

**The Greener, the Higher:
Labor Demand of Automotive
Firms during the Green
Transformation**

Thomas Fackler, Oliver Falck, Moritz Goldbeck, Fabian Hans, Annina Hering

Impressum:

CESifo Working Papers

ISSN 2364-1428 (electronic version)

Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH

The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute

Poschingerstr. 5, 81679 Munich, Germany

Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de

Editor: Clemens Fuest

<https://www.cesifo.org/en/wp>

An electronic version of the paper may be downloaded

- from the SSRN website: www.SSRN.com
- from the RePEc website: www.RePEc.org
- from the CESifo website: <https://www.cesifo.org/en/wp>

The Greener, the Higher: Labor Demand of Automotive Firms during the Green Transformation

Abstract

We investigate differences in labor demand between German automotive firms specializing in green propulsion technology and those with a focus on combustion engines. To this end, we introduce a firm-level labor demand index based on the near-universe of online job postings and firms' patent portfolios. Workforce adjustments are a crucial dimension of technology-related structural change, and labor demand as a highly reactive decision parameter is an ideal measure to detect employment adjustments. Our index enables us to distinguish labor demand by firms' greenness in real-time, a notable advantage over survey or administrative data. In a difference-in-differences setup, we exploit the poly-crisis triggered by unexpected escalations of trade conflicts and sustained by consequences of the pandemic and the war in Ukraine. We find green firms' labor demand is significantly and persistently higher than before the outbreak of the poly-crisis, by 34 to 50 percentage points compared to firms with a focus on combustion technology. This gap widens over time and is not driven by unobserved firm heterogeneity. Green firms systematically adjust labor demand towards production and information technology jobs.

JEL-Codes: C550, J230, M510, O140, O330.

Keywords: low carbon technology, firm employment decisions, sustainability, disruptive innovation.

Thomas Fackler
Surrey Business School
University of Surrey / United Kingdom
t.fackler@surrey.ac.uk

Oliver Falck
ifo Institute – Leibniz Institute at the
University of Munich / Germany
falck@ifo.de

*Moritz Goldbeck**
ifo Institute – Leibniz Institute at the
University of Munich / Germany
goldbeck@ifo.de

Fabian Hans
Indeed Hiring Lab
fhans@indeed.com

Annina Hering
Indeed Hiring Lab
hering@indeed.com

*corresponding author

June 5, 2024

We thank Pawel Adrjan for helpful comments as well as Tim Lixfeld and Raunak Mehrotra for excellent research assistance.

1 Introduction

Although swift greening of our economies is urgently needed to mitigate the enormous damages from climate change (Kotz et al., 2024), firms often transition to green technologies only sluggishly (Igami, 2017; Aghion and Howitt, 1990; Arrow, 1962) as this requires disruptive innovation (Christensen et al., 2006; Abernathy et al., 1978). A prime example are German carmakers, who maintained global market leadership for several decades by incrementally improving combustion technology but now struggle with the green transformation (Falck et al., 2023; Aghion et al., 2016; Barbieri, 2016). 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 has a chance to meet regulatory emission reduction targets (Ater and Yoseph, 2022; Skeete, 2017). Automotive firms adopt different strategies in response. Especially incumbents are faced with the choice between transitioning to green technology to remain competitive in the long term or maximizing short-term profits by selling combustion technology as long as possible while saving on investments (Igami, 2017; Wesseling et al., 2015). As a result, there is a large heterogeneity between automotive firms’ greenness.

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). Economically however, 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), and adjusting workforce’s skills accordingly (Consoli et al., 2016; Czernich et al., 2021). Unfortunately, labor market data beyond the industry level is lacking, which prevents comprehensive evidence-based assessments regarding heterogeneous labor market effects with respect to firms’ greening strategies.

In this paper, we track firm-level labor demand in the German automotive industry from January 2018 through April 2024 and differentiate between firms following a green or brown strategy, where green refers to battery-electric, hybrid, or fuel-cell technologies and brown to combustion technology. To this end, we leverage online job ads (OJA) data by *Indeed* that captures the near-universe of the industry’s job postings and allows us to observe firm-level labor demand in real-time. To assess greenness, 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). By combining OJA and patent data, we derive a firm-level labor demand index that enables us to look beyond the industry level and is consistent with traditional measures based on surveys or administrative data. We then exploit the poly-crisis, which hit the automotive

industry in 2019 triggered by unexpected escalations of trade conflicts and was sustained by the pandemic and supply chain disruptions, to investigate differences in the labor demand response with respect to firms' greenness in a difference-in-differences setup. 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). The poly-crisis represents a large and sustained shock to the industry and triggered significant labor demand reactions. Our labor demand index allows us to elicit aggregate and compositional differences in the labor demand adjustment of green and brown firms during the poly-crisis.

