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

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Abstract

Workforce adjustments are a crucial dimension of technology-related structural change, and labor demand as a highly reactive decision parameter is a suitable measure for timely detection of such employment adjustments. 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. Our real-time capable index enables us to differentiate labor demand by firms' greenness, 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, competitor product entry, 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 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.

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

JEL: C55; J23; M51; O14; O33

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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), 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). 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 predominantly to battery-electric vehicles but also includes hybrid and 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, to investigate differences in the labor demand response with respect to firms' greenness in a difference-in-differences setup. The crisis was triggered by unexpected competitiveness of an entrant's product[1] as well as escalations of trade conflicts and was sustained by the pandemic and supply chain disruptions. 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 strategic reactions by firms that are reflected in labor demand changes. 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. In contrast, we focus on the company perspective by differentiating labor demand of firms that develop green versus brown technology. Thereby, our approach improves upon most survey and administrative time series that only capture industry-level dynamics. Second, we advance the measurement of labor demand using OJA data. Webb (2019) links patent with occupational task content to measure job exposure

[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.

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.

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.[2] 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

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

the same firm, this gives us a sample of 3,199 firms with significant patenting activity in powertrain technologies.[3] 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.[4] With our method, we are able to classify 18,138 powertrain patents that are specific to green or brown technology, which amounts to 35.7% of automotive patents. 29.3% of powertrain patents in our sample are related to green technology.

For this sample of patent-active automotive firms, we compute multiple metrics. First, we use the size of their entire patent portfolio, i.e., all patents (classified and non-classified) filed during the observation period, as a proxy for firm size. This proxy of 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 standards[5], 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

[3]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.

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

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

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:

$$\mathrm{LD}_{ft} = \sum_{\phi=f,\kappa=t} \mathrm{OJA}_{ij\phi\kappa} \tag{1}$$

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 suppliers[6], 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 (Adrjan 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

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

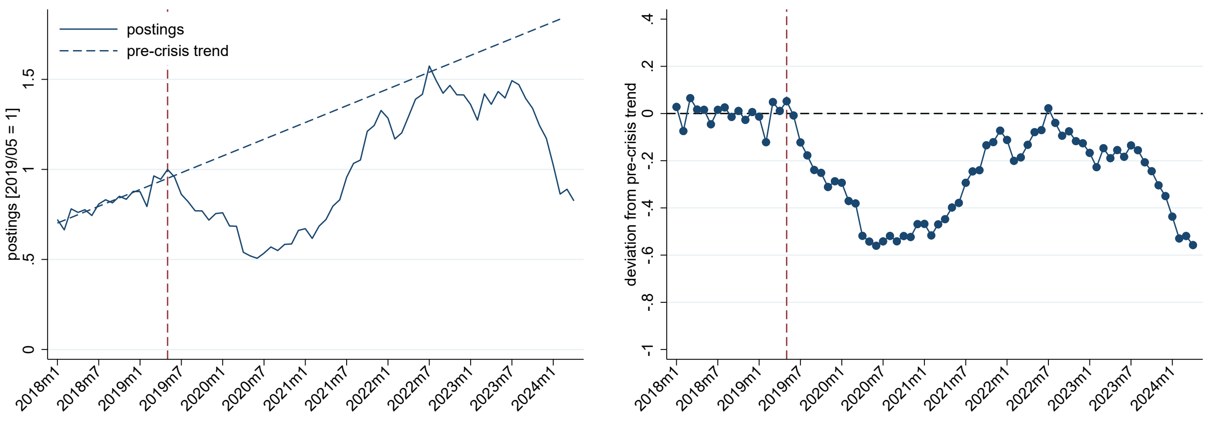
in the premium segment (The Verge, 2019) threatened German carmakers' business model. The industry reacted with large-scale cost savings and restructuring efforts, including significant job cuts over the coming years (Süddeutsche Zeitung, 2019; Manager Magazin, 2019a,b). The poly-crisis was reinforced 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

$$\mathrm{LDI}_t = \frac{\sum_{\tau=t} \mathrm{LD}_{f\tau}}{\sum_{\tau=05/19} \mathrm{LD}_{f\tau}}. \tag{2}$$

