Did the 2022 global energy crisis accelerate the diffusion of low-carbon technologies? *

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Abstract

This paper develops measures of the diffusion of a comprehensive range of low-carbon technologies in 35 countries from 2019 to 2022 using text analysis of job postings and earnings calls transcripts. It documents a rapid acceleration in the diffusion of low-carbon technologies in 2022–with hiring in related roles doubling from 2019–that is driven by technologies related to renewable energy, vehicles, thermal performance, and electrical generation and storage. Rapid growth occurred in three quarters of the countries studied and 228 of 300 subnational regions, although was fastest in Europe. It studies the role of the global energy crisis in triggering this accelerated technology diffusion, focusing on 16 advanced economies. It finds that establishments in countries that had a higher pre-crisis dependence on imports of natural gas, and were thus more exposed to the price shock, differentially increased hiring for low-carbon technology related roles from March 2022 onwards. Within more exposed countries, establishments with a higher pre-crisis energy intensity also saw a differential increase in hiring relative to less energy intensive ones.

Key words: technology diffusion, low-carbon transition, clean energy, global energy crisis, job postings, energy prices, Russia-Ukraine war

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1. Introduction

There is wide agreement that achieving net-zero emissions globally will require a rapid increase in the pace and scale of deployment of low-carbon technologies (LCTs). Despite the central importance of LCT deployment, however, to date there has been limited empirical evidence on the *diffusion* of multiple LCTs across time and space, with research focusing instead primarily on indicators of invention and innovation. For example, a wide economics literature has studied low carbon patenting activity (e.g. Popp [2002], Aghion et al. [2016], Dechezleprêtre et al. [2013], Popp [2019]) and a growing literature focuses on declining LCT costs (e.g. Way et al. [2022], Grubb et al. [2021]). Research that measures LCT diffusion has typically studied the adoption of a specific LCT in a specific industry or country (e.g. studying the efficiency of vehicles (Knittel [2011]) or residential energy efficiency (Costantini et al. [2017]).

This paper aims to fill this gap by providing new empirical evidence on proxies for the diffusion of a comprehensive range of LCTs across regions, countries, industries and occupations over time, until the end of 2022. We first follow a growing literature that infers the spread of new technologies through their footprint in the demand for new tasks or skills in the text of job postings (e.g. Acemoglu et al. [2022], Goldfarb et al. [2023]) and mentions in the quarterly earnings calls of the world's largest firms, in a similar vein to Bloom et al. [2021].

It uses a high-frequency dataset of online job postings from 35 countries from Lightcast (formerly Burning Glass Technologies, henceforth BGT) from 2019 to the end of 2022, with data spanning back to 2014 for a subset of 16 of these countries. It creates a comprehensive list of keywords relating to LCTs from the European Patent Office (EPO)'s Y02 classification of patents related to 'climate change mitigation technologies', hand-extracting all technology-related nouns from the titles and descriptions in the Y02B, Y02C, Y02E, Y02T and Y04S classifications. It then classifies job postings as being LCT-related if they mention any of these LCT keywords in the text (or close synonyms). It additionally uses a dataset of the transcripts from quarterly shareholder earnings calls meetings of publicly listed firms from 2014 to 2022, constructing an analogous measure of the extent to which publicly listed firms are discussing LCTs in their shareholder meetings.

It finds that there was a rapid increase in LCT-related hiring in 2022, particularly in the second half. Using a subset of data for 16 advanced economies for which online job postings

data is available since 2014, it finds that growth in LCT-related hiring was very modest from 2014 to 2018, but subsequently accelerated rapidly in 2022. The share of all online job postings mentioning LCTs more than doubled between 2019 and 2022, including an increase by three-quarters from under 1 percent of all online job postings at the end of 2021 to 1.7 percent by the end of 2022. For an expanded dataset of 35 countries, there was a similar pattern of only modest growth from 2019 to 2021 and then rapid growth in 2022.

Rapid growth in LCT-related hiring occurred in three quarters of the countries studied, although was strongest in Europe. The rate of growth in the share of jobs related to LCTs in 2022 relative to 2021 was highest in France, Luxembourg, Germany and Australia. In the US, the share of job postings related to LCTs increased by 37 percent, from 0.39 percent in 2021 to 0.54 percent in 2022.

Four groups of LCTs had particularly large increases from 2021 to 2022: those related to renewable energy, new energy vehicles, improved thermal performance, and electrical generation and storage. In particular, of the nearly one million more LCT job postings in 2022 compared to 2021, nearly three quarters were related to just seven LCTs: electric vehicles, renewable energy - general (mentions of 'alternative', 'clean', or 'renewable' energy), solar energy, insulation, ev charging, heat pumps, and wind energy. There were 3.3 times as many electric vehicle job postings in 2022 as in 2021, and 2.3 times as many electric vehicle charging job postings, for example. Rapid growth in LCT-related openings in 2022 occurred in 19 of the 20 ISIC 1-digit industries, but was particularly pronounced in the manufacturing, electricity and heat supply, and construction industries. Growth was fastest for high skilled occupations, but rapid growth occurred for all skill types.

Mentions of LCTs in quarterly earnings calls transcripts also increased rapidly in 2022, although growth started somewhat earlier than for job postings. The share of earnings calls mentioning LCTs started to increase rapidly in the first quarter of 2021, following steady but modest growth since 2014. This is consistent with the findings of Bloom et al. [2021] that firms start discussing emerging technologies before deploying or commercializing them. The LCTs experiencing the most rapid growth in mentions in earnings calls were very similar to those in the job postings: renewable energy, electric vehicles, solar energy, ev charging, energy storage, and wind energy.

The paper next turns to exploring one potential explanation for the rapid increase in LCT-

related labor demand in 2022: the substantial and largely unanticipated increase in energy prices as a result of the global energy crisis and, particularly, the Russian invasion of Ukraine. In the wake of the Russian invasion, the price of natural gas in Europe doubled between January 2022 and August 2022 and the impact quickly spread to affect all fossil fuel prices and electricity prices in energy importing countries around the world. In August 2022, half of European countries had wholesale electricity prices over 11 times as high as their January 2019 levels. However, the impact of the energy crisis was felt unevenly across countries, industries, firms and consumers. In the US, for example, the benchmark Henry Hub natural gas price remained largely unchanged throughout the crisis. Countries were differentially exposed depending on their import reliance and energy mix, while firms were differentially exposed depending on their ex-ante energy intensity. [1]

It first examines whether there was a differential increase in LCT-related hiring during the crisis in the firms most exposed to the rise in energy prices, due to their *ex-ante* energy intensity of production and location in countries that were more dependent, before the invasion, on imports of natural gas or all fossil fuels. It finds that there was a differential increase in LCT-related hiring after February 2022 in establishments located in countries that were more dependent on imports of natural gas or all fossil fuels. In addition, within more natural gas import-dependent countries, firms that were more energy-intensive before the energy crisis differentially increased their LCT-related hiring after the crisis.

Using an event study design, it finds that this differential increase in LCT-related hiring for firms that were more exposed to the price shock began in March 2022. From that point onwards there was a statistically significant increase in LCT-related job postings in several months by more energy-intensive firms in countries with greater exposure to the increase in energy prices. This effect became the most pronounced in December 2022. Much of this increase in LCT postings was for jobs related to one technology group - energy generation - which includes jobs related to renewable energy, heat pumps, low-carbon fuels, decentralized energy and efficient power generation.

Finally, it shows that these results are robust to excluding firms in fossil fuel producing industries, which may have benefitted from the energy price shock. It also shows that *ex ante* country level natural gas and fossil fuel import dependence are not correlated with any

[1] Exposure was also potentially contingent on the extent to which governments responded to the crisis by subsidising the cost of electricity or other energy sources.

baseline country characteristics, while ex ante firm level exposure (the interaction of firm energy intensity and country import dependence) is also not correlated with any baseline firm characteristics, like firm size, sales or profitability. Taken together these results suggest that firms responded to the higher energy prices by expanding human capital investments in low-carbon technologies, reflecting innovation or switching to cleaner energy sources.

This research adds a number of new insights on the global diffusion of low-carbon technologies, the impact of the 2021-2022 energy crisis, and the impact of energy prices on low-carbon technology diffusion. First, it sheds new light on recent patterns of low-carbon technology diffusion, contributing to, and building on, the existing stock of knowledge about low-carbon patenting and adoption of specific technologies. Our findings of only modest growth in LCT-related labor demand and discussions in earnings calls from 2014 to 2020 are consistent with the research of Popp et al. [2021] and IEA [2020] on patterns of low-carbon patenting, given that we would expect diffusion of technologies to occur with a lag after patenting. The former paper finds that patent counts for building energy efficiency, solar PV, hybrid and electric vehicles and wind energy stagnated in the 2010s but experienced a second growth wave beginning in 2016. The latter also finds that LCT patenting stagnated between 2014 and 2016 and then started growing again from 2017, with the key driver of LCT growth since 2017 in cross-cutting technologies such as batteries, hydrogen and smart grids, that serve as enablers of the transition. Our findings of rapid, near-exponential, growth in LCT-related labor demand in multiple countries at once are also consistent with the work of Way et al. [2022] that many LCTs have followed Wright's Law with costs falling as a function of cumulative deployment, and Grubb et al. [2021] that low-carbon patenting is cumulative, resulting in patterns of diffusion that would be expected to be non-linear.

It also adds new insights on the impacts of energy price shocks and the 2021-2023 energy crisis in particular. To date, there has been limited empirical evidence on the economic impact of this surge in energy prices on technology adoption or innovation, with the existing research focused mostly on the negative consequences for output and employment (e.g. Ferriani and Gazzani [2022], Lan et al. [2022], Di Bella et al. [2022]) or being theoretical. Our findings that more energy import dependent countries differentially increased LCT-related hiring during the key crisis months could reflect input-saving technical change, consistent with the macroeconomic theory of Hassler et al. [2021], who model how markets economize

on scarce natural resources, with an application to fossil fuels. Such a response would also be consistent with the empirical findings of Fontagne et al. [2023] that in response to energy price increases during 1996-2019, French manufacturing firms reduced their energy demand and improved their energy efficiency.

Our findings are also consistent with the work of Umar et al. [2022], who evaluate the impact of the Russian-Ukraine war on financial returns in the metals, conventional energy, and renewable energy markets by exploiting the timing of the invasion, finding a significant increase in returns for the renewable energy industry. In addition, our findings also support the hypothesis of Zhunussova [2022] that higher energy prices from the crisis could have positive implications on the clean energy transition, along with their simulation results, which suggest that the combination of higher projected carbon prices and energy prices would reduce emissions in Europe. Our findings could also reflect the impact of the energy crisis on relative perceptions around energy security, fossil fuels and clean energy sources in exposed countries. Steffen and Patt [2022], for example, present early evidence on how the war has changed public support for policies related to the phase-out of fossil fuels, and for policies supporting the phase-in of clean energy alternatives, using a population survey in Switzerland. It also contributes more broadly to the wider literature on the implications of the Russia-Ukraine war, including the work of Garicano et al. [2022] on the reshaping of supply chains, exchange rate impacts and macroeconomic impacts and the work of Di Bella et al. [2022] on macroeconomic consequences for Europe.

Finally, our results also contribute to the literature on green or clean energy jobs. For the US, Curtis and Marinescu [2022] use the same online job postings dataset from BGT, but focus only on the growth in wind and solar energy jobs from 2010 to 2019. These authors use a different method for classifying jobs based on the job titles and skills listed in the postings, in contrast to our method using the full text of the advert. Our calculation of the LCT share of job postings in the USA (0.39 percent in 2019) is nearly double the 0.2 percent they find, reflecting both the wider scope of our focus on all LCTs and potentially the wider corpus of text from the job postings used in our analysis. Our findings on the industry composition of LCT-related jobs and the high-skilled nature of LCT-related jobs are similar to their findings, however.

Another closely related paper is that of Saussay et al. [2022], who also study low-carbon jobs using the BGT job postings data in the USA from 2010-2019. Their approach builds on

the ONET's definition of tasks that are considered 'green' and extracts a list of 250 low-carbon keywords that the authors then search for using the skills extracted by BGT from the job postings. Using this method, they find a higher 1.3 percent share of "low-carbon job postings". Our findings on the skill-bias of LCT-related job postings are also consistent with their finding that low-carbon jobs have higher skill requirements.

Our research adds to, and complements these papers, in three important ways. First, our technology based approach allows us not only to study green jobs but to measure the technological footprint of the low-carbon transition specifically. Second, by using the full text of the job postings, we can analyze an increased number of countries in the BGT data, and may be able to more comprehensively identify LCT-related jobs, relative to an approach using only the skills in the job postings. Third, by considering a wide range of countries and extending our analysis to the end of 2022, this paper is able to study global patterns of LCT diffusion and explore the impact of the energy crisis.

The rest of the paper is structured as follows. Section 2 presents the data sources and measurement of LCTs. Section 3 provides a set of stylized facts about the diffusion of LCTs as measured using the online job postings and earnings calls datasets. Section 4 explores the impact of the global energy crisis on accelerating the diffusion of LCTs via an event study design. Finally, Section 5 concludes.