Our results show that the labor demand of green firms is significantly and persistently higher throughout the poly-crisis. On average, green firms feature 34 to 50 percentage points more postings than brown firms compared to before the poly-crisis, depending on the model specification. This result is not driven by differences in specialization in powertrain technology and firm size, nor by unobserved firm heterogeneity. The gap in labor demand between green and brown firms widens over time, from about 20 percentage points at the beginning of the poly-crisis to up to almost 60 percentage points by the end of 2023. Since then, the gap shrinks again to around 35 percentage points. The labor demand adjustment in response to the poly-crisis is structurally different between green and brown firms. Compared to the pre-crisis trend, green firms' labor demand increases especially strongly in information technology and production and less for technical and traditional engineering roles. Overall, our findings suggest a persistent outperformance of green relative to brown firms in the German automotive industry with respect to labor demand and structural employment adjustments triggered by the poly-crisis.

Our contribution is twofold. First, we add to the literature on labor market effects of the green transformation. 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) 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. We focus on the firm perspective by focusing on labor demand of firms that develop green versus brown technology. Second, 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 Lehtonvirta, 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.

The remainder of this paper is organized as follows. Section 2 introduces the data and our empirical method, results are presented in Section 3, and Section 4 concludes.

2 Data and empirical methods

Labor demand index 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 greenness, and combine this information with the near-universe of online job postings from *Indeed* to track firms' labor demand.

We source data on patents from *Patstat*, 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 classify patents into clean, gray, and dirty depending on their technology class.¹ Clean technologies relate to either battery-electric, hybrid, or fuel-cell propulsion technology while both dirty and gray technologies relate to combustion engine technology. Gray technologies are efficiency-enhancing combustion engine technologies. Since patents may fall into multiple technology classes, we define patents as clean whenever they feature at least one clean technology class, as gray whenever they do have at least one gray but no clean technology class, and as dirty when they are assigned a dirty but no gray or clean technology class. Here we use a binary definition of green and brown patents that merges gray and dirty combustion technology into one group. We call all patents classified in this way powertrain patents, as opposed to non-classified patents, which do not have a clean, gray, or dirty technology class. This classification comprehensively captures powertrain patents, in contrast to more narrow 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 the European Patent Office's *Patstat* database (2022 Autumn Edition), 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, this gives us a sample of 3,199 firms with significant patenting activity in powertrain technologies.² 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.³ 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.

¹Clean, gray, and dirty patents include those whose International Patent Classification (IPC) symbols start with B60L, B60K, B60W, H01M, F02, H01G, and H02J.

²Note 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.

³For 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 firms 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.

Our second data source are online job postings by *Indeed*, whose database captures the near-universe of online job postings 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). *Adrjan and Lydon (2023)* demonstrate the *Indeed* data is representative for major labor markets. Job ads originate from both from employers directly posting on the platform and from other internet sources such as companies' career sites and applicant tracking systems. *Indeed* de-duplicates ads for the same job posted on multiple sources. Job ad versions posted directly by the employer are prioritized. 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 standards⁴, e.g., generic postings are not allowed. *Indeed* is present in Germany since 2008, with more than 880,000 new postings per month, on average (Indeed, Q1 2024). In our data, we observe monthly job postings from January 2018 through April 2024.

To link OJA 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 or AG. In the first matching tier, we apply exact matching to link company names in the OJA 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 joint sample of 2,166 firms that are both in the *Indeed* and the *Patstat* data. In total, these firms account for 1,517,654 distinct job postings over the observation period.

As a real-time capable measure of labor demand, we compute the number of open job postings in each month since January 2018 for each firm:

$$LD_{ft} = \sum_{\phi=f, \kappa=t} OJA_{i j \phi \kappa} \quad (1)$$

⁴*Indeed* job postings standards: https://indeed.my.site.com/employerSupport1/s/article/115005915763?language=en_US; last accessed 05/27/2024.

with labor demand LD_{ft} of disambiguated firm f in month t and online job posting i in occupational category j of firm f in month t . Rarely, there are firm-specific gaps in data availability for technical reasons during the data collection process. For large firms, i.e., OEMs and large automotive suppliers⁵, 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 leads to 0.44% of interpolated month-firm observations.