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



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

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:

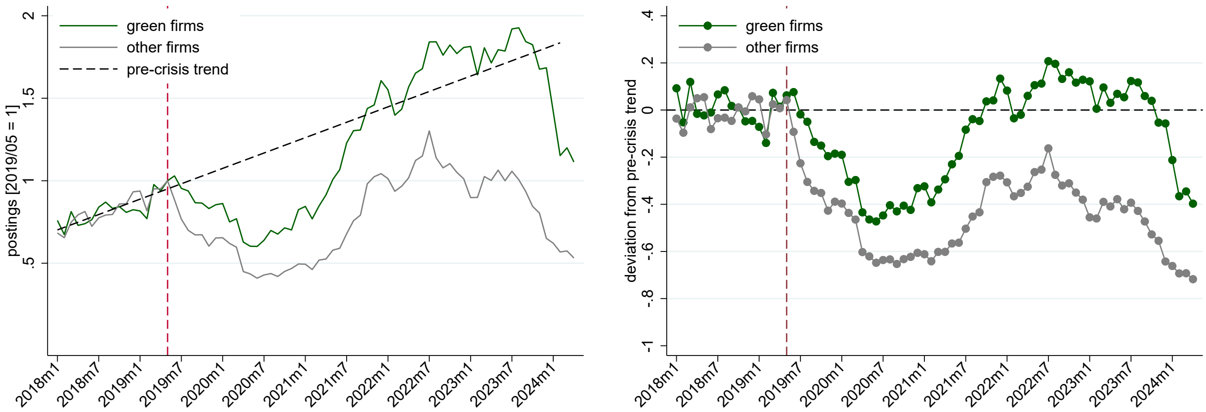
$$\mathrm{LDI}_{gt} = \beta_0 + \beta_1(\mathrm{post}_t * \mathrm{green\_firms}_g) + \beta_2\,\mathrm{green\_firms}_g + \delta_t + \varepsilon_{gt} \tag{3}$$

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 $\mathrm{green\_firms}_g$ 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. Note that we apply the difference-in-differences estimator here to distinguish the response of green and brown firms' labor demand. As the poly-crisis represents a series of fundamental shifts challenging the automotive industry, the coefficient reflects a counterfactual world where all these developments were put on hold and green and brown firms would have evolved similarly. Rather than understanding our coefficient as the result of a specific one-time treatment, we focus our interpretation on differences in the dynamic patterns in the labor market responses of green compared to brown firms.

3 Results

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

Figure 2: Labor demand and firm greenness



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

Sources: Indeed, Patstat.

Results of the difference-in-differences regression reported in Table 1 confirm these findings. Column (1) shows the results of a model without year $\times$ 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, 2024) and administrative data on vacancies[7], 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.

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

With naturally larger confidence intervals, the point estimate of this specification suggests that green versus brown firms' labor demand is, on average, 48.7 percentage points higher after May 2019. Overall, these results suggest green firms' labor demand during the poly-crisis is, on average, 36 to 53 percentage points higher than brown firms' labor demand.