2. Data and measurement

Our primary measures of LCT diffusion are derived from scraped online job postings. In the absence of detailed data on the deployment of multiple technologies across firms, regions, industries and countries, these real-time rich text data sources have been increasingly used as a barometer for the diffusion of new technologies, as reflected through their skills demand footprint or extent (see for example Acemoglu et al. [2022] and Bloom et al. [2021]). This data is particularly useful for studying rapid advances in new technologies that have not yet been clearly defined or captured by statistical agencies using traditional data sources. This section first describes the key datasets, and then discusses the definition and measurement of LCTs.

2.1 Online job postings

Our main measure of LCT diffusion uses data on scraped online job postings from Lightcast (formerly Burning Glass Technologies, henceforth BGT) for 35 countries. We include data for a sample of 580,441,273 job postings from 16 of these countries, which are predominantly advanced economies in Western Europe and North America, have data starting from at least 2014 ('the 2014 Cohort'). These countries represented 46 percent of global GDP in 2019. Data on 23,536,782 job postings in an additional 19 countries is available from 2019 onwards ('the 2019 Cohort'). These countries represented a further 5.4 percent of global GDP in 2019. [2]

BGT scrape what they estimate to be over 40,000 online job boards and company websites to aggregate the job postings, parse and deduplicate them into a systematic, machine-readable form, and create labor market analytic products. Thanks to the breadth of their web crawling techniques, BGT believes the resulting database captures a near-universe of jobs that were posted online.

The BGT data has the advantages of its richness and breadth. The text data allows us to search for jobs related to specific and granular technologies. Take the example of 'heatpumps'. There is not yet an occupation classification, even at the most granular disaggregation, for heatpump installers, meaning that it would not be possible to use traditional labor market surveys to measure the growth in jobs related to the deployment of heatpumps. While there may be datasets on heatpump sales, these are unlikely to be available consistently at a high time series frequency, across countries and within regions and industries. The BGT data also includes some 70 standardized fields for each vacancy, allowing us to pick up jobs related to granular technologies and classify them by detailed industries, regions, occupation codes and skill types.

However, the data also comes with certain shortcomings. First and most notably, it only includes jobs posted online and this subset of vacancies may not be fully representative of all vacancies, while vacancies are also a flow measure of labor demand, rather than a measure of the stock of employment. A growing literature has now shown that online job postings tend to be over-representative of higher-skilled occupations and industries, although recent research

[2] For the 2014 cohort these countries are the US, Canada, UK, Australia, New Zealand, Singapore, Denmark, Norway, Italy, Austria, Belgium, Switzerland, Germany, France, Luxembourg, Netherlands. For the 2019 cohort it additionally includes Ireland, Czech Republic, Croatia, Hungary, Malta, Poland, Portugal, Romania, Slovenia, Slovakia, Spain, Sweden, Estonia, Finland, Lithuania, Latvia

has generally found that in advanced economies a very high share of jobs are now posted online. For the US, BGT shows that the share of jobs online as captured by BGT is roughly 85% of the jobs in JOLTS in 2016. For the UK, Javorcik et al. [2022] show it covers approx 86 percent of all job vacancies in the UK Vacancy Survey.

The subset of vacancies posted online may also vary over time and across countries. In the Online Appendix we provide a detailed benchmarking of the BGT data for all 35 countries by comparing it with data sources including total population, active labor force, employment and estimates of total job vacancies. The ratio of total online job vacancies to employment would be expected to vary across countries in light of different separation rates, different rates of replacement relative to firm growth and also different shares of jobs posted online relative to offline. However, we might expect it to be broadly correlated with the overall vacancy share, online and offline, in the economy. Online Appendix Figure A1 explores the correlation between each country's ratio of BGT job postings to total jobs and the job vacancy rate as measured using traditional labor force surveys. There is generally a positive relationship between these two metrics, with small high income countries like Singapore, Switzerland and Luxembourg being over-represented in the BGT data and Eastern European countries like the Czech Republic, Hungary, Latvia and Estonia being under-represented.

A final downside of online job postings data is that it measures stated, but not necessarily realized demand. So while there could be many online job postings for heatpump installers, if there are no candidates to fill these jobs then the heatpumps may not be installed. For a complete picture, one would also like to see hires, separations, wages, and internal training, but to the best of our knowledge, there is no data available to construct analogous measures of LCT diffusion.

2.1.1 Occupation and industry classifications

The BGT data includes national occupation classifications and the ISCO classification for EU countries. We crosswalk these national classifications to the ISCO, with more details on this process described in the Online Appendix. We then use the ISCO classification to categorize occupations by skill level as follows. The high skilled category includes Managers, Technical and Professional occupations. The mid skilled category includes Clerical & Sales, Skilled Trades, and Operatives. The low-skilled category includes Cleaners,

labourers, and other 'elementary workers'. We also parse out research-related occupations, defined at the three-digit ISCO level as Physical and Earth Science Professionals (211), Engineering Professionals (excluding Electrotechnology) (214), Electrotechnology Engineers (215), University and Higher Education Teachers (231), Social and Religious Professionals (263), and Physical and Engineering Science Technicians (311). Finally, we define production-related occupations at the two-digit ISCO level as Stationary Plant and Machine Operators (81) and Assemblers (82).

The data also includes national industry classifications and the ISIC classification for EU countries. We also use crosswalks to covert all national classifications to ISIC and use this as our primary industry classification, with more details on this process provided in the Online Appendix.

2.2 Earnings calls transcripts

As a secondary measure of diffusion for comparison we also use data from Refinitiv Eikon on the transcripts from quarterly shareholder earnings calls meetings of publicly listed firms from 2014 to 2022. This data is increasingly used by economists to measure firm uncertainty (e.g. Hassan et al. [2019]), firm sentiment (e.g. Hassan et al. [2020]) and proxies for whether new technologies are 'disruptive' in terms of being widely discussed in boardrooms (e.g. Bloom et al. [2021]). In total it covers 3,585 firms in the same 35 countries and years for which there is BGT data. Over two-thirds of these earning calls were by US-based firms (68 percent of all earnings calls since 2014), although a smaller share of earnings calls that mention LCTs (57 percent) were by US-based firms.

2.3 Defining and measuring LCTs

Our starting point to create a list of keywords for LCTs was to use the European Patent Office (EPO)'s Y02 classification of patents related to 'climate change mitigation technologies' defined as 'technologies or applications which can be considered as countering the effects of climate change'. This patent classification is regularly updated by the EPO with the aim of comprehensively tagging patents related to climate mitigation. It covers seven main categories, namely energy, greenhouse gases (GHG) capture, buildings, industry (including

agriculture), transport and waste and wastewater management. A classification scheme for smart grids, Y04S, has also been developed and we include that as well. We use the Y02 classification for two reasons. First, it is continually updated, meaning it includes more recent LCTs, which is important when studying a rapidly involving technological field. Second, it is more comprehensive than other commonly used lists of LCTs.[3]

We hand-extracted all the technology-related nouns from the titles and descriptions in the Y02B, Y02C, Y02E, Y02T and Y04S classifications. We then expanded these with synonyms, hypernyms and hyponyms from WordNet, Dictionary.com and google trends and kept only 'bigrams', following Bloom et al. [2021]. This resulted in a list of 237 English-language keywords, which are included in Online Appendix Figure A.3. We then expanded this with the singularized and pluralized versions of these words, resulting in a final list of 451 English language keywords. We then used a professional translation company to translate these lists of keywords into the 27 other official languages of the countries included in the dataset and to identify relevant synonyms of these words. We then searched for the keywords in the job postings in both the official languages of each country and English. We then classify a job advert as related to each LCT if it includes at least one keyword associated with that LCT in the text. We do the same for the earnings calls transcripts.

We organize these 46 LCTs in a four-level hierarchy. At the lowest level are the actual 451 keywords that are searched for in the job advert or earnings call text, each of which is associated with one of 46 technologies. We then group these technologies into one of 19 Technology Groups. To avoid double-counting of job postings and earnings calls that contain multiple keywords related to the same technology (e.g. "electric cars', "electric engine", and "electric vehicle"), our dataset on LCT-related job postings and earnings calls is calculated as the total number of job postings or earning calls that mentioned a single technology regardless of the number of different related keywords (for the same technology) that the text contains. Statistics on total LCT postings were similarly adjusted to count each LCT-mentioning advert as a single job advert, regardless of the number of different technologies mentioned in the job advert.

[3]Alternative lists of LCTs include the International Energy Agency (2021)'s Clean Energy Technology Guide or the classifications of Dussaux et al. [2022]. However, we found all of these to be more limited in scope, less recently updated or more challenging to turn into a list of technology-related keywords than the Y02B classification.

TABLE 1. TOP TEN TECHNOLOGIES IN JOB ADVERTS AND EARNINGS CALLS

Top Technologies	Adverts	Top Technologies	Earnings Calls
renewable energy - general	1304835	renewable energy - general	7965
solar energy	1056369	electric vehicles	5587
insulation	920535	biofuels	3507
electric vehicles	793571	solar energy	3310
wind energy	478912	wind energy	2647
biofuels	335225	energy storage	1566
heat pumps	326242	insulation	1536
nuclear	288860	carbon capture	1301
ev charging	230087	ev charging	1146
energy storage	220982	nuclear	1023

2.3.1 LCT-related job postings

We find a total of 4,857,876 LCT-related job postings since 2014 across the 16 countries with data for all nine years, and an additional 1,311,327 LCT-related job postings since 2019 in the 19 countries with data since then. This represents 0.8 percent and 5.6 percent (respectively) of the total job postings across these countries over the entire time periods. The keywords found in the highest number of job postings are "insulation", "renewable energy", "renewable energies", and "electric car". Totals for the top 30 keywords are found in Appendix Table A7. Aggregated up to technologies, the most prevalent technologies mentioned in job postings are renewable energy (as an umbrella term), solar energy, insulation, electric vehicles and wind energy. Table 1 lists the technologies with the highest number of total postings. The total postings for all 46 technologies over the entire period is included in Online Appendix Table A4. Table A6 in the Online Appendix also lists the fastest growing technologies - decentralized energy, presence detection sensors and EV charging.

Appendix Table A1 lists the countries included in the dataset, including the first year for which data from that country appears in the BGT postings dataset and the total number of job postings, both LCT-related and overall. The countries with the highest share of LCT-related job postings across all nine years are Switzerland, Italy, Norway, and Denmark and while there are also high shares of LCT-related job postings in the data since 2019 of Slovakia, Spain, Czech

Republic, and Sweden. Nearly all countries experienced a large increase in the share of all job postings related to LCTs between 2014 and 2022, as is shown in Figure 2(a)).

What are these LCT-related job postings capturing? A hand examination of the job postings including these keywords demonstrates that these job postings are picking up the full 'Schumpeterian trilogy' of invention, innovation and diffusion of the technologies. A subset of examples is provided in the Online Appendix. They include jobs related to the invention of LCTs. One example of this is a job advert for a PhD studentship in Materials science for lower-emissions aircraft. They also include job postings related to innovation in LCTs. One example of this is a job advert for a General Manager at an Electric Vehicle company. Then they also reflect the deployment of LCTs at the energy-systems level, for example a job advert for a solar farm operative, deployment at the household level, for example an advert for a household heat pumps technician. Finally, they also reflect within-firm deployment, for example an advert for a corporate sustainability manager.

Appendix Section A.5 provides comparisons of our job postings diffusion trends versus alternative measures of diffusion for select LCTs. Trends in electric vehicle-related job postings and EV sales are correlated in most countries.

2.3.2 Mentions of LCTs in earnings calls transcripts

We find a total of 20,529 earnings calls in the 2014 cohort that mention a low-carbon technology, with another 1,311 LCT earnings calls in the 2019 cohort countries. This represents 14.4 percent and 22.0 percent (respectively) of the total earnings calls across these countries over the entire time periods. Table 1 lists the technologies with the highest number of total mentions in earnings calls, which are roughly similar to those mentioned in job postings, with the addition of carbon capture and nuclear energy. The keywords with the highest number of mentions are 'renewable energy', 'electric vehicles', and 'clean energy' with the top 30 keywords by mention listed in Appendix Table A7.

2.4 Factset firm-level data

We also match the BGT job postings dataset to firm-level data provided by FactSet, a private company that collates data on firm market intelligence and networks, including inter-firm and intra-firm linkages. Factset's data is collated from scraped source documents including

annual reports/filings, investor presentations, press releases, and company websites. Factset provides various data products. Factset Fundamentals provides consolidated data on financial statements and other firm information for publicly traded companies. Factset Revere includes data on entities supply chain relationships, including on suppliers, customers, competitors and partnerships. Moreover, the covered linkages are not limited to firm-to-firm, but also capture firm-to-affiliate relations. We combine these two data sources to construct a final dataset of 169,420 entities with bilateral relationship information between 2012 to 2022. Entities are defined as *de jure* corporate institutions (e.g., firms and affiliates). Of these, a subset of around 46,000 entities (27%) have available information from Factset Fundamentals for at least for one year within the same period.

2.5 CDP emissions data

We also use data from the Carbon Disclosure Project (CDP) Full GHG Emissions database for company information on GHG emissions and fuel consumption by type in 2020. CDP provides one of the most extensive and advanced global source of firm-level emissions. The dataset covers approximately 6,400 firms in 80 different countries, and contains reported and estimated Scope 1, 2 and 3 GHG emissions at the firm level. Moreover, CDP also provides information on reported and estimated fuel consumption, as well as purchased steam, heat, electricity and cooling (SHEC) in megawatts per hour (MWh) equivalent. CDP works together with companies to develop their emissions reporting and in return incorporates their emissions in a global database, which is also used to produce emissions estimates for companies that do not disclose. CDP's disclosure platform builds on the recommendations from the 2017 Task Force on Climate-related Financial Disclosures (TCFD), which is increasingly recognized as the global standard for emission reporting. It translates these TCFD recommendations and pillars into disclosure questions and a standardized annual format. This leads to a detailed survey, which participating firms fill out every year. CDP then conducts consistency checks for every company, to verify that each data point aligns with other information that companies report internally (e.g., ensuring consistency between reported energy use and Scope 2 emissions) or externally (from other data sources). Large outliers are investigated in detail by reviewing companies' survey responses, and potentially removed. If a datapoint appears to be misreported, and the company is one of the top 200

highest emitters from the previous year, they are contacted for clarification. For missing or possibly misreported data, an estimate is provided alongside the reported value. In the 16 countries considered, the CDP data covers 4793 firms.

2.6 Matching of datasets

The BGT dataset extracts company names from the raw text of the online job postings, where one can be identified. We took these company names as a starting point, obtaining around 10 million unique BGT company names related to at least one job posting from 2012 to 2022 belonging to the 16 countries we study. These names are parsed from the raw text of the job posting and are not cleaned or matched to other postings from the same firm. We next took different variations of the BGT company names, including taking them in lower case, removing punctuation and special symbols, and removing company suffixes (e.g., Ltd., Corp., LLC, A.G., etc.).

We then used two types of matching methods to link BGT and FactSet. Drawing on the information available, we first limited the matching of companies to the country where its headquarters was legally reported to be located, according to FactSet. Our first step was to perform an exact matching exercise searching for each Factset entity name within the BGT data using each of the different company name variations sequentially. We then reduced the list of BGT company names by dropping the ones that had been already matched exactly with FactSet and proceeded to perform a fuzzy matching exercise. This was necessary even after conducting the exact matching because of variations in spelling or punctuation that could cause an exact match to fail, leading to an incomplete or inaccurate match. We next performed a fuzzy match of each Factset company with the BGT dataset using company names in lower case and without punctuation marks, utilizing the term frequency-inverse document frequency method to conduct the main fuzzy matching procedure, and then the Levenshtein distance method as a double step verification of the name matching. Combining the results from the exact and fuzzy matching, we obtained a first subset of 80,000 matched Factset entities out of the 169,420.

As a second step, we expanded the FactSet Relationships dataset by incorporating ownership and structure information, allowing us to search for affiliates of the 169,420 entities as well. For example, if the Factset entity was 'Alphabet', from the entity structure data we

can obtain the full family of affiliates, including 'Google', 'YouTube', and 'Waze'. This resulted in a new expanded dataset that included nearly 2.5 million entities, including the parent companies from the original sample. We then performed a second exact and fuzzy matching exercise searching for this expanded list of company names in the BGT data for all countries (i.e., in this step, we did not limit the matching to the headquarters country). This second step allow us to identify 440,000 affiliates in the BGT data belonging to 108,000 entities in the FactSet Relationships dataset. After combining the results from the first and second step and dropping duplicated matches[4], our final matched dataset includes 109,000 FactSet entities (65% of the 169,420 entities from the supply chain data) linked to almost 1.5 million company names in BGT.

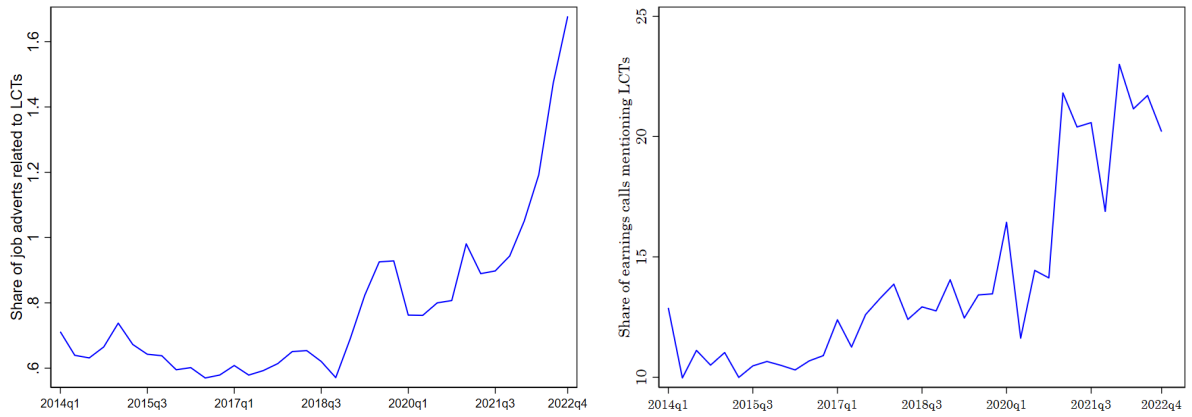
Our final dataset is aggregated at the establishment level, with establishments defined as firm-country-subnational region triplets (subnational regions are typically the highest-level administrative subdivision in each country).[5] Note that while we focus only on establishments in 16 countries with BGT data, these may be of firms headquartered in other countries.

To identify the Factset firms with potential operations in the 16 BGT countries, we narrowed down the sample, retaining only those firms that had at least one establishment in one of the 16 BGT countries, according to information reported by FactSet or BGT, resulting in a sample of 128,764 firms in the FactSet Relationships dataset. Then, we removed every affiliate without information on the subnational region, leaving us with 126,358 firms. Out of this 126,358 firms, we successfully identified 107,981 in BGT ($\approx$ 85%).

Finally, we made the link to CDP using available information on ISIN and CUSIP codes, and following the same matching procedure as detailed above, keeping a dataset with 4,793 firms ($\approx$ 74% of all firms in CDP). We then proceeded to built a balanced panel of firm's establishments-year-month data spanning from January 2020 to December 2022.

[4]The duplicate-elimination criteria is detailed in Appendix A4.

[5]This follows Acemoglu et al. [2020] who define establishments of a firm as the collection of firm job vacancies in each US commuting zone. Sub-national regions are generally defined at Territorial Level 2 (TL2) in OECD Regional Statistics, the "first government layer after the national or federal one." https://www.oecd.org/regional/regional-statistics/geographical-definitions.htm



(a) Job postings

(b) Earnings calls

Figure 1: Share of LCT-related job postings and earnings calls

Notes: Panel (a) displays the share of all online job postings in the 16 countries that mention LCTs. Panel (b) displays the share of all quarterly earnings calls of publicly listed firms that mention LCTs

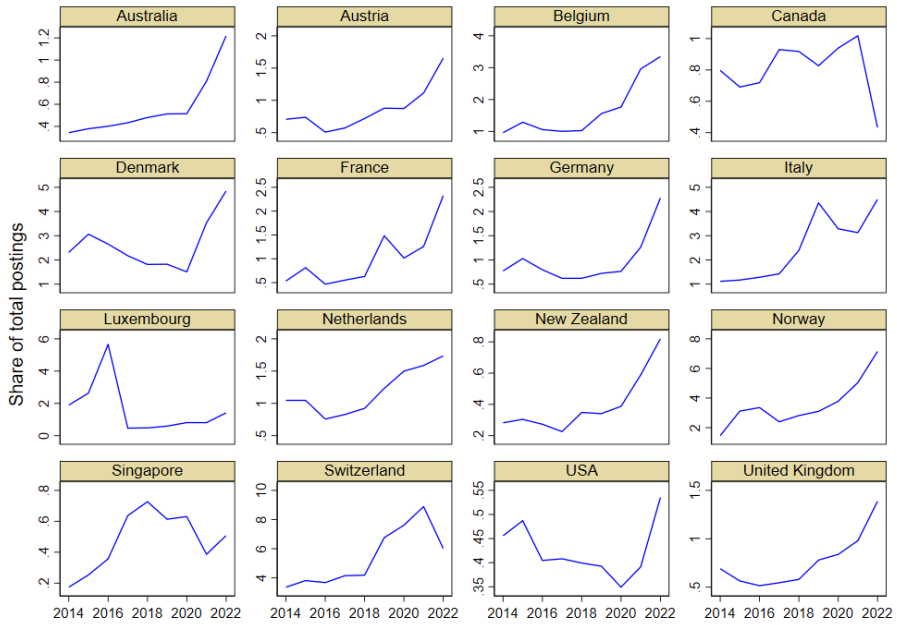
3. The rapid diffusion of low-carbon technologies in 2022

We next document several facts about the diffusion of LCTs over time with a focus on the accelerated diffusion in 2022. We focus on the 16 countries with data starting in 2014 and demonstrate consistent evidence for the remaining 19 countries with data starting only in 2019 in the Online Appendix.

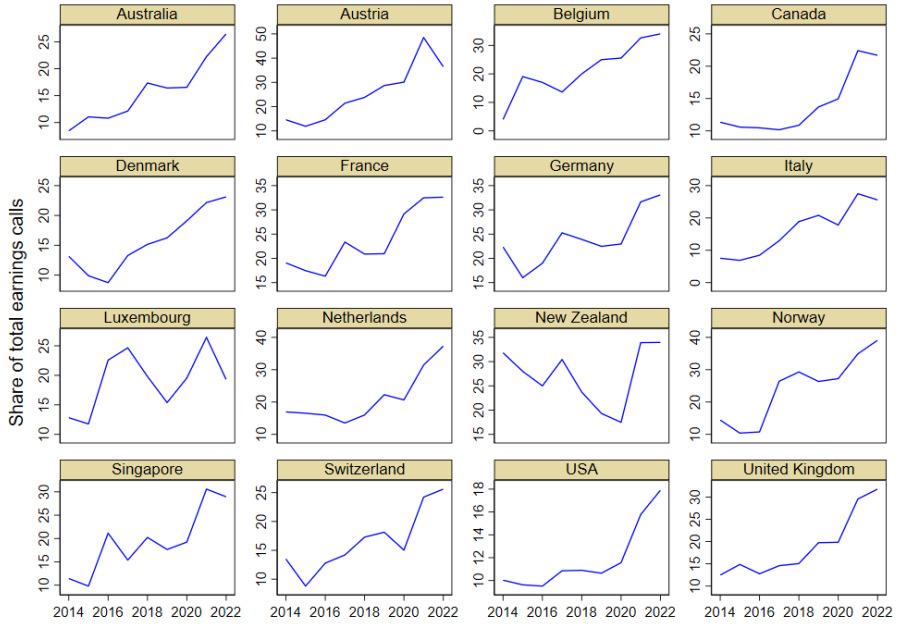
Fact 1: There was rapid growth in LCT-related hiring and discussions in earnings calls in 2022

Figure 1(a) displays the quarterly share of all online job postings posted in these 16 countries that mention LCTs from 2014 to 2022. While the share of all job postings related to LCTs grew only moderately between 2014 and 2018, it began increasing afterwards and eventually more than doubled between 2019 and 2022, reaching above 1 percent in the first quarter of 2022 and 1.7 percent by the fourth quarter. This growth in LCT-related job postings appears to have been preceded by firms discussing LCTs in their shareholder earnings calls (Figure A5(b)). The share of earnings calls mentioning LCTs increased earlier from the second half of 2021, but was nearly twice as high in 2022 as in 2019. When extending this analysis to all 35 countries with data from 2019 onwards, we find a similar rapid rate of growth in 2022 for both job postings and earnings calls, as is displayed in Online Appendix Figure A5.

Fact 2: Rapid LCT growth across all countries and in most subnational regions, but strongest in



(a) Job postings



(b) Earnings calls

Figure 2: Share of LCT-related job postings and earnings calls by country

Notes: For 16 countries with data starting in 2014. Panel (a) displays the share of all online job postings that mention LCTs by year. Panel (b) displays the share of all quarterly earnings calls of publicly listed firms in these countries that mention LCTs.

Europe

The share of job postings related to LCTs increased in 2022 in nearly all countries with data from 2014 (Figure 2(a)). The rate of growth in the share of jobs related to LCTs in 2022 relative to 2021 was highest in France, Germany, Luxembourg, and Australia. The only countries in the sample where the share of LCT-related hiring in 2022 was not at least 25 percent higher than in 2021 were Belgium (where there was a large increase in 2021), the Netherlands, Switzerland, and Canada (the latter two peaking in 2021). In the US, the share of job postings related to LCTs increased by 37 percent, from 0.39 percent in 2021 to 0.54 percent in 2022. Our calculation of the LCT share of job postings in the USA (0.39 percent in 2019) is similar to the findings in two recent papers: nearly double the 0.2 percent share found by Curtis and Marinescu [2022], who only include solar and wind energy job ads, and under one-quarter the 1.3 percent share of "low-carbon job ads" found by Saussay et al. [2022], who use a much wider definition (including, for example, "bus driving").[6] Turning to the further 19 countries with data from 2019, 10 out of 19 saw growth above 25 percent in their share of LCT-related job postings in 2022, as is shown in Online Appendix Figure A6.

For earnings calls, at the country level we find that growth in the share of calls mentioning LCTs started increasing earlier, in 2021 (Figure 2(b)). The countries with the highest growth in the share of earnings calls mentioning LCTs between 2020 and 2022 were New Zealand, the Netherlands, Switzerland, and the UK.

At the subnational level, 228 of the 300 subnational regions in our sample experienced an increase in the share of LCT-related job postings in 2022 from 2021. The increases were particularly large in several areas of Bulgaria, Greece, and the Baltics.

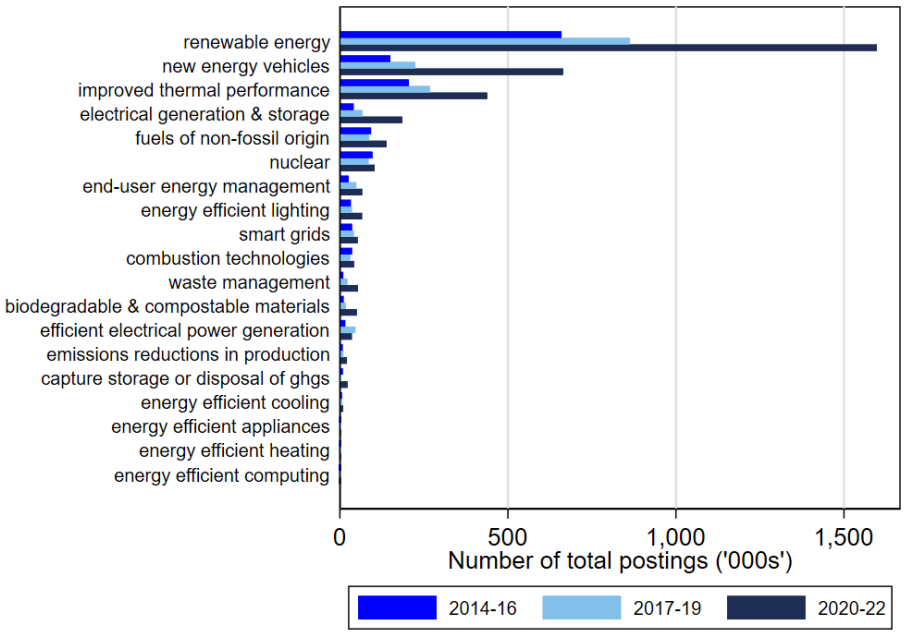
Fact 3: Growth was driven by low-carbon technologies related to renewable energy, new energy vehicles, thermal performance, and electrical generation and storage

The number of job postings increased in nearly all LCT categories in 2022. Much of the overall increase was driven by LCTs that already had a high share of job postings in previous periods, as is illustrated in Figure 3(a). Four groups of LCTs had particularly large increases from 2021 to 2022: those related to renewable energy, new energy vehicles, improved thermal

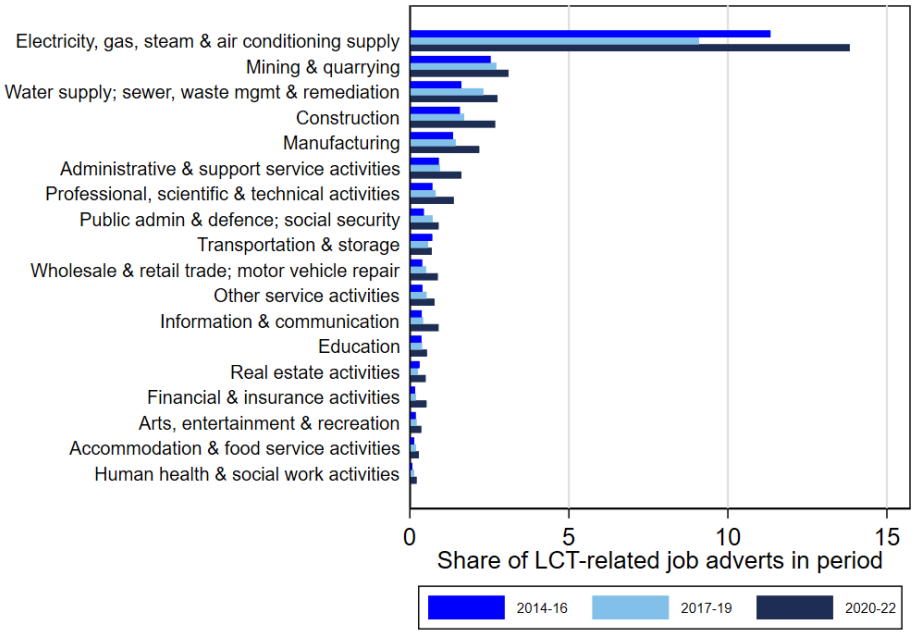
[6]Both Saussay et al. [2022] and Curtis and Marinescu [2022] also use a slightly different corpus of BGT job postings' text to search for keywords, using a cleaned list of "skills" extracted from each job advert (only available from US job ads) rather than the 'raw' text of the job advert.

performance, and electrical generation and storage. In particular, of the nearly one million more LCT job postings posted in 2022 compared to 2021, nearly three quarters were related to just seven LCTs: electric vehicles, renewable energy - general (mentions of 'alternative', 'clean', or 'renewable' energy), solar energy, insulation, ev charging, heat pumps, and wind energy. For example, there were 3.3 times as many electric vehicle job postings in 2022 as in 2021, and 2.3 times as many electric vehicle-related charging job postings.

Patterns of growth in LCTs mentioned in earnings calls over this period were similar (see Appendix Figure A7). Comparing the total number of LCT mentions in earnings calls during the 2020-2022 period versus 2017-2019, a high share of the growth was driven by an increase in mentions of LCTs relating to renewable energy (25 percent of the total increase), electric vehicles (18 percent), solar energy (9 percent), ev charging (5 percent), energy storage (also 5 percent), and wind energy (4 percent). In addition, there was significant growth in mentions of technologies relating to carbon capture in the earning calls (13.5 times as many in 2020-22 as in 2017-19) and biofuels.



(a) Number of LCT-related job postings by technology group



(b) Share of LCT-related job postings by ISIC section

Figure 3: LCT-related job postings by technology and industry

Notes: Panel (a) displays the total number of online job postings in the 16 countries for each LCT category in each time period. Panel (b) displays the total number of online job postings in the 16 countries by 1 digit ISIC section.

Fact 4: Growth occurred in nearly all industries, but was driven by jobs in administrative and support activities, manufacturing, utilities and construction

Pooling across the years, the share of all job postings that are LCT-related is highest in the 1 digit ISIC sections of 'Electricity, gas, steam and air conditioning supply', followed by 'Mining and quarrying', as is shown in Figure 3(b).[7] All of these 20 industries except for one experienced rapid growth in 2022, with the fastest growth in 2022 for electricity, gas, steam and air, manufacturing and construction. However, the industries making the greatest contribution to the growth in 2022 were 'Administrative & support service activities', contributing 16.7 percent of the increase in LCT-related job ads in 2022, reflecting the industry's high share of job postings on aggregate (note that many of these jobs may be from temporary employment agencies). 'Manufacturing' and 'Electricity, gas, steam and air conditioning supply' industries accounted for 13.7 and 9.6 percent, respectively, of the increase in LCT job postings in 2022. Another 4.1 percent of the 2022 increase in LCT job ads was in 'Construction', with growth in LCT-related job postings recording nearly double that industry's share of overall job growth.

Fact 5: Growth was fastest for higher-skilled jobs, and in research occupations, but occurred across jobs

We next classify the job postings by skill levels, as discussed in Section 2. In 2022 around two-thirds of all LCT-related job postings across the 16 countries were for high skilled jobs, higher than the 58 percent for all online job postings. Only just under 5 percent of LCT-related job postings were for low-skilled jobs, compared to around 8 percent for all postings. These shares have remained broadly consistent over time. However, there is significant variation across LCT types. Certain LCT categories, such as waste management, improved thermal performance (e.g. building contractors installing insulation), and energy efficient cooling and appliances (eg. repairers) have under a third of jobs in high skilled occupations.

Figure 4 decomposes the share of LCT-related job postings by skill level.[8] The share of

[7]We define industries at the one-digit ISIC Section level because 69 percent of all job postings contain industry information at this level. However, while all European job postings have an industry identified, this information is missing for 60 percent of postings in Singapore, 28 percent in the USA, and 44 percent in the UK.

[8]Occupation skill levels are as defined in ISCO, where High skill includes Managers, professionals, and technicians; Medium skill includes Clerical, service and sales workers, Skilled agricultural and trades workers, and Plant and machine operators, and assemblers; and Low skill includes 'Elementary occupations'.

LCT-related postings increased for jobs at all three skill levels in 2022, though the increase was largest for high-skill jobs.

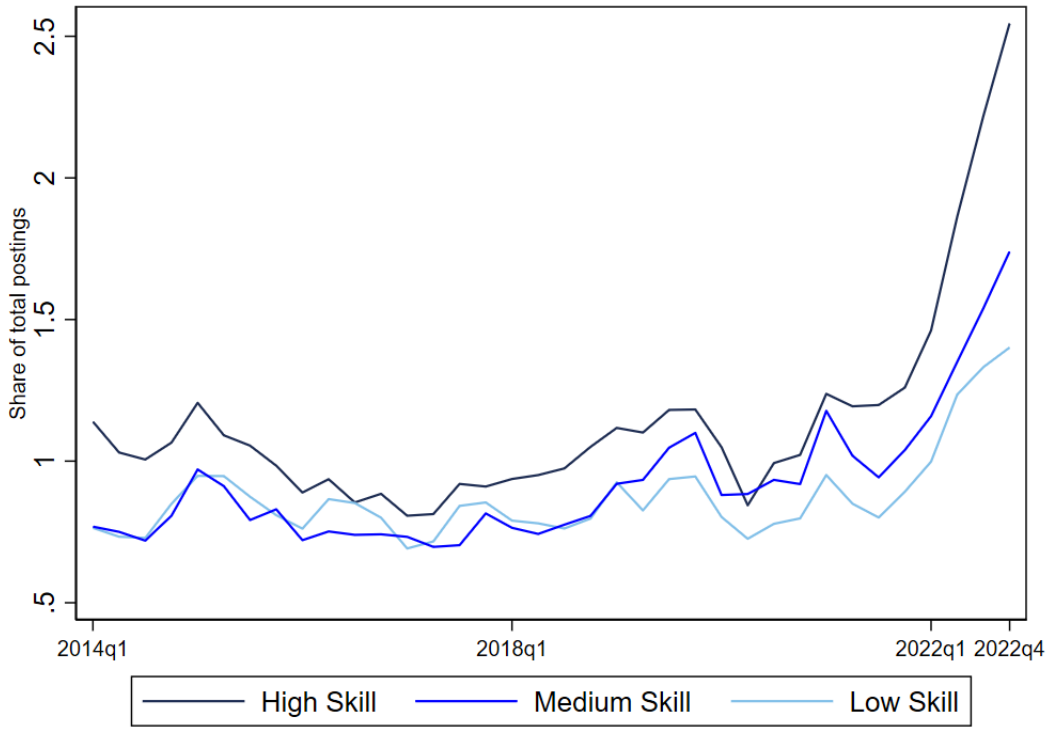


Figure 4: Share of LCT-related job ads by occupation skill level

Notes: This figure displays the number of job postings as a share of total job postings in the 16 countries by quarter. Occupation skill levels are as defined by ISCO occupational groupings.

To understand whether the growth in LCT-related jobs was driven by production of LCTs, invention of LCTs or diffusion of LCTs, we also explore the breakdown by these different categories. Production-specific roles and research roles are defined as outlined in Section 2.1.1. We assume that all jobs that are not specifically related to production or research are more likely to be reflective of deployment of these technologies. Figure 5 shows the share of all LCT job postings that are in research or production-related occupations each quarter. The share of LCT-related job postings in research occupations ranges from 15 to 20 percent per quarter, much higher than the research share of all job postings, while the share of LCT postings in production roles ranges from 3-6 percent (with the rest in neither category). The share of all research roles and production roles that are related to LCTs is much lower than for the full sample. The rapid growth in the LCT share has been driven primarily by the 'Other' category and to some degree research roles, providing suggestive evidence that growth reflects

deployment of these technologies to a greater extent than production of them. Research-related LCT job ads typically experienced the fastest quarter on quarter growth since the second half of 2021.

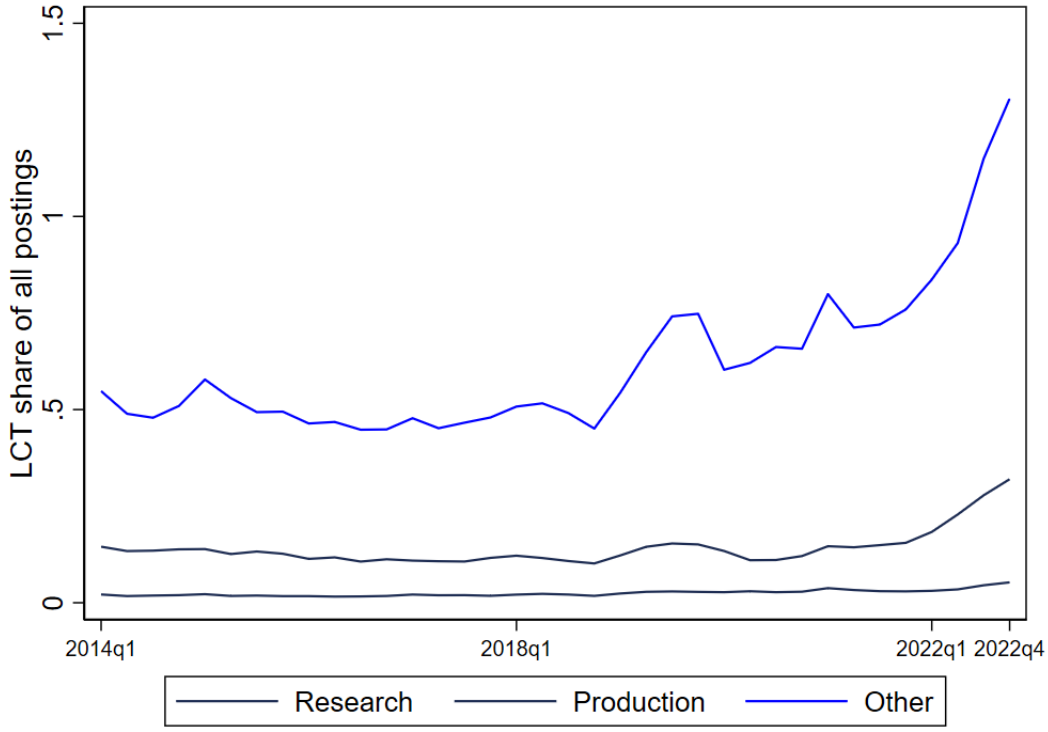


Figure 5: Share of LCT-related job ads by occupation type

Notes: This figure displays the share of all job ads of each occupation type in the 16 countries by quarter. Occupation types are as defined in Section 2.1.1.

The research-share of jobs varies widely across LCTs, with one-third of all ads related to 'emissions reductions in production' technologies in 2020 to 2022 in research occupations but under 5 percent of job ads related to 'waste management' technologies. Over time there has been a large increase in the share of research-related job postings for technologies related to 'capture, storage or disposal of GHGs', an area of growing research. On the other hand, certain technologies have also seen declines over time in the share of research-related job ads indicative of diffusion of these technologies, notably those relating to energy efficiency such as energy efficient cooling, energy efficient appliances and energy efficient heating.

The share of LCT-related job ads in research occupations far exceeds the share of all job ads in research occupations in 11 of the 16 countries, while others have experienced a decline in the share of research LCT job ads.

4. The impact of the global energy crisis

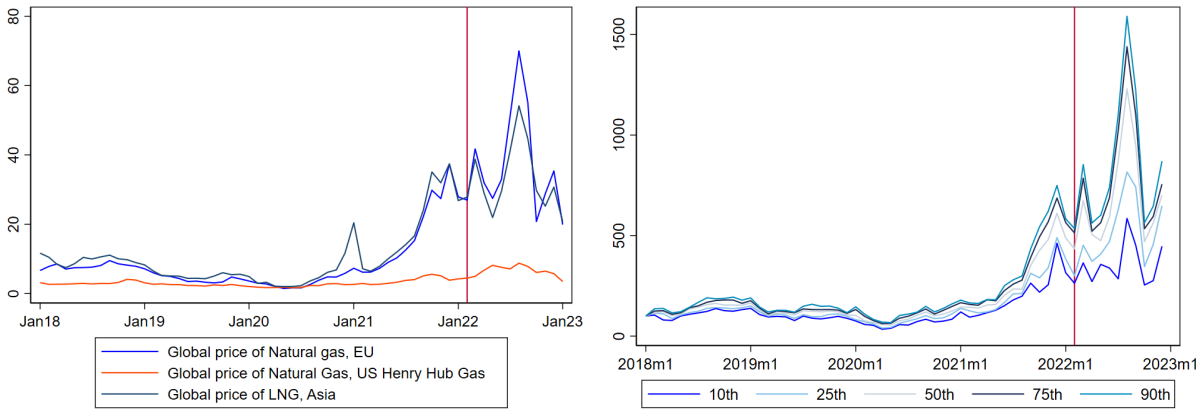
4.1 Background on the energy crisis

The 2021-2023 global energy crisis begin in the aftermath of the COVID-19 pandemic in 2021. Natural gas prices in the EU and Asia started to increase steadily in 2021 in response to a supply-demand gap following the loosening of COVID-19 restrictions, which coincided with a tight liquefied natural gas (LNG) market and relatively low gas storage volumes.[9] The monthly average natural gas price in the EU and Asia more than doubled in 2021, while the US Henry Hub Gas price stayed relatively flat, as is shown in Figure 6(a)). Rising prices subsequently escalated into a widespread global energy crisis following the Russian invasion of Ukraine in February 2022. Russian exports had accounted for about one-third of the EU's and the UK's supply of natural gas via pipeline between 2016 and 2020 [EIA, 2022]. The invasion threatened the energy supply from Russia to Europe and international sanctions resulted in a reduction in gas imports from Russia, the suspension of the Nord Stream 2 pipeline's certification and the halting of gas deliveries through the Nord Stream 1 pipeline. In the first half of 2022, Russia's natural gas exports by pipeline to the European Union and the United Kingdom fell by nearly 50 percent compared with the previous five-year average [EIA, 2022].

The EU natural gas price peaked in August 2022 at a record high of double its level in January 2022, although the US natural gas price remained relatively unaffected. In the EU, the increase in energy prices translated into a significant increase in wholesale electricity prices in all countries, although there was also sizable variation in the extent to which countries were affected, as is shown in Figure 6(b). In August 2022, half of European countries had wholesale electricity prices over 12 times as high as their January 2018 levels. Figure 7 displays wholesale electricity price data for the 35 countries in the expanded sample (excluding Cyprus due to the unavailability of monthly data). The country with the highest increase in prices between the beginning of 2019 and the peak of the shock was Germany, while New Zealand, Canada and Australia are the countries with the lowest changes.

These increases in wholesale prices were also differentially passed through to household energy prices as governments varied in the extent to which they introduced subsidies to consumers. For example, subsidies on household electricity resulted in a decline in electricity

[9] We mainly focus on the 2022 natural gas supply shock in our baseline analysis, but discuss spillovers to other fossil fuels in Section 4.4.2.



(a) European, USA, and Asian Benchmark Natural Gas Prices

(b) EU wholesale electricity prices across distribution (2018=100)

Figure 6: Natural gas and electricity price changes

Notes: Vertical line at February 2022. Panel a) displays the monthly average price in USD per Million Metric British Thermal Units, not seasonally adjusted. *Source:* International Monetary Fund, retrieved from FRED, Federal Reserve Bank of St. Louis series PNGASEUUSDM, PNGASUSUSDM, and PNGASJPUSDM. Panel b) displays monthly European wholesale electricity price data, with each percentile calculated over all EU countries in the sample and electricity price indices re-based to 2018. Prices are not seasonally adjusted. *Source:* Ember monthly European wholesale electricity price data.

prices in the second half of 2022, while natural gas prices continued to remain high.

4.2 Measuring exposure to the energy price shock

In this section, we next explore the role of the global energy crisis in driving this increase in LCT-related hiring in 2022. To do so, we explore whether there was a differential increase in the posting of LCT-related job postings in establishments that were more exposed to the energy crisis, due to their firm-level energy intensity and country-level ex-ante dependence on foreign energy imports.

The initial increase in natural gas prices dissipated to affect other fossil fuel prices due to both the substitution of natural gas for other energy sources as well as restrictions on supplies of other fuels. We focus on natural gas import dependence in our baseline analysis and explore spillovers to other fossil fuels, and hence dependence on imports of all fossil fuels, in Section 4.4.2.

Our main specifications are at the establishment-level, which are defined as a given firm's job postings in each subnational region of a country. We proxy firm-level fossil fuel energy

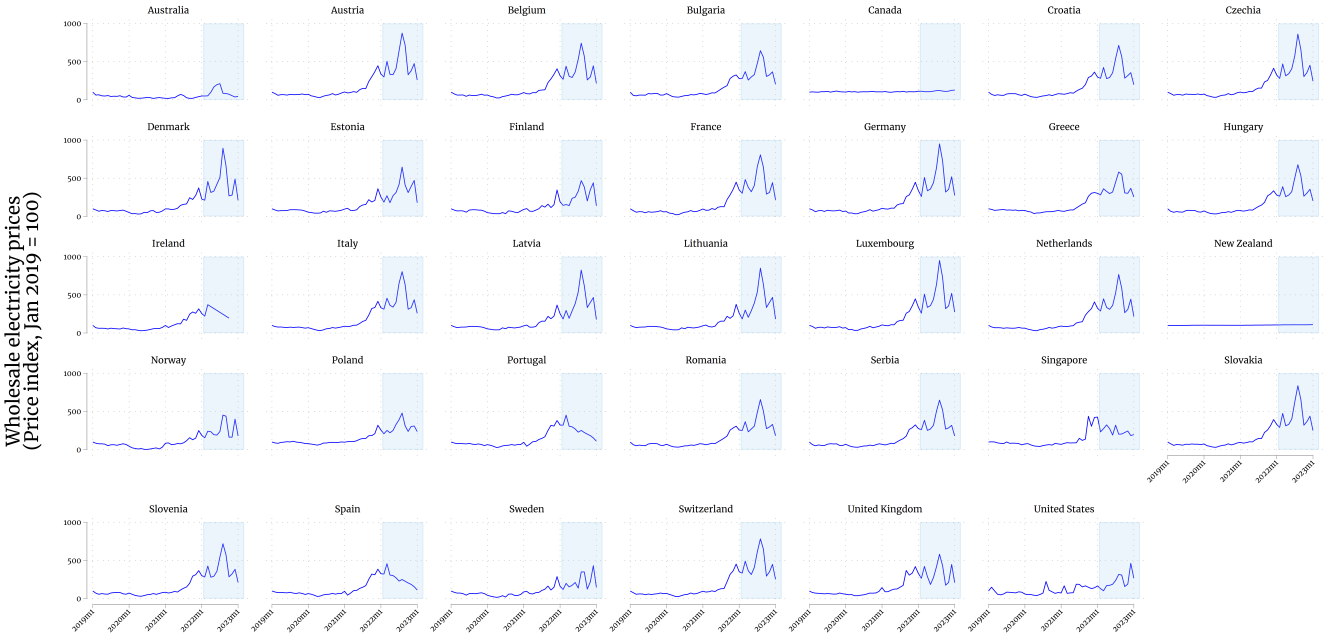


Figure 7: Wholesale electricity prices by country

Notes: The figure depicts a monthly price index of the wholesale electricity prices across 34 countries in the expanded sample. Area in blue covers the post-February 2022 energy price shock period. Prices are not seasonally adjusted. *Sources:* Australian Energy Market Operator, Canada Energy Regulator, European wholesale electricity price database - Ember (Europe), Ministry of Business, Innovation and Employment (New Zealand), National Electricity Market of Singapore, Office of Gas and Electricity Markets (United Kingdom), Energy Information Administration (United States).

intensity as the ratio of energy consumption to sales in 2020.[10] Specifically, as described in Section 2.6, we match data on firms' reported or estimated consumption of fuel and purchased steam, heat, electricity, and cooling (in MWh) from the Carbon Disclosure Project (CDP) to data on each firm's sales from FactSet Fundamentals in order to estimate each firm's energy consumption per dollar of revenue. We then match this firm-level data to data on firms' job postings from BGT, resulting in a sample of 185,214 establishments that belong to 4,788 firms (including only those firms in BGT that are included in the CDP data). Finally, we interact the firm-level energy intensity with measures of country-level natural gas and fossil fuel import dependence (see below) in order to account for exposure to the global energy price shock. This results in establishments of the same firm having different ex-ante exposure based on the country in which they are located. The constant firm-level energy intensity component

[10]Annual energy consumption is available only for 2020. While this value may have been impacted by the economic effects of the COVID-19 pandemic in 2020, we focus on energy *intensity*, i.e. energy consumption relative to sales, and since both are measured as of 2020 we believe this ratio is likely relatively constant across years.

of this interacted exposure measure reflects that adoption of the technologies that influence a given firm's energy intensity are constant within a firm, across countries, at least in the baseline period before the 2022 energy shock.

At the country level, we measure baseline pre-crisis national exposure to the energy price shock as the dependence in 2019 on foreign imports of either natural gas or all types of fossil fuel energy. We use data from the IEA World Indicators on net energy imports, net of exports, refueling for ocean and air shipping ('international marine bunkers' and 'international aviation bunkers', respectively) and stock changes. We calculate net imports as a share of total energy supply.[11]

There is substantial variation across countries in terms of their exposure to the energy price shock, according to each of the import-based measures used (Figure 8). The light blue bars show the share of total energy use from imports of all fossil fuels in 2019, which was over half of energy consumed in seven countries, and over 90 percent of total energy use in Singapore and Luxembourg. While six countries have no net natural gas imports (dark blue bars), five countries use imported natural gas for over one-fifth of their total energy use. The countries with the highest imported natural gas dependence are Italy, Belgium, and Singapore.

[11] Note this measure is zero-censored, so that net exporters have a value of zero net imports.

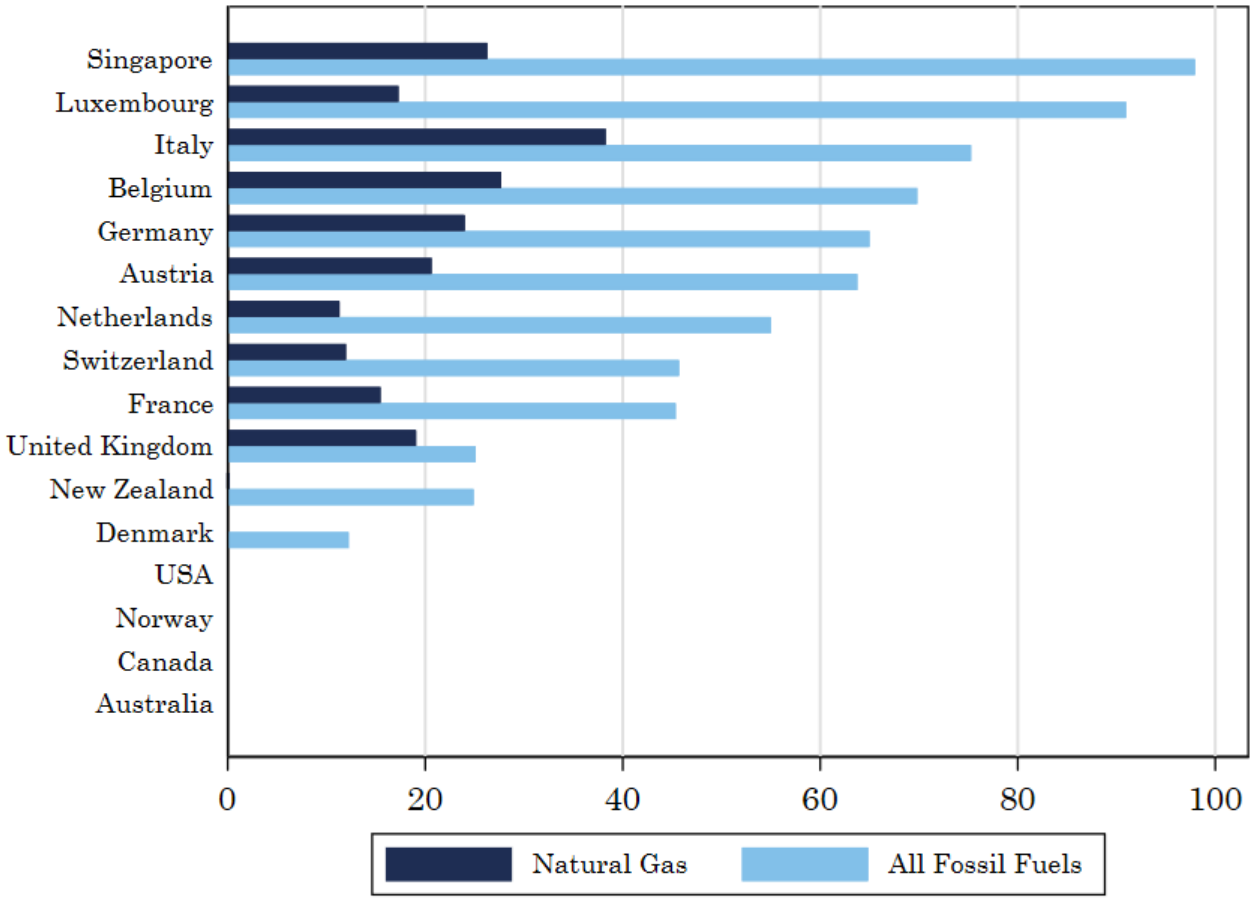


Figure 8: Country-level energy crisis ex-ante exposure

Notes: This figure displays the country-level dependence on imported natural gas or all fossil fuels in 2019, as measured by the ratio of net imports to total energy supply. Net exporters are recorded as zero import dependence.

4.3 Empirical analysis

We are primarily interested in whether the firms with the greatest *ex-ante* exposure to the unexpected rise in energy prices from the energy crisis increased their postings for LCT-related jobs in response to the 2022 energy shock. We first estimate the following regressions of the change in LCT-related job postings before and after February 2022 by the *ex-ante* exposure of firms and countries to the energy shock:

$$\text{IHS}(LCT_{j,c,t}) = \alpha_0 + \beta_1(\mathbf{I}(YM_t \geq Feb2022) * Exposure_c) + \psi_j + \zeta_t + \epsilon_{j,c,t} \quad (1)$$

$$\text{IHS}(LCT_{j,c,t}) = \alpha_0 + \beta_1(\mathbf{I}(YM_t \geq Feb2022) * Exposure_c * EnergyIntensity_i) + \psi_j + \zeta_t + \epsilon_{j,c,t} \quad (2)$$

$$\begin{aligned}\text{IHS}(LCT_{j,c,t}) = \ & \alpha_0 + \beta_1(\mathbf{I}(YM_t \geq Feb2022) * Exposure_c) \\ & + \beta_2(\mathbf{I}(YM_t \geq Feb2022) * EnergyIntensity_i) \\ & + \beta_3(\mathbf{I}(YM_t \geq Feb2022) * Exposure_c * EnergyIntensity_i) \\ & + \psi_j + \zeta_t + \epsilon_{j,c,t}\end{aligned} \quad (3)$$

where the dependent variable $\text{IHS}(LCT_{j,c,t})$ is the inverse hyperbolic sine transformed number of LCT-related job postings by establishment j (located in country c) in year-month t. The explanatory variables of interest are $\mathbf{I}(YM_t \geq Feb2022)$ an indicator equal to 1 if YM_t is February 2022 or later, $Exposure_c$ the 2019 ex-ante national exposure to the energy price shock (share of total energy use from imported natural gas or, in Section 4.4.2, all fossil fuels), and $EnergyIntensity_i$ an estimate of *firm*-level energy intensity (consumption of fuel and purchased steam, heat, electricity, and cooling (SHEC) in MWh divided by sales in 2020). Each regression is run at the level of establishments j, defined as the firm-country-region triplet of firm i in a certain subnational region of a country c, in a month t. In the first specification, we include only the interaction between year-month indicators and $Exposure_c$, as well as establishment and monthly fixed effects. In the second specification, we also interact the country-level import-dependence measure $Exposure_c$ with firm-level energy intensity, $EnergyIntensity_i$. In the third specification, we additionally control for the interaction between $\mathbf{I}(YM_t \geq Feb2022)$ and $Exposure_c$ as well as the interaction between $\mathbf{I}(YM_t \geq Feb2022)$ and $EnergyIntensity_i$.

Table 4 provides results from these regressions of the firm's number of LCT job postings in year-month t on an indicator for whether t is before or after February 2022, interacted with the ex-ante exposure and emissions intensity measures.

We find that establishments in countries that were *ex ante* more reliant on natural gas saw an increase in LCT-related postings after February 2022 (column 1). Establishments from more energy-intense firms also differentially increased their LCT-related job postings after February 2022, relative to establishments in less energy intense firms, within countries with a similar *ex-ante* dependence on natural gas imports, as is shown in column (3).

A firm with one-standard deviation higher baseline energy intensity hired 1.1 more LCT-related jobs after February 2022.

TABLE 2. BASELINE PRE/POST CRISIS RESULTS

	Dep var: Total LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.155***		0.153***
	(0.049)		(0.049)
Post-February 2022 × Country exposure × Firm exposure		0.154**	0.034**
		(0.065)	(0.015)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	1,982,647	1,982,647	1,982,647
Adjusted R-squared	0.608	0.607	0.608

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from Q2 2021 to Q4 2022 (with singleton observations automatically dropped). Dependent variable is inverse hyperbolic sine of total number of LCT-related job postings by establishment in month. Country exposure measure is the fraction of total energy use from imported natural gas in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). Only firms with information in CDP included in the regressions. Coefficients on Post-February 2022 × Country exposure × Firm exposure multiplied by 10,000.

We next explore the timing of these LCT hiring increases in more detail. We estimate the following event study regressions to evaluate the role of exposure to the energy crisis on the creation of LCT-related jobs by establishment j in country c in month t:

$$\text{IHS}(LCT_{j,c,t}) = \alpha_0 + \beta_1(YM_t * Exposure_c * EnergyIntensity_i) + \psi_j + \zeta_t + \epsilon_{j,c,t} \quad (4)$$

where, as above, the dependent variable $\text{IHS}(LCT_{j,c,t})$ is the inverse hyperbolic sine transformed number of LCT-related job postings by establishment j (located in country c) in

year-month t. We estimate the differential effect of the energy shock on hiring each month via the interaction between the year-month indicator YM_t and the same explanatory variables of interest above: $Exposure_c$ one of the measures of the 2019 ex-ante national exposure to the energy price shock (share of total energy use from imported natural gas or all fossil fuels) and $EnergyIntensity_i$ an estimate of ***firm***-level energy intensity (consumption of fuel and purchased steam, heat, electricity, and cooling (SHEC) in MWh divided by sales in 2020). Each regression is again run at the level of establishments j, defined as the firm-country-region triplet of firm i in a certain subnational region of a country c, in a month t.

All event study regressions are run at the monthly level from the third quarter of 2021 and full year of 2022, with an omitted base period of 2021Q2. While the Russia-Ukraine invasion began in Q1 2022, there were some signs of anticipation of the invasion, with prices rising in the final half of 2021, and hence we take the second quarter of 2021 as the base period. We cluster standard errors at the country level throughout.

The coefficients from these event studies are plotted in Figure 10. These plot the coefficient β_1 in Equation 4, on the interaction of the year-month indicator with the country-level import-dependence measure $Exposure_c$ and the firm-level energy intensity, $EnergyIntensity_i$. We find that more energy-intensive firms in countries with greater dependence on imported natural gas increased their LCT-related hiring from March 2022, with mostly significant coefficients from that point onwards and the strongest effects in December 2022.

Appendix Figure A9 includes coefficient plots illustrating similar (but noisier) results where we additionally control for the interaction between YM_t and $Exposure_c$ as well as the interaction between YM_t and $EnergyIntensity_i$.

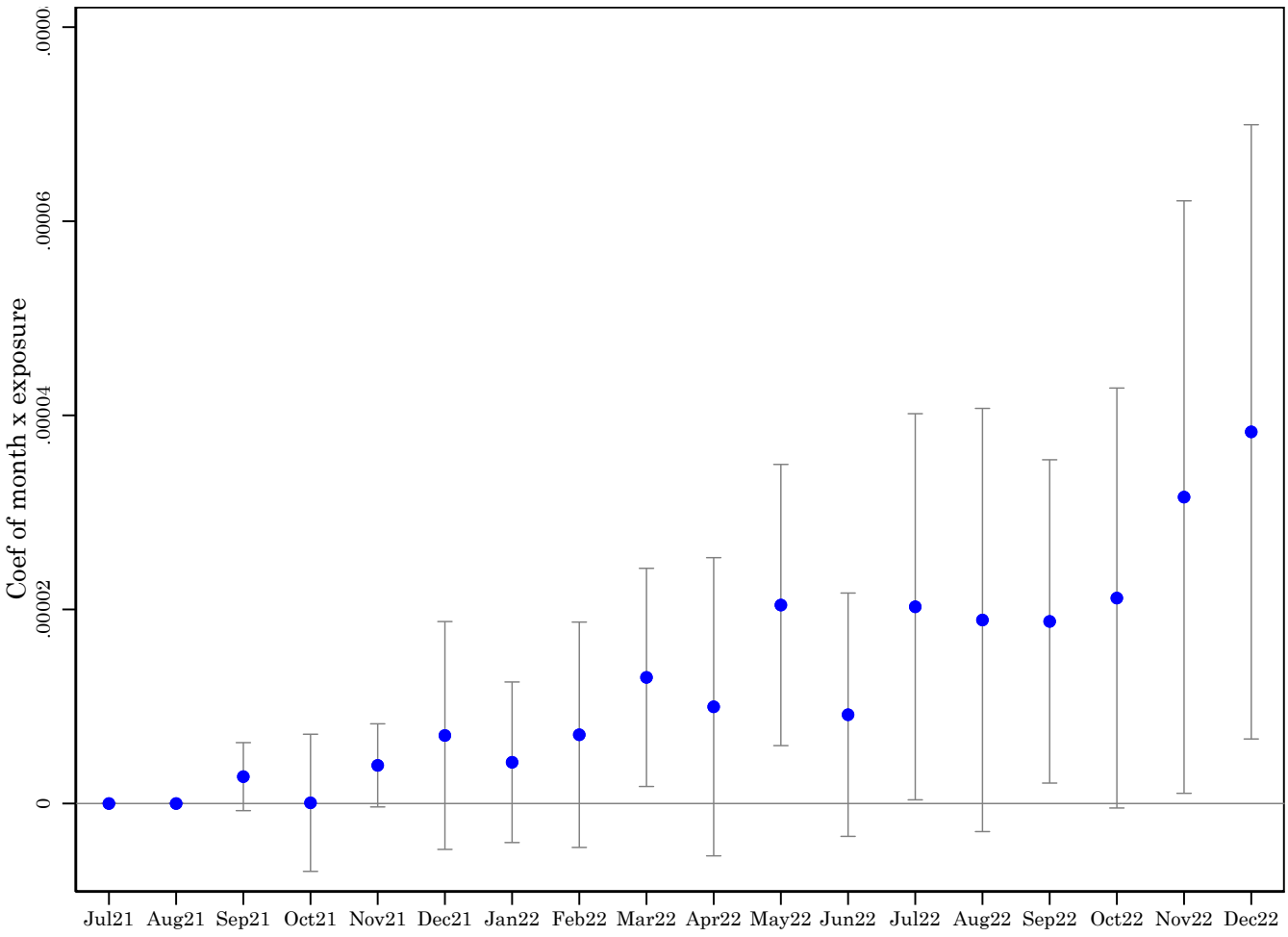


Figure 10: Baseline event study of LCT job postings on exposure based on country natural gas import dependence and firm energy intensity

Notes: This figure displays the estimated coefficients and 95% confidence intervals of the interaction between each year-month and the interaction of ex-ante energy import dependence and energy intensity from Equation (4). Point estimates from the events studies shows the change in the number of LCT-related job ads posted by an establishment each month from July 2021 to December 2022. Regressions include year-month and establishment fixed effects. Standard errors are clustered by country. Further details in text.

4.4 Mechanisms and robustness

4.4.1 Results by low-carbon technology group

The dependent variable in the above regressions is total LCT job postings by an establishment in each month. As the results shown in Section 3 show, some LCTs increased faster than others during 2022. We test whether overall LCT adoption in response to the 2022 energy shock was driven by adoption of certain types of LCTs by re-defining the dependent variable in the regression of the firm's number of LCT job postings in year-month t on an indicator for whether t is before or after February 2022, interacted with the ex-ante exposure and emissions intensity measures, as the number of job ads related to LCTs in one of five aggregate technology groups (as listed in Appendix Table A5). Table 3 below provides the coefficients on the interaction terms between the indicator for a year-month after February 2022 and the ex-ante country natural gas import dependence and firm energy intensity. It shows a significant increase in LCT jobs related to generation LCTs by establishments of more energy-intense firms in countries with greater ex-ante exposure to the 2022 energy price shock. It also shows a weakly significant increase in job ads related to vehicles and waste/materials LCTs by establishments in countries with greater ex-ante natural gas import dependence, though no differential increases for more energy-intensive firms in those countries.

TABLE 3. BASELINE PRE/POST CRISIS RESULTS BY TECHNOLOGY TYPE

	Dep var: Job ads by agg. LCT group (IHS transformation)				
	Vehicles	Generation	Consumer	Energy-use	Waste/materials
	(1)	(2)	(3)	(4)	(5)
Post-February 2022 × Country exposure	0.100*	0.061**	0.005	0.016	0.019*
	(0.053)	(0.028)	(0.004)	(0.016)	(0.011)
Post-February 2022 × Country exposure × Firm exposure	-0.017	0.064***	-0.003	0.011	-0.016
	(0.013)	(0.016)	(0.003)	(0.007)	(0.010)
Year-month FE	Yes	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	Yes	Yes	Yes	Yes	Yes
Observations	1,982,647	1,982,647	1,982,647	1,982,647	1,982,647
Adjusted R-squared	0.478	0.588	0.411	0.588	0.580

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from Q2 2021 to Q4 2022 (with singleton observations automatically dropped). Dependent variable is inverse hyperbolic sine of LCTs-related job ads in each aggregate technology group by establishment in month. Aggregate technology groups listed in Appendix Table A5. Country exposure measured as ratio of total energy use from imported natural gas in 2019. Firm exposure is energy intensity, calculated as fuel and purchased energy consumption of the firm divided by its sales (both in 2020). Only firms with information in CDP included in the regressions. Coefficients on Post-February 2022 × Country exposure × Firm exposure multiplied by 10,000.

4.4.2 Spillovers to other fossil fuels

Our baseline analysis focuses on the key role of natural gas prices in the 2021-2023 global energy crisis. However, this energy crisis also impacted supplies of other fossil fuels, both due to their substitution for natural gas and due to direct supply reductions: in addition to reduced natural gas imports, the EU also enacted bans on imports of Russian crude oil (in December 2022), refined petroleum products (in February 2023), and coal and other solid fossil fuels (in April 2022). In 2020, Russia was the third largest oil producer in the world, behind the United States and Saudi Arabia, with 60% of its oil exports going to Europe. In 2021, the EU sourced more than 27% of its oil imports and 46% of its coal imports from Russia.

We expect a dampened impact of country fossil fuels import exposure on LCT adoption, compared to specifically natural gas import exposure, due to the later timing of import reductions for non-gas fossil fuels as well as greater ability for these fuels to substitute from Russian to other suppliers, compared to natural gas delivered primarily via pipeline. In this section we modify the previous measurement of country exposure to be the ratio of *all fossil fuels* imports to total energy supply. In Table 4 we find that establishments in countries with greater *ex ante* reliance on imports of all fossil fuels experienced an increase in LCT-related postings after February 2022 (column 1). However, unlike for natural gas import dependence, we do not find a statistically significant differential increase in LCT-related job postings after February 2022 in establishments from more energy-intense firms, relative to establishments in less energy intense firms, within countries with a similar *ex-ante* dependence on all fossil fuel imports, after controlling for the interaction with firm exposure only. (shown in column 3).

In Figure 12 we plot the coefficients β_1 from the event study regression described in Equation 4 with country exposure now defined as the ratio of all fossil fuels imports to total energy supply. We find these coefficients are smaller in magnitude than when country exposure is defined based on natural gas imports. There are slightly earlier effects, as the first coefficient that is statistically significant from zero is in December 2021, and then again in March 2022 and in April onwards.

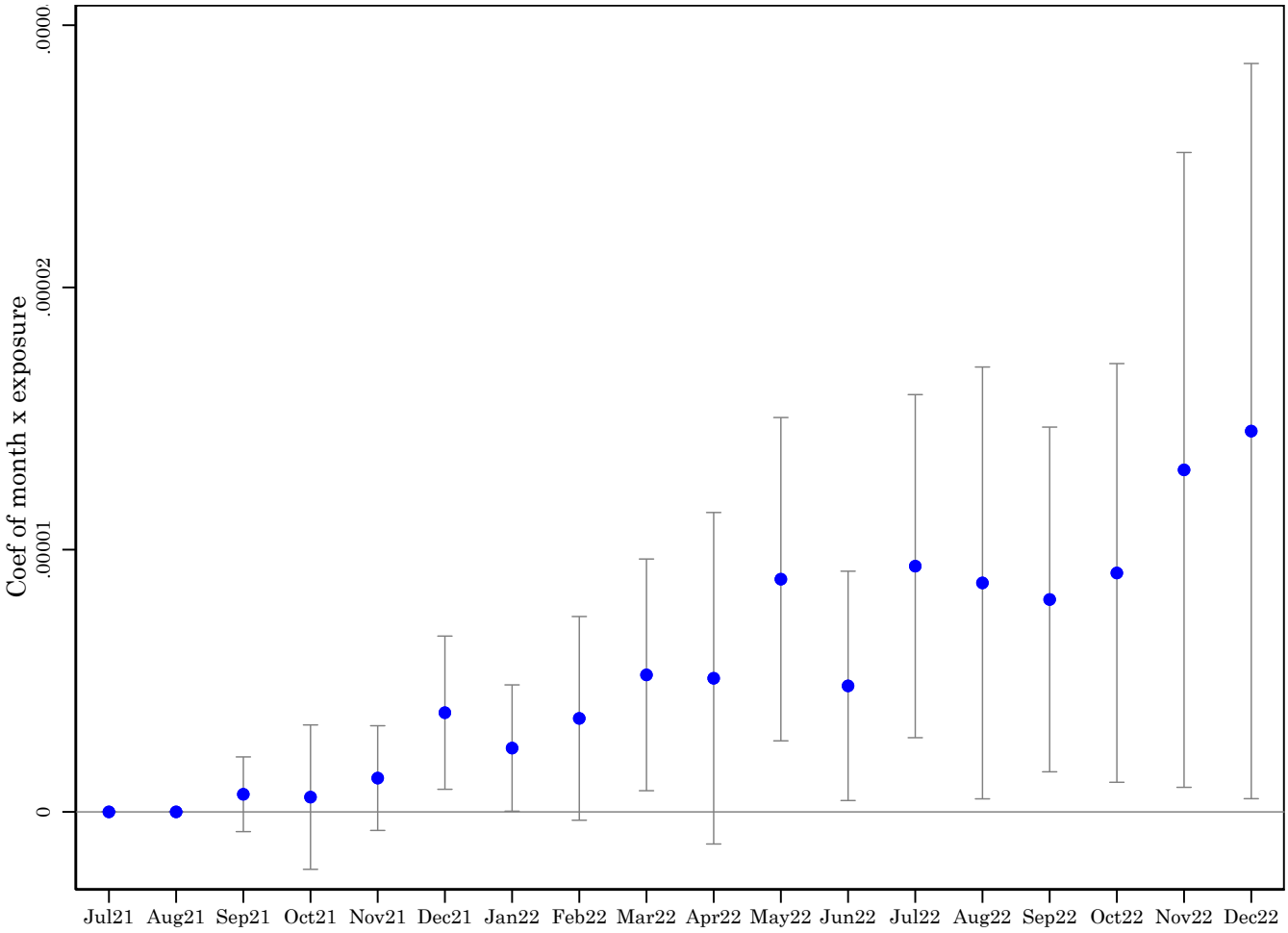


Figure 12: Baseline event study of LCT job postings on exposure based on country fossil fuel import dependence and firm energy intensity

Notes: This figure displays the estimated coefficients and 95% confidence intervals of the interaction between each year-month and the interaction of ex-ante energy import dependence and energy intensity from Equation (4). Point estimates from the events studies shows the change in the number of LCT-related job ads posted by an establishment each month from July 2021 to December 2022. Regressions include year-month and establishment fixed effects. Standard errors are clustered by country. Further details in text.

TABLE 4. BASELINE PRE/POST CRISIS RESULTS USING ALL FOSSIL FUEL IMPORT DEPENDENCE

	Dep var: Total LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.064***		0.063***
	(0.018)		(0.018)
Post-February 2022 × Country exposure × Firm exposure		0.067**	0.014
		(0.026)	(0.008)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	1,982,647	1,982,647	1,982,647
Adjusted R-squared	0.608	0.607	0.608

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from Q2 2021 to Q4 2022 (with singleton observations automatically dropped). Dependent variable is inverse hyperbolic sine of total number of LCT-related job postings by establishment in month. Country exposure measures are fraction of total energy use from imported fossil fuels in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). Only firms with information in CDP included in the regressions. Coefficients on Post-February 2022 × Country exposure × Firm exposure multiplied by 10,000.

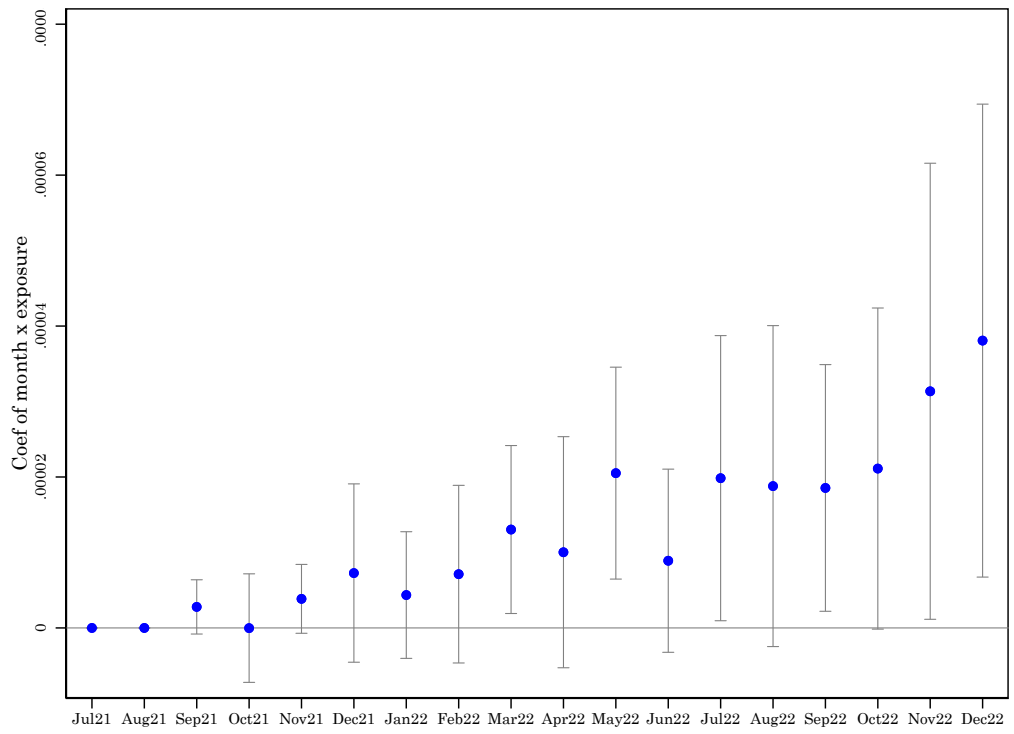
4.4.3 Excluding fossil fuel establishments

In this section, we verify that the increase in LCT adoption by the most exposed firms was not driven–or dampened–by fossil fuel sector firms specifically. It could be possible that energy shock may have impacted firms that primarily consume fossil fuels (or electricity generated from fossil fuels) differently than firms that sell fossil fuels or related products. We define fossil fuel firms based on classification by CDP as firms that primarily earn revenue from Coal extraction and processing (27% of our sample), Oil and gas extraction (9%), Oil and gas marketing and retailing (25%), Oil and gas pipelines and storage (11%), and Oil and gas refining (27%). Only 1.3% of our sample is composed of establishments of fossil fuel firms. We repeat the regressions from Table 4 of each establishment's number of LCT job postings in year-month t on an indicator for whether t is before or after February 2022, interacted with the ex-ante exposure and emissions intensity measures, but with the sample now limited to all non-fossil fuel firms. We find a similar increase in LCT adoption by non-fossil fuel firms in our sample, as shown in Table 5. Figure 13 plots coefficients from similar regressions on each month, showing the timing of the increase in LCT adoption by non-fossil firms is similar as to all firms.

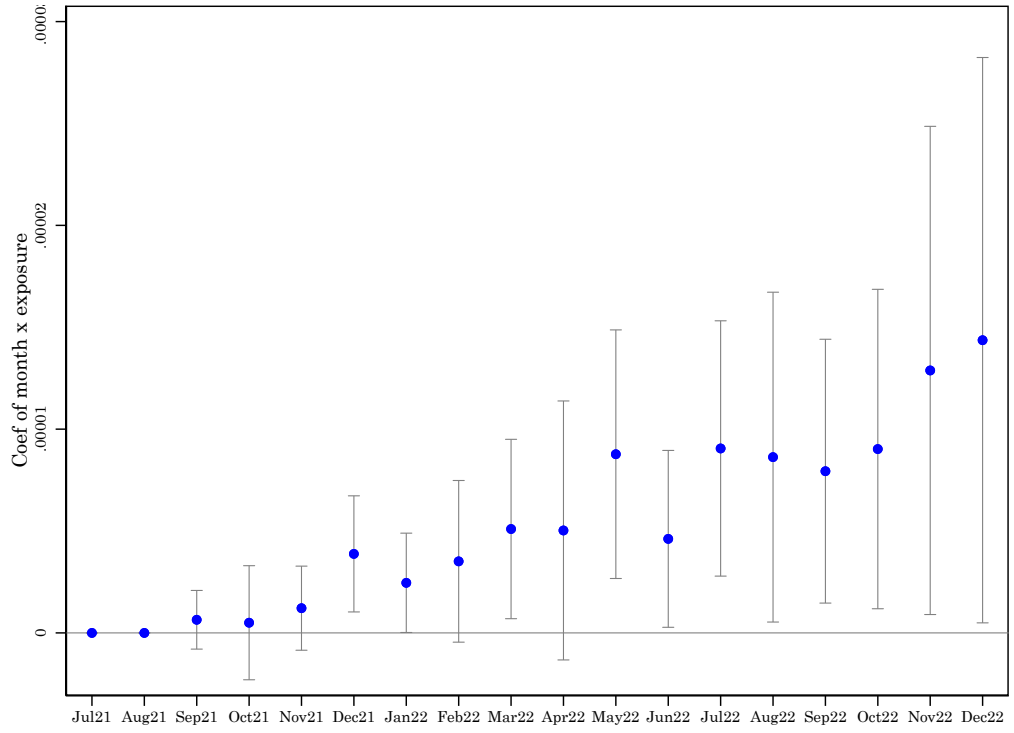
TABLE 5. PRE/POST CRISIS RESULTS EXCLUDING FOSSIL FUEL PRODUCERS

	Dep var: Total LCT job ads (IHS transformation)					
	All natural gas			All fossil fuels		
	(1)	(2)	(3)	(4)	(5)	(6)
Post-February 2022 × Country exposure	0.155***		0.153***	0.063***		0.063***
	(0.048)		(0.048)	(0.018)		(0.018)
Post-February 2022 × Country exposure × Firm exposure		0.153**	0.033**		0.066**	0.013
		(0.063)	(0.014)		(0.025)	(0.008)
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes	No	No	Yes
Observations	1,960,547	1,960,547	1,960,547	1,960,547	1,960,547	1,960,547
Adjusted R-squared	0.608	0.608	0.608	0.608	0.608	0.608

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from Q2 2021 to Q4 2022 (with singleton observations automatically dropped). Excluded fossil fuel firms are as defined in CDP. Dependent variable is inverse hyperbolic sine of total LCT-related job ads by establishment in month. Country exposure measures are ratio of total energy use from imported natural gas or all fossil fuels in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). See text for further details.



(a) Natural gas import dependence and energy intensity



(b) Fossil fuel import dependence and energy intensity

Figure 13: Event study, excluding fossil fuel firms

Notes: This figure displays the estimated coefficients and 95% confidence intervals of the interaction between each year-month and the interaction of ex-ante energy import dependence and energy intensity from Equation (4). Point estimates from the events studies shows the change in the number of LCT-related job ads posted by an establishment each month from July 2021 to December 2022. Excluded fossil fuel firms are as defined by CDP. Regressions include year-month and establishment fixed effects. Standard errors are clustered by country. Further details in text.

4.4.4 Shift-share robustness checks

One potential concern is that our measures of exposure to the 2022 energy price shock may be correlated with other country or firm-level characteristics that are correlated with LCT adoption. Following Goldsmith-Pinkham et al. [2020], in this section each ex-ante exposure measure is regressed on a range of possible confounders.

The country-level exposure variables are first regressed on other country-level baseline characteristics. Results are provided in Table 6. Total natural gas and all fossil fuel import dependence are not correlated with any of a range of country-level characteristics measured before 2020.

TABLE 6. INVESTIGATING CORRELATES OF COUNTRY-LEVEL EXPOSURE

	Natural gas import dependence	Fossil fuels import dependence
	(1)	(2)
Distance from Russia	-0.0005	0.0000
	(0.0008)	(0.0024)
Emissions intensity of GDP	23.6045	113.2747
	(78.2389)	(229.5823)
GDP per capita	-0.0000	0.0007
	(0.0002)	(0.0006)
Gasoline price at pump	16.1188	61.2419
	(19.1152)	(56.0911)
Gross capital formation (% of GDP)	-0.7835	-1.8510
	(1.1673)	(3.4254)
Human Capital Index (World Bank)	-33.9524	-75.9173
	(99.8588)	(293.0231)
Manufacturing % of GDP	1.2555	4.2657
	(0.8048)	(2.3615)
Renewables % of electricity output	-0.1398	-0.4233
	(0.1220)	(0.3581)
Observations	16	16
Adjusted R-squared	0.186	0.064

Note: Sample is 16 countries with establishments in establishment-level data sample. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01.

Next, the firm-level energy intensity and firm-by-country-level exposure measures are regressed on other ex-ante firm characteristics (as of 2019), with results provided in Table 7. All firm-level characteristics are as provided in Factset with the exception of total job postings (from BGT) and the proxy for firm labor productivity, which is calculated as the ratio of firm sales to total job postings. While the firm-level energy intensity exposure is weakly correlated with the firm's debt-assets ratio (negatively) and gross margin (positively), these correlations no longer hold when exposure is measured as the product of the firm-level energy intensity and country-level import dependence as in the baseline analysis.

TABLE 7. INVESTIGATING CORRELATES OF FIRM X COUNTRY-LEVEL EXPOSURE

	Firm-level	Firm x country natural gas	Firm x country fossil fuels
	(1)	(2)	(3)
Sales	0.007	0.000	0.000
	(0.008)	(0.000)	(0.001)
Capital-sales ratio	-111.943	-2.384	-7.442
	(68.184)	(2.998)	(8.640)
Debt-assets ratio	-397.277*	-10.116	-29.502
	(208.395)	(10.654)	(31.189)
EBITDA	-0.140	-0.003	-0.009
	(0.095)	(0.005)	(0.014)
Gross margin	414.647*	10.148	29.776
	(224.657)	(11.312)	(33.145)
Labor productivity (proxy)	-0.052	-0.000	-0.002
	(0.048)	(0.003)	(0.007)
Observations	74,971	74,971	74,971
Adjusted R-squared	0.000	0.000	0.000

Note: All firm characteristics as of 2019. Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is all establishments of firms with 2019 Factset Fundamentals data on firm characteristics and 2020 CDP energy consumption data.

4.4.5 Robustness check: controlling for fossil fuel subsidies and LCT industrial policies

This section checks the robustness of the baseline results by adding controls to the regression shown in Table 4 is estimated. First, controls are added for the amount of fiscal subsidies spent on fossil fuel subsidies to consumers and producers, as a share of GDP, using data from the OECD.[12] We find that there is no substantial change to our key results when controlling for this potential confounder.

TABLE 8. PRE/POST CRISIS RESULTS CONTROLLING FOR FOSSIL FUEL SUBSIDIES

	Dep var: Total LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.191***		0.189***
	(0.045)		(0.045)
Post-February 2022 × Country exposure × Firm exposure		0.113**	0.044**
		(0.044)	(0.015)
Fossil fuel subsidies (% GDP)	-0.010	0.024	-0.010
	(0.013)	(0.015)	(0.013)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	1,954,918	1,954,918	1,954,918
Adjusted R-squared	0.609	0.608	0.609

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from Q2 2021 to Q4 2022 (with singleton observations automatically dropped). Dependent variable is inverse hyperbolic sine of total number of LCT-related job postings by establishment in month. Country exposure measure is the fraction of total energy use from imported natural gas in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). Data on fossil fuel subsidies from OECD Inventory of Support Measures for Fossil Fuels, 2023. Only firms with information in CDP included in the regressions. Coefficients on Post-February 2022 × Country exposure × Firm exposure multiplied by 10,000.

We next control for industrial policies related to key low-carbon technologies as recorded in the Global Trade Alert database, which tracks and describes announcements of government policies in a country that discriminate against foreign commercial interests (i.e. non-tariff trade barriers). Results are reported in Table 9. We find that while the number of relevant industrial policies in a country does predict low-carbon technology adoption, controlling for it does not substantially affect our estimates of the role of pre-crisis exposure in differential firm adoption of LCTs.

[12] Data on fossil fuel subsidies from OECD Inventory of Support Measures for Fossil Fuels, 2023. https://doi.org/10.1787/87dc4a55-en

TABLE 9. PRE/POST CRISIS RESULTS CONTROLLING FOR INDUSTRIAL POLICIES

	Dep var: Total LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.107836***		0.105425***
	(0.019139)		(0.019150)
Post-February 2022 × Country exposure × Firm exposure		0.099127***	0.038359***
		(0.021749)	(0.009783)
# LCT Industrial Policies	0.000002***	0.000003***	0.000002***
	(0.000000)	(0.000000)	(0.000000)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	1,796,280	1,796,280	1,796,280
Adjusted R-squared	0.613	0.613	0.613

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from Q2 2021 to Q4 2022 (with singleton observations automatically dropped). Dependent variable is inverse hyperbolic sine of total number of LCT-related job postings by establishment in month. Country exposure measure is the fraction of total energy use from imported natural gas in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). Data on industrial policies from the Global Trade Alert database. Only firms with information in CDP included in the regressions. Coefficients on Post-February 2022 × Country exposure × Firm exposure multiplied by 10,000.

4.4.6 Robustness check: modifying sample period

This section checks the robustness of the baseline results by modifying the time period over which the pre/post-February 2022 regression in Table 4 is estimated. This baseline regression is estimated over the months from Q2 2021 to Q4 2022. Each of the panels in Table 10 re-estimates these regressions with the monthly sample starting at each of the four successive previous quarters. There are no substantial changes to our results with these extended time periods. Appendix Figure A10 provides results similar to the baseline coefficient plot in Figure 10 but with the sample period extended to begin in July 2020 (with coefficients shown for changes in LCT hiring relative to Q2 2020).

TABLE 10. BASELINE PRE/POST CRISIS RESULTS WITH MODIFIED SAMPLE TIME PERIOD

(a) Q2 2020 START

	Dep var: Total LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.173***		0.171***
	(0.055)		(0.056)
Post-February 2022 × Country exposure × Firm exposure		0.167**	0.034**
		(0.075)	(0.016)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	3,307,979	3,307,979	3,307,979
Adjusted R-squared	0.554	0.553	0.554

(b) Q3 2020 START

	Dep var: Total LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.171***		0.169***
	(0.055)		(0.055)
Post-February 2022 × Country exposure × Firm exposure		0.164**	0.033*
		(0.074)	(0.016)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	2,975,717	2,975,717	2,975,717
Adjusted R-squared	0.570	0.569	0.570

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from indicated starting time to Q4 2022 (with singleton observations automatically dropped). Dependent variable is inverse hyperbolic sine of total number of LCT-related job postings by establishment in month. Country exposure measures are fraction of total energy use from imported natural gas in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). Only firms with information in CDP included in the regressions. Coefficients on Post-February 2022 × Country exposure × Firm exposure multiplied by 10,000.

BASELINE PRE/POST CRISIS RESULTS WITH MODIFIED SAMPLE TIME PERIOD

(c) Q4 2020 START

	Dep var: Total LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.166***		0.164***
	(0.054)		(0.054)
Post-February 2022 × Country exposure × Firm exposure		0.160**	0.033*
		(0.071)	(0.017)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	2,643,747	2,643,747	2,643,747
Adjusted R-squared	0.583	0.583	0.583

(d) Q1 2021 START

	Dep var: Total LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.161***		0.159***
	(0.051)		(0.052)
Post-February 2022 × Country exposure × Firm exposure		0.157**	0.033*
		(0.069)	(0.016)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	2,312,819	2,312,819	2,312,819
Adjusted R-squared	0.597	0.596	0.597

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from indicated starting time to Q4 2022 (with singleton observations automatically dropped). Dependent variable is inverse hyperbolic sine of total number of LCT-related job postings by establishment in month. Country exposure measures are fraction of total energy use from imported natural gas in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). Only firms with information in CDP included in the regressions. Coefficients on Post-February 2022 × Country exposure × Firm exposure multiplied by 10,000.

4.4.7 Placebo check

This section includes a variety of placebo tests to verify the baseline results. It first repeats the same pre/post February 2022 regressions as in Equations 1-3 and event study regressions as in Equation 4, but with the dependent variable as all non-LCT job postings. These regression results are shown in Table 11 and Figure 15 for the baseline specifications with country exposure based on natural gas import dependence. