of brown firms, with the gap widening through 2022 before narrowing in 2023. Green firms especially expand hiring in production and information technology roles, highlighting differences in occupational demand across technologies.

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

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

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1 Introduction

Technological innovation is not only the main engine of economic growth (Solow, 1957; Romer, 1990) but also a key lever for addressing societal challenges such as global warming (Acemoglu et al., 2012). The diffusion of new technologies in the economy typically triggers structural change (Schumpeter, 1942; Bresnahan et al., 2002; Autor, 2015; Acemoglu and Restrepo, 2018), and understanding the interaction between technology and the labor market is crucial to design 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 (Autor et al., 2003; Goos et al., 2014; Frey and Osborne, 2017). However, this approach fails whenever skills and tasks are not inherently relatable to a technology, resulting in significant ambiguity (Autor, 2013; Spitz-Oener, 2006; Nedelkoska and Quintini, 2018; Arntz et al., 2017; Villani et al., 2025). A simple example is the automotive sector, where engineers and production workers with similar skills and tasks can be employed in either 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 (Klepper, 2002; Malerba, 2002; Breschi et al., 2003) or task- or skill-based occupational taxonomies (Handel, 2017; Fernández-Macías and Bisello, 2020; Villani et al., 2025). 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 (Hershbein and Kahn, 2018; Gutiérrez et al., 2020). 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 of 2,166 patent-active German automotive firms 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 (Aghion et al., 2016; Hall et al., 2001; Griliches, 1998) 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 tapping 1.52 million online job postings (OJP) collected 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 technology, 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; Popp et al., 2019; OECD, 2024; Dechezleprêtre et al., 2023). 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, and (Elliott et al., 2024) provide evidence on cross-country green transition dynamics. However, Villani et al. (2025) show that occupational-based classifications of green jobs often generate false positives and false negatives and frequently fail to capture actual employment shifts linked to the green transition. Rather than classifying occupations, we focus on the company's product 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 future (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' 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.

[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.

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 technology as *green* and technology classes related to internal combustion technology as *brown*. 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.

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

[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.

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 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

[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.

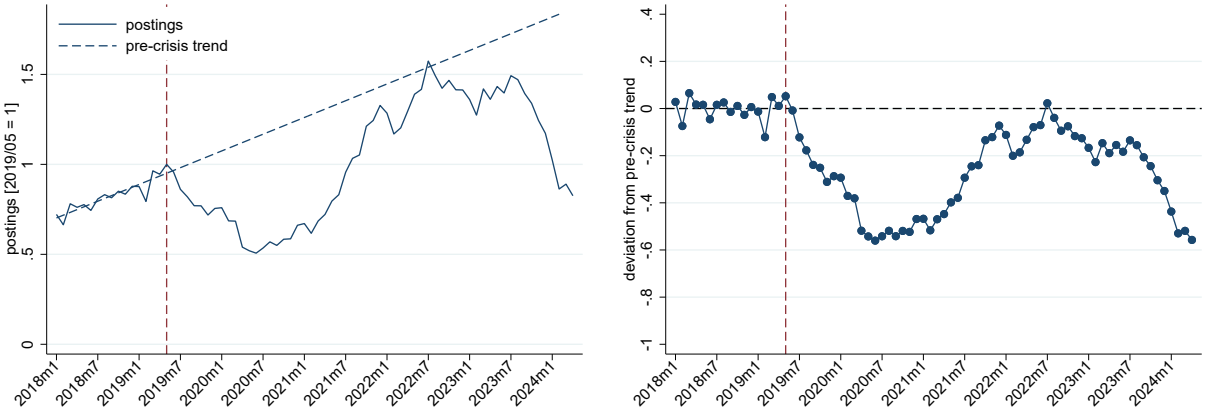
month) and interpolate detected gaps. We first apply a linear interpolation to the gap and then smooth the data with moving average (with a narrower window that includes 3 months before and after the current one). This procedure leads to 0.44% of interpolated month-firm observations.

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 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.

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

Figure 1: Automotive industry labor demand



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

Sources: Indeed, Patstat.