Table 1: Difference-in-differences

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

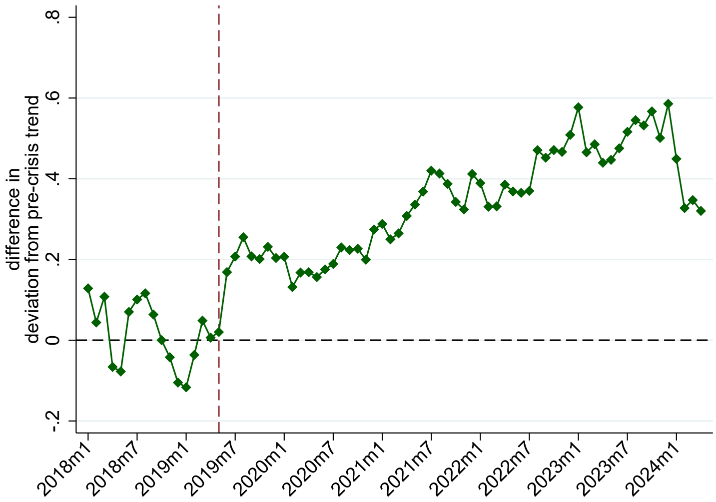
Notes: Robust standard errors in parentheses and clustered at the firm level in column (4). * $p > 0.01$, ** $p > 0.05$, and *** $p > 0.1$. *Sources:* Indeed, Patstat.

Since the average effect estimated in Table 1 neglects potential dynamics already apparent in Figure 2, we plot the evolution of the effect from the conservative specification using the deviation from the pre-crisis trend in Figure 3. Before the poly-crisis, the difference between green and brown firms hovers around zero. After May 2019, the difference in the deviation from pre-crisis trend of labor demand jumps to around 20 percentage points and remains at this level until the end of 2020. Starting 2021, the difference further increases as green firms' labor demand recovers more strongly than brown firms' labor demand. The gap between green and brown firms continuously widens until the end of 2022, when it reaches a maximum of just below 60 percentage points. During 2023, the gap stays roughly constant before it drops to about 35 percentage points at the end of 2023 and remains at this level until April 2024. The generally widening gap between green and brown firms implies that green firms were able to expand their advantage over brown 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.[8] 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

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

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.

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.[9] 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 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.

[9] 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.

Table 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*** (0.025)	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 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 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.

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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 job category: normalized LDI

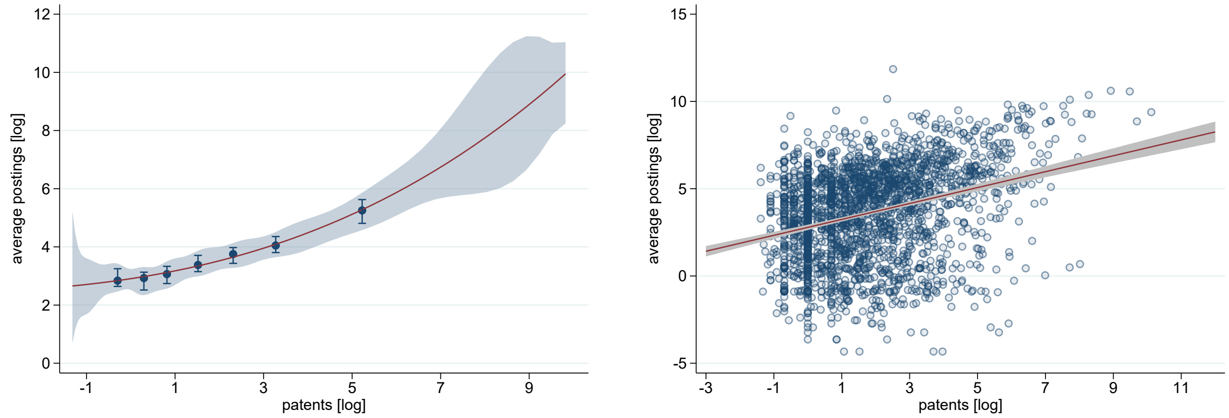
	(1) **all jobs**	(2) installation & maintanance	(3) software development	(4) management	(5) project management	(6) sales	(7) IT operations & helpdesk	(8) production & manufacturing	(9) administrative assistance	(10) marketing
Post × green	0.504***	0.213***	0.628***	0.330***	0.423***	0.193***	0.641***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