In addition, we leverage the classification of job titles in the postings into 60 consistent occupational categories that are similar to two-digit occupational codes used by statistical agencies, with some wider groupings (Adrián and Lydon, 2023). Table A.1 reports the descriptions of all job title categories. 52 out of 60 occupational categories appear in our sample, but many of them 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 often occurring occupational categories. Similar to Equation 1, we calculate LD_{jft} by summing up the number of monthly open postings by firm for each of these occupational categories.

Labor demand during the poly-crisis In the first half of 2019, a poly-crisis hit the German automotive industry (Economist, 2019). 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, announcements of a tightening of environmental regulation (FAZ, 2019), continued economic weakness (Financial Times, 2019), the start of ‘Dieselgate’ court proceedings against top management (DW, 2019; SEC, 2019) as well as the launch of Tesla’s Model Y in the premium segment (The Verge, 2019) threatened German carmakers’ business model. The industry reacted with large-scale cost savings and restructuring efforts, including significant job cuts over the coming years (Süddeutsche Zeitung, 2019; Manager Magazin, 2019a,b). The poly-crisis was reinforced by the pandemic with a drop in demand and supply chain disruptions in 2020 (Karamoozian et al., 2024; Aksoy et al., 2024) and by the war of Russia against Ukraine and the resulting energy crisis in 2021 (Hutter and Weber, 2022).

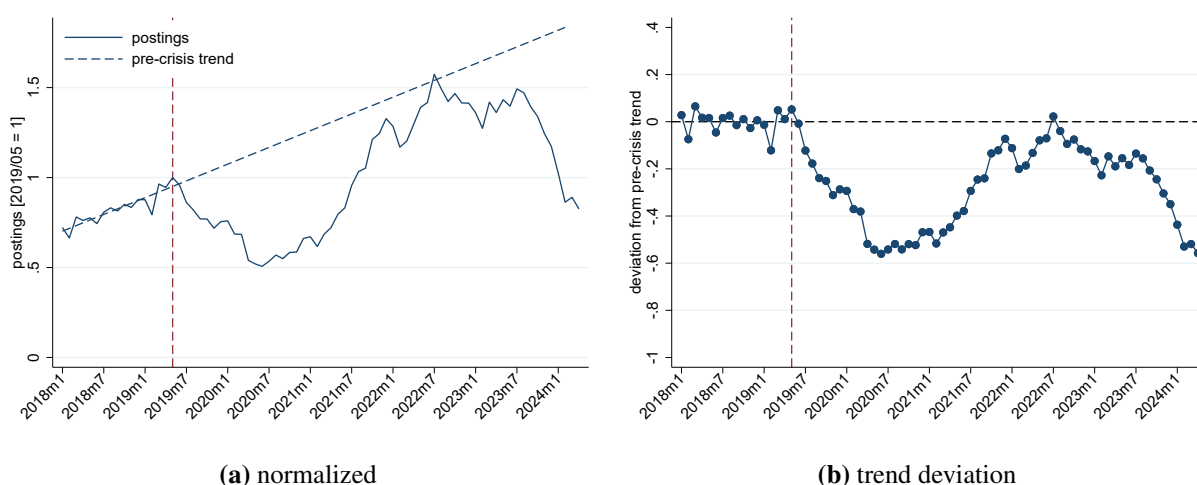
We construct our labor demand index (LDI) for the automotive industry by normalizing aggregate labor demand to May 2019, after which firms started to react to the poly-crisis shock

$$LDI_t = \frac{\sum_{\tau=t} LD_{f\tau}}{\sum_{\tau=05/19} LD_{f\tau}}. \quad (2)$$

⁵Suppliers are identified using the 2021 *Meyer Industry Research* list of top 100 German automotive suppliers.

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 in the beginning of 2020. Labor demand stays 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



Sources: Indeed, Patstat.

The observed pattern is consistent with industry dynamics. The poly-crisis was deepest during the pandemic (see also [Figure A.4](#)), with stay-at-home mandates and supply shortages ([Puls et al., 2021](#)). 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.

Difference-in-differences model The green share from patent portfolios and firm-level data linkage allows us to distinguish labor demand of green and brown firms. To this end, we compute our labor demand index for firms above and below the median green share of two thirds of classified powertrain patents. To assess the difference in labor demand dynamics between green and brown firms, we estimate a parsimonious difference-in-differences model via ordinary least squares, which compares the development of labor demand for green and brown firms during relative to before the poly-crisis:

$$\text{LDI}_{gt} = \beta_0 + \beta_1(\text{post}_t * \text{green_firms}_g) + \beta_2 \text{green_firms}_g + \delta_t + \varepsilon_{gt} \quad (3)$$

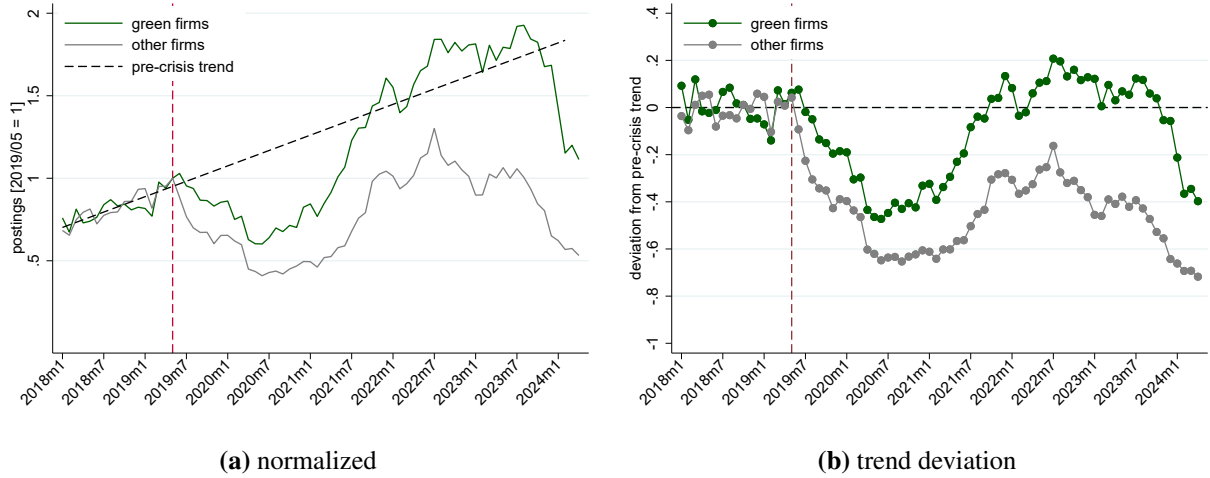
where LDI_{gt} is the (normalized) labor demand index in month t for green ($g = 1$) or brown ($g = 0$) firms, post_t indicates months after May 2019, and green_firms_g is a dummy equal to one for green firms and zero for brown firms. Additionally, we include year \times month fixed effects to capture dynamics common to both green and brown firms. ε_{gt} is an error term. We use heteroscedasticity-robust Huber-White standard errors. Our coefficient of interest is β_1 and captures the average difference in labor demand between green and brown firms before relative to during the poly-crisis.

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

Figure 2: Labor demand and firm greenness



Sources: Indeed, Patstat.

the indexed *Indeed* data is consistent with steadily increasing labor shortages in Germany (see, e.g., [Hering, 2024](#)) and administrative data on vacancies⁶, 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

⁶IAB-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*** (0.062)	0.504*** (0.037)	0.336*** (0.025)	0.487* (0.258)
Green firms	0.038 (0.033)	-0.005 (0.015)	-0.004 (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.

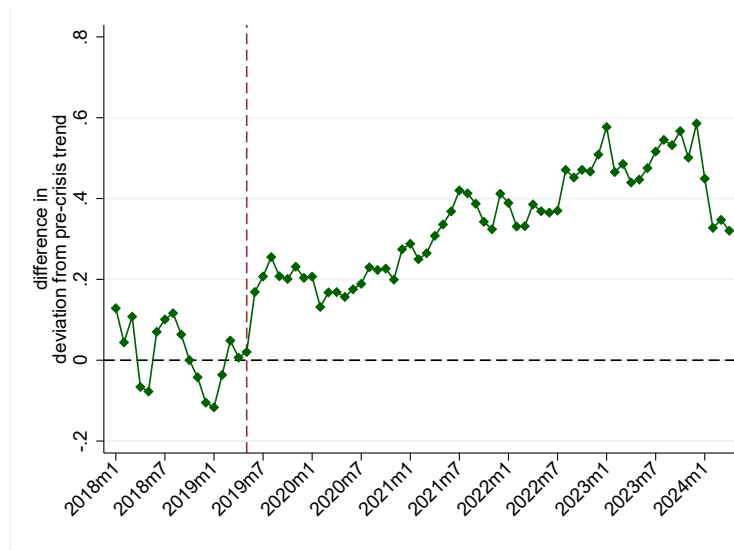
Green and brown firms potentially differ in other aspects but greenness. Our firm-level estimation in column (4) of [Table 1](#), which includes firm fixed effects, already mitigates potential concerns regarding unobserved firm heterogeneity.⁷ Nevertheless, we present additional tests. Two channels seem 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.⁸ 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](#) reports results of the trend deviation model specification for each of the 19 occupational categories. 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, green firms post significantly more jobs in the area

⁷[Figure A.6](#) plots a dynamic version of model (4) in [Table 1](#).