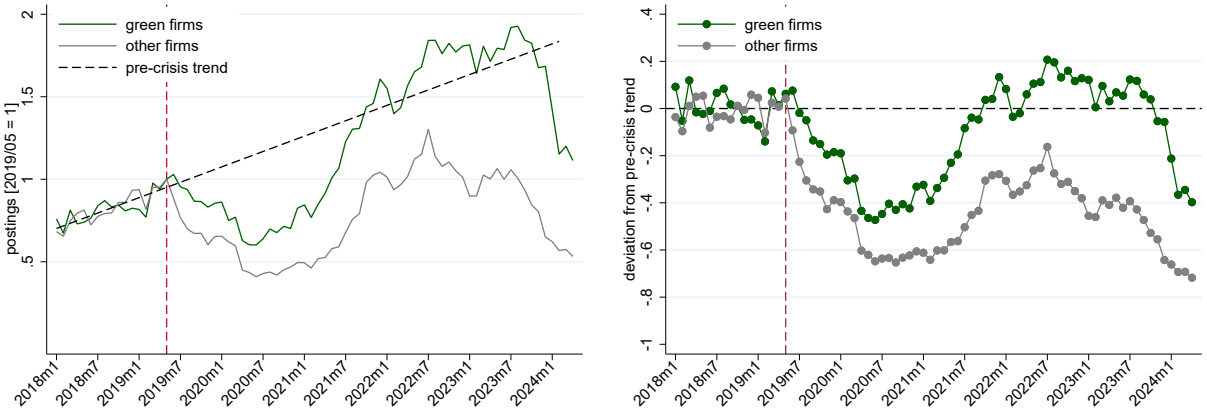
of employees in the automotive sector not declining further. Overall, both general industry dynamics and external data substantiate the effectiveness of our index in capturing labor demand appropriately.

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.

Results of the difference-in-differences regression reported in Table 1 confirm these findings. Column (1) shows the results of a model without year $\times$ 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,

Figure 2: Labor demand and firm greenness



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

Sources: Indeed, Patstat.

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.

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.

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.

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.

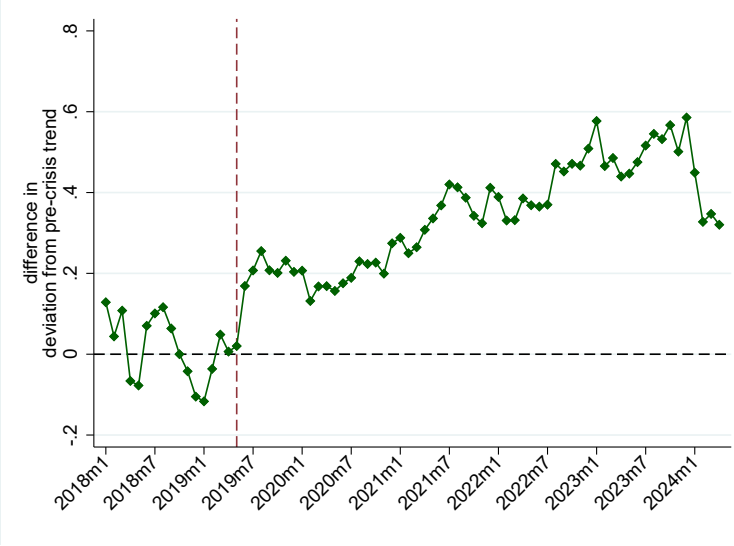
Green and brown firms potentially differ in aspects other than greenness. Our firm-level estimation in column (4) of Table 1, which includes firm fixed effects, already mitigates potential concerns regarding unobserved firm heterogeneity.[10] Nevertheless, we present additional tests. Two channels seem 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 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,

[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.

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.

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.

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.

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.

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.