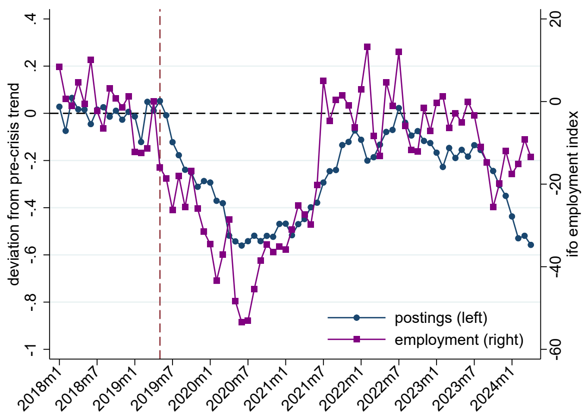
(a) binscatter **(b)** scatterplot

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.

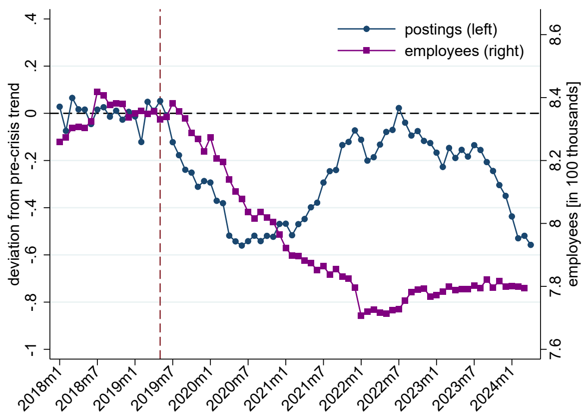
Figure A.2: Job categories

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



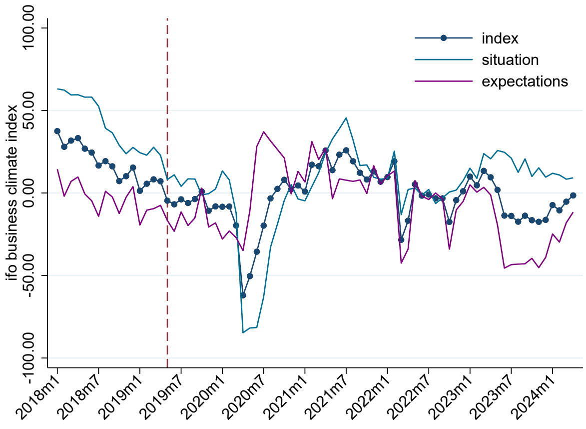
(a) employment survey



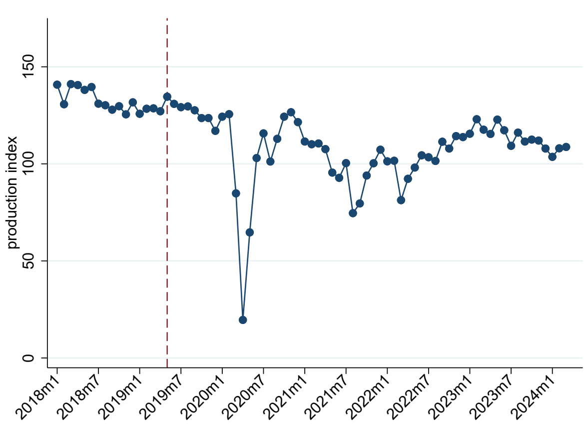
(b) employees

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



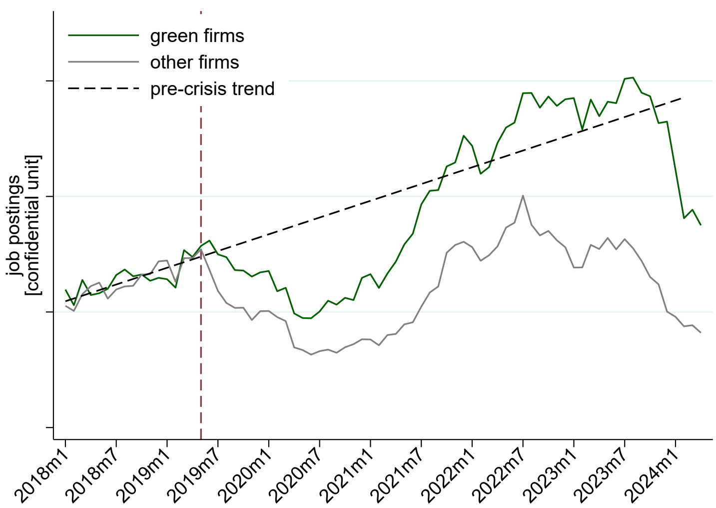
(a) business climate survey



(b) production index

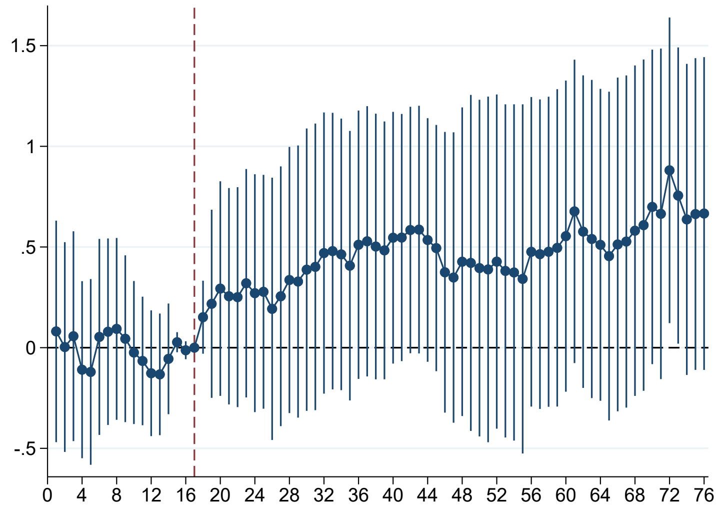
Note: The left panel shows the three components of the ifo Business Climate Index for the automotive sector (C290000: "Manufacture of motor vehicles trailers and semi-trailers"). Firms are asked to assess their current business situation as well as their expectations for their future business situation.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



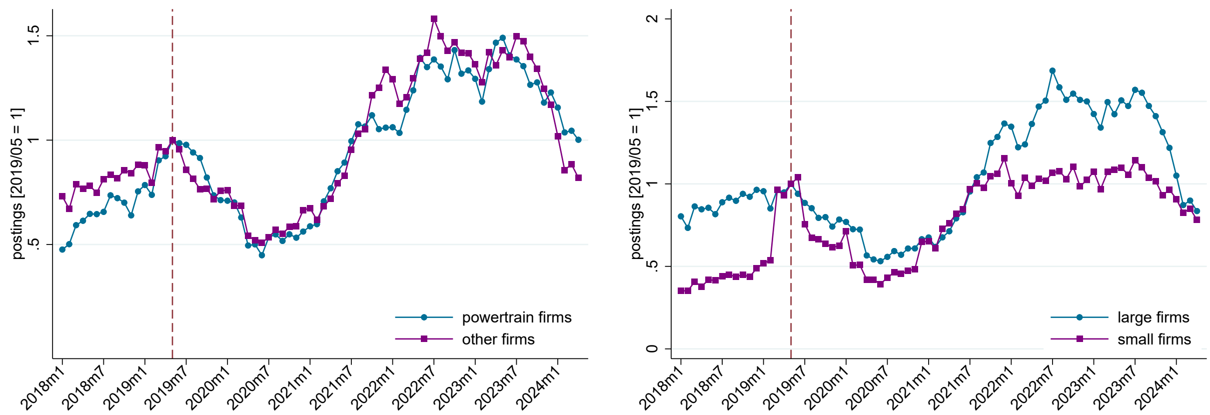
Note: The number of postings is multiplied by a constant for confidentiality.
Sources: Indeed, Patstat.

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.