⁸Note 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.

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: Difference-in-differences by occupational category

	(1) all jobs	(2) installation & maintenance	(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*** (0.025)	0.195*** (0.030)	0.308*** (0.035)	0.284*** (0.027)	0.308*** (0.031)	0.123*** (0.029)	0.404*** (0.021)	0.386*** (0.026)	0.260*** (0.022)	0.299*** (0.028)
Green firms	-0.004 (0.019)	-0.148*** (0.028)	0.116*** (0.033)	-0.019 (0.017)	-0.007 (0.026)	0.124*** (0.021)	-0.083*** (0.019)	-0.028* (0.016)	0.014 (0.014)	-0.158*** (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*** (0.023)	0.308*** (0.048)	0.191*** (0.028)	0.298*** (0.038)	0.324*** (0.037)	0.320*** (0.043)	0.218*** (0.039)	0.029 (0.077)	1.102*** (0.111)	0.246*** (0.038)
Green firms	0.075*** (0.016)	-0.283*** (0.045)	-0.033 (0.023)	-0.052 (0.032)	-0.016 (0.016)	0.111*** (0.026)	-0.062*** (0.020)	-0.256*** (0.071)	-0.051 (0.053)	-0.067*** (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.

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.2](#) 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

The automotive industry is currently experiencing its most significant transformation ever, primarily centered around the shift to green technologies. As with previous disruptive technological transformations, effects on employment are the most contentious topic in the public and policy debate. Yet, evidence-based assessments are difficult because up-to-date, high-quality data on labor market performance beyond the industry level is scant. We demonstrate how to overcome this issue 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 poly-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 programs. Lastly, while our analysis for the German automotive industry shows that green firms perform better in terms of generating employment opportunities than brown firms, our analysis does not inform about the overall employment effects of the industry's green transformation.

Our results have several policy implications. Importantly, we observe no evidence for 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 of brown firms to become greener remains unclear, skill requirements for their employees will likely change irrespective of remaining with their firm or switching the employer. Thus, learning about skill requirements and job prospects in green automotive firms 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.

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

- , “Could 400,000 German car industry jobs go?,” *DW*, 2020.
- Economist**, “It is time to worry about Germany’s economy,” *Economist*, 2019.
- 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.
- 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.

- Kotz, Maximilian, Anders Levermann, and Leonie Wenz**, “The economic commitment of climate change,” *Nature*, 2024.
- 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.
- Mezzaninica, 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.
- 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.

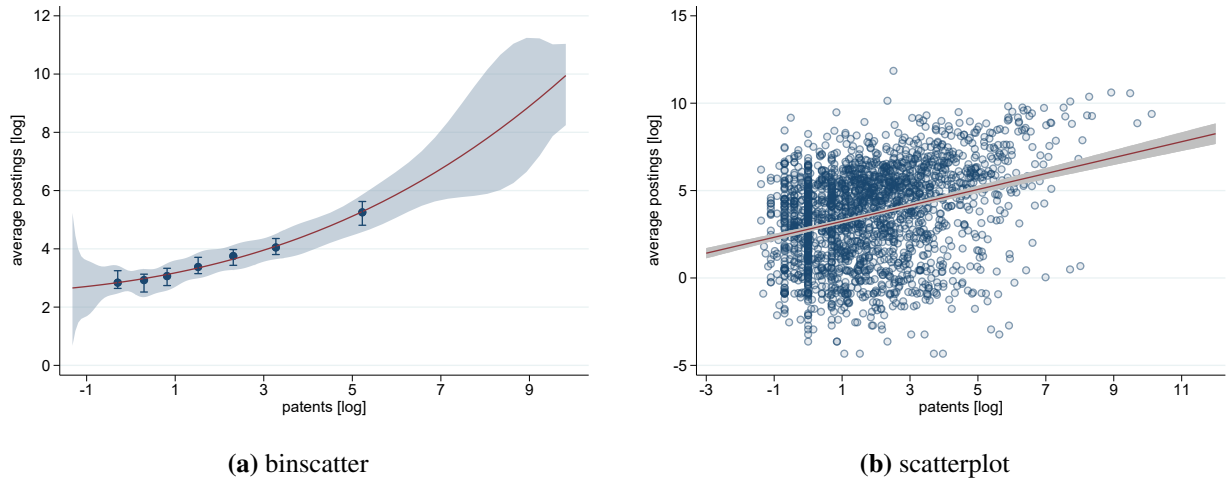
Table A.2: Difference-in-differences by job category: normalized LDI

	(1) all jobs	(2) installation & maintenance	(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*** (0.037)	0.213*** (0.031)	0.628*** (0.043)	0.330*** (0.030)	0.423*** (0.038)	0.193*** (0.030)	0.641*** (0.033)	0.554*** (0.040)	0.487*** (0.039)	0.339*** (0.030)
Green firms	-0.005 (0.015)	-0.120*** (0.023)	0.080*** (0.023)	-0.018 (0.015)	-0.010 (0.024)	0.107*** (0.017)	-0.060*** (0.013)	-0.026* (0.015)	0.010 (0.011)	-0.130*** (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*** (0.032)	0.238*** (0.042)	0.267*** (0.034)	0.439*** (0.048)	0.394*** (0.044)	0.485*** (0.055)	0.306*** (0.049)	-0.104 (0.067)	1.331*** (0.133)	0.373*** (0.056)
Green firms	0.072*** (0.015)	-0.211*** (0.033)	-0.026 (0.019)	-0.048* (0.028)	-0.014 (0.013)	0.095*** (0.022)	-0.050*** (0.015)	-0.195*** (0.053)	-0.045 (0.050)	-0.060*** (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.

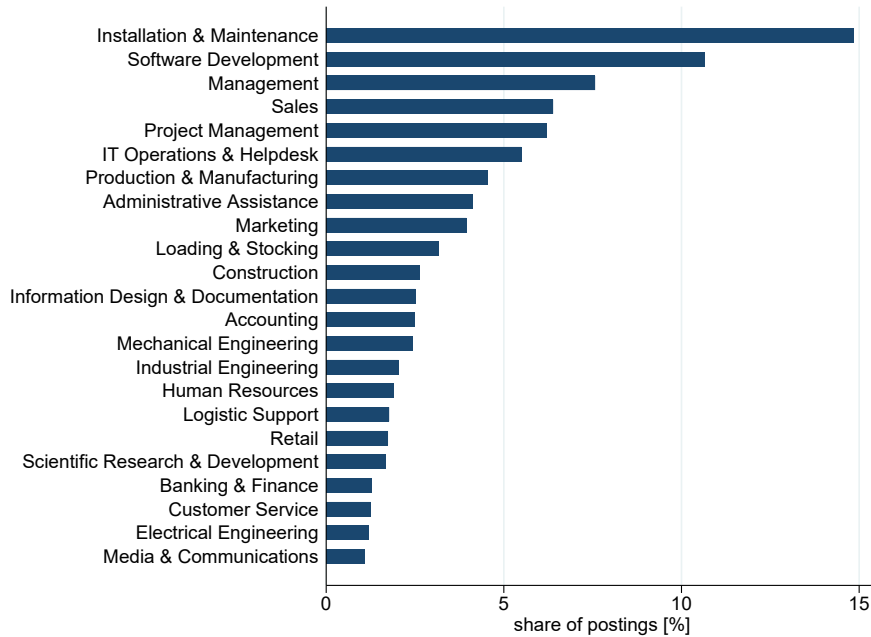
A.2 Figures

Figure A.1: Firm size: patents and postings



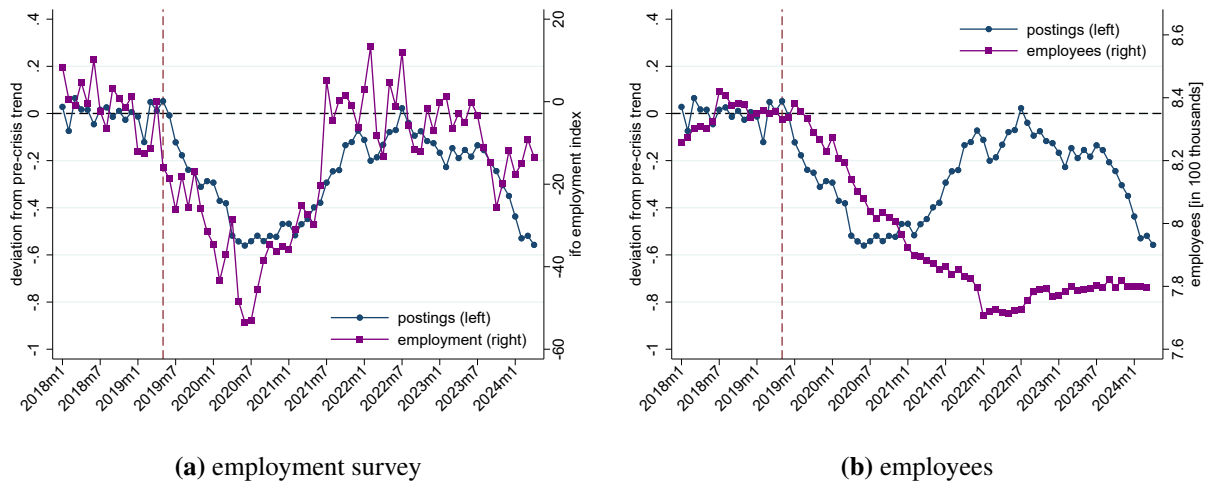
Note: The left panel shows a binscatter representation by Cattaneo et al. (2024) with 95% confidence intervals and a third-order polynomial fit. The right panel shows the raw data in a scatterplot with a linear fit and 95% confidence interval. *Sources:* Indeed, Patstat.

Figure A.2: Job categories



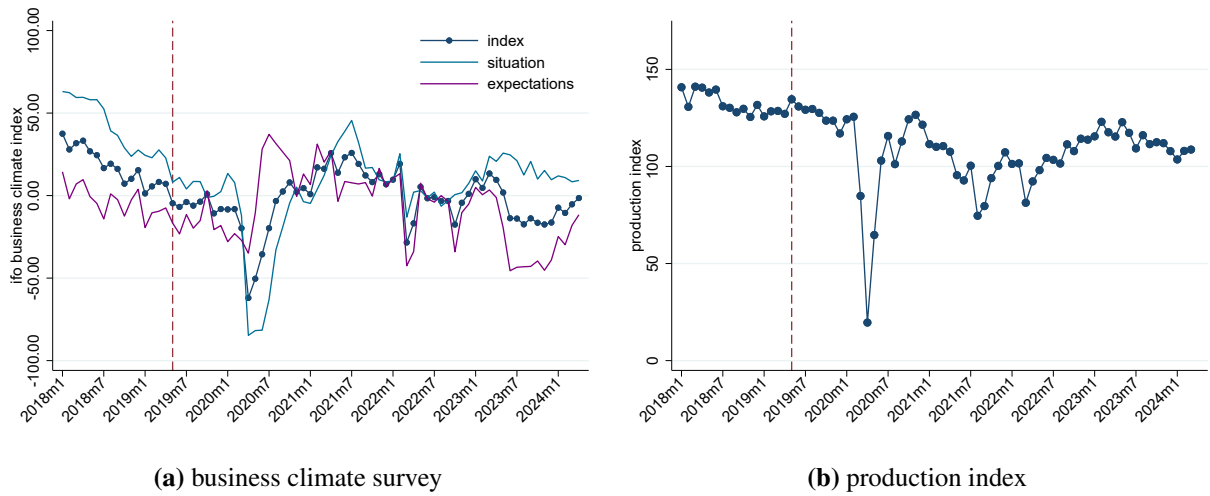
Note: Plot shows job categories with a share in overall postings in our sample above 1%. *Sources:* Indeed.

Figure A.3: Job postings and employment



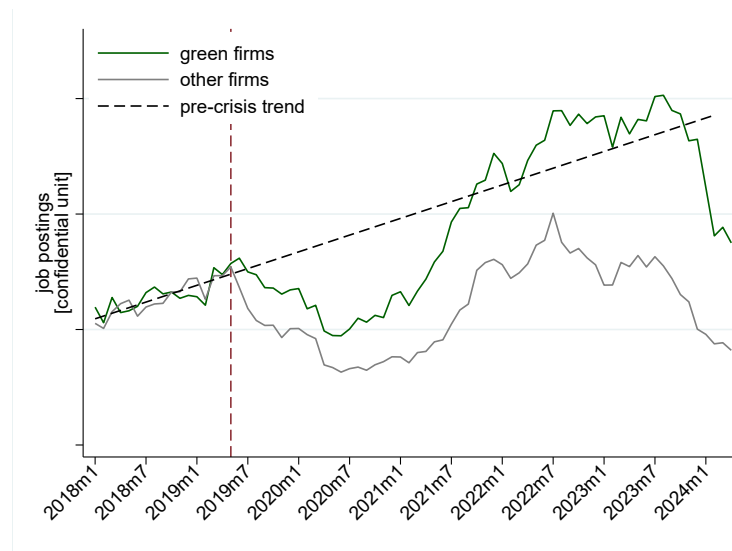
Note: The ifo employment index for the automotive sector (C290000: “Manufacture of motor vehicles trailers and semi-trailers”) is seasonally adjusted and based on a survey question regarding employment plans for the next three months. The number of employees from the statistical office reflects employees 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



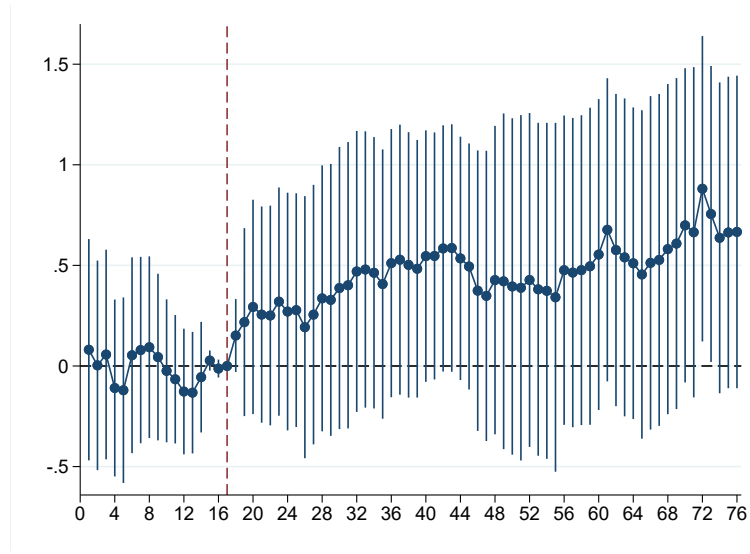
Note: The left panel shows the three components of the ifo Business Climate Index for the automotive sector (C290000: “Manufacture of motor vehicles trailers and semi-trailers”). Firms are asked to assess their current business situation as well as their expectations for their future business situation.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



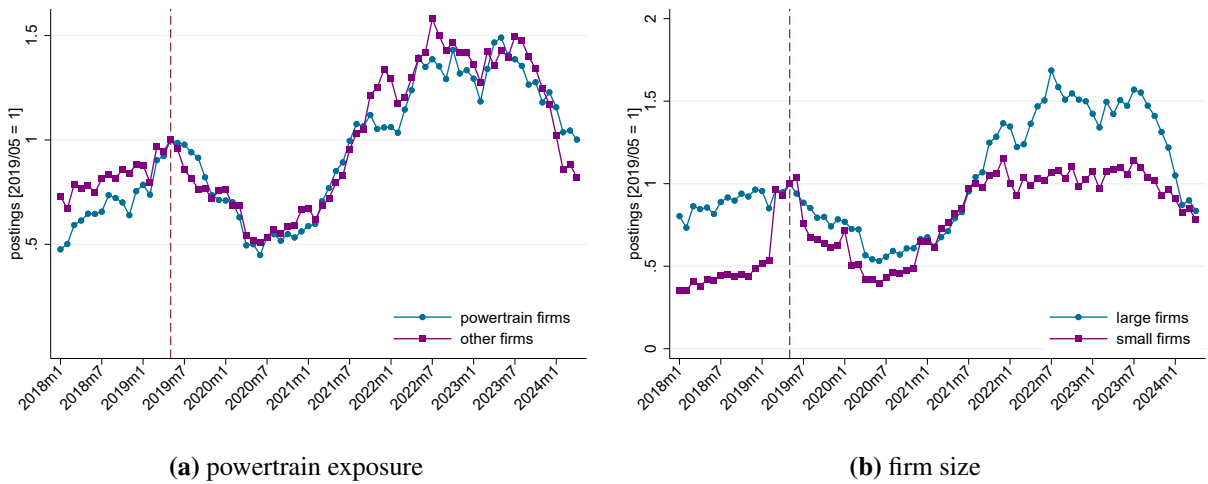
Note: The number of postings is multiplied by a constant for confidentiality.
Sources: Indeed, Patstat.

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



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