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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

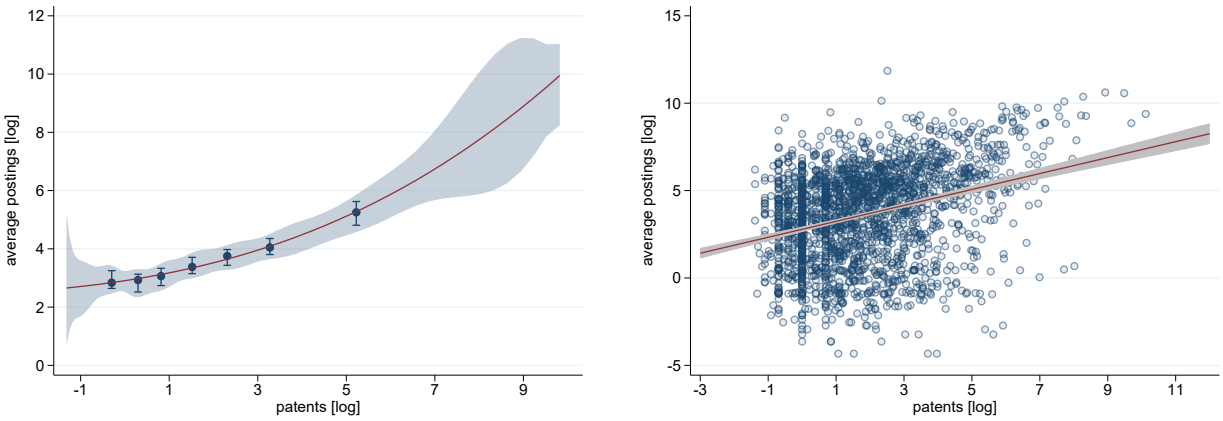
	(1) **all jobs**	(2) installation & maintanance	(3) software development	(4) management	(5) project management	(6) sales	(7) IT operations & helpdesk	(8) production & manufacturing	(9) administrative assistance	(10) marketing
Post × green	0.504***	0.213***	0.628***	0.330***	0.423***	0.193***	0.641***	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

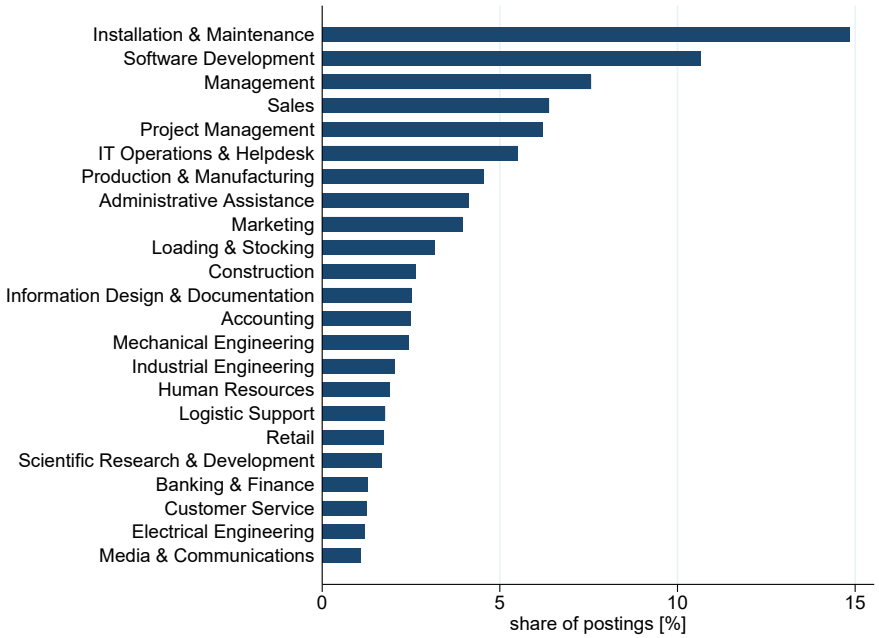
Figure A.1: Firm size: patents and postings



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

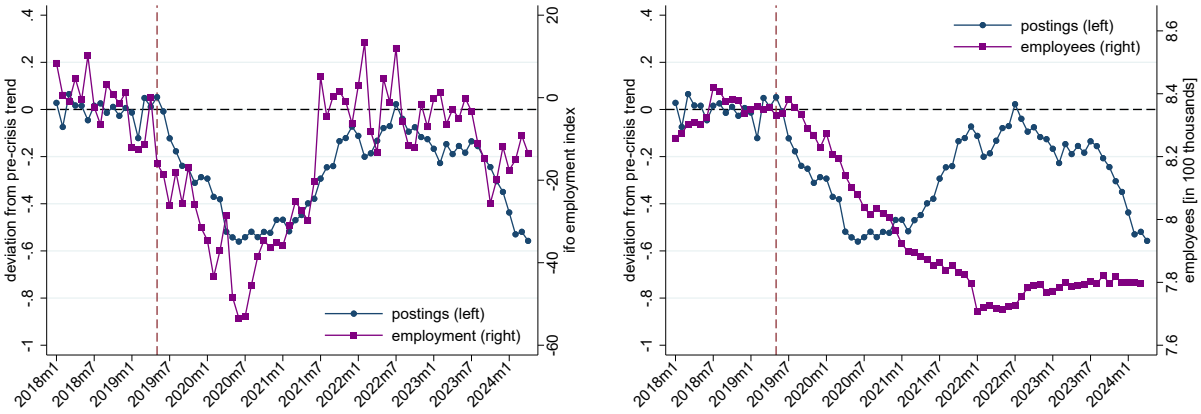
Note: The left panel shows a binscatter representation by Cattaneo et al. (2024) with 95% confidence intervals and a third-order polynomial fit. The right panel shows the raw data in a scatterplot with a linear fit and 95% conficence interval. *Sources:* Indeed, Patstat.

Figure A.2: Job categories



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

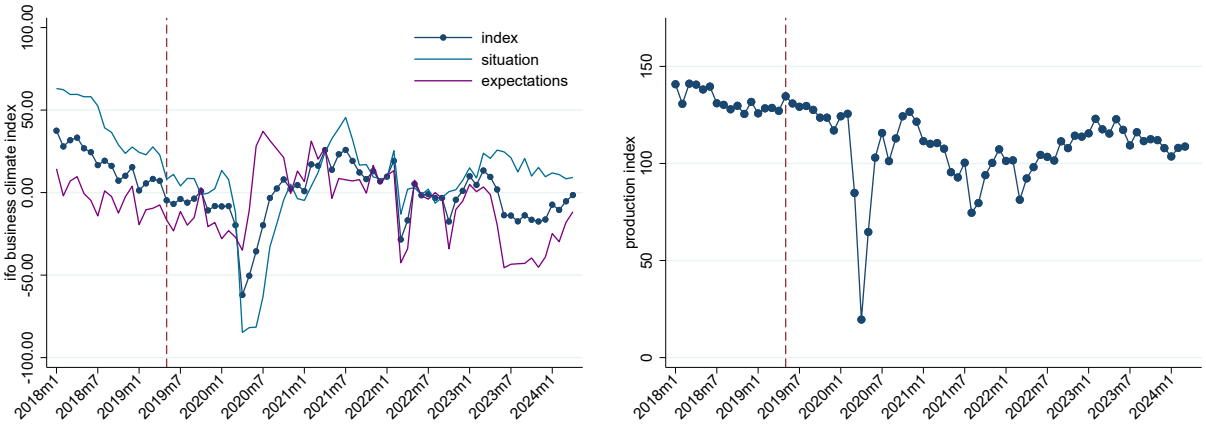
Figure A.3: Job postings and employment



(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.

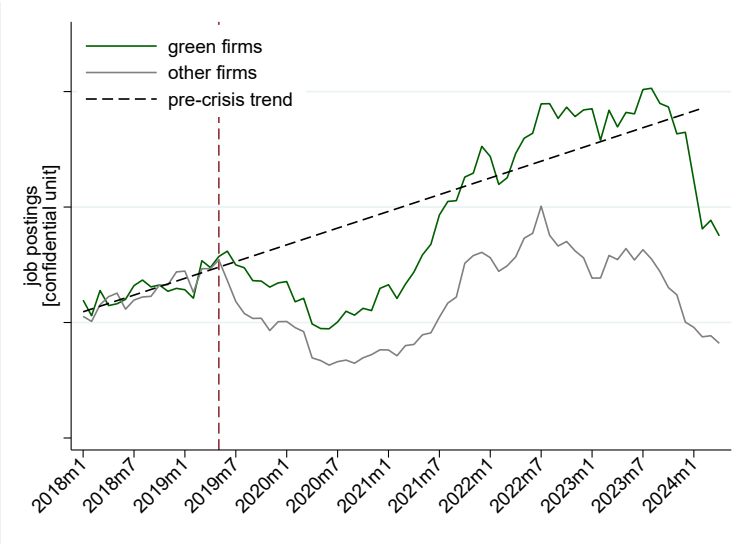
Figure A.4: Business climate indicators



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

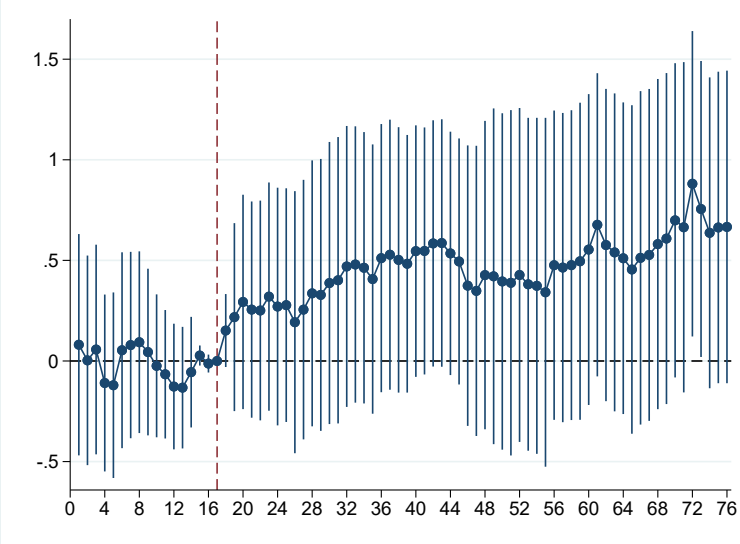
Note: The left panel shows the three components of the ifo Business Climate Index for the automotive sector (C290000: "Manufacture of motor vehicles trailers and semi-trailers"). Firms are asked to assess their current business situation as well as their expectations for their future business situation. 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



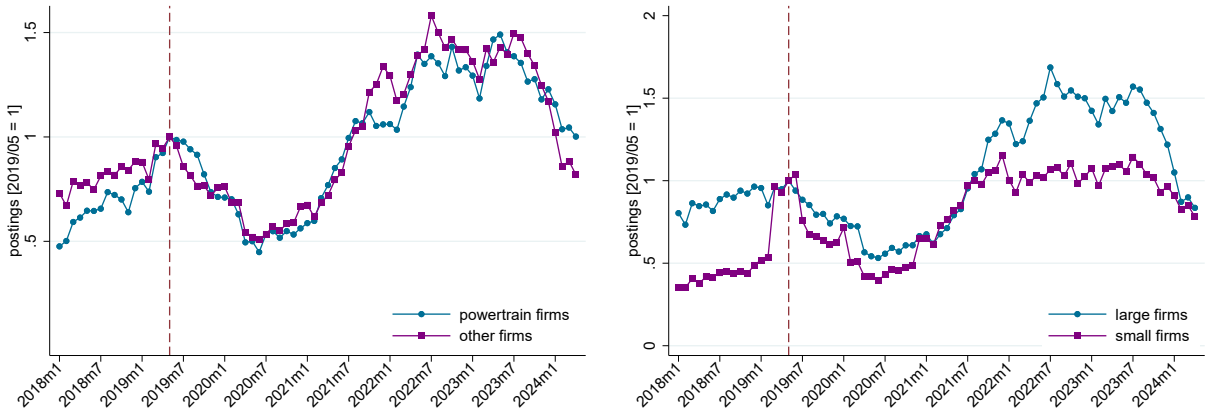
Note: The number of postings is multiplied by a constant for confidentiality. *Sources:* Indeed, Patstat.

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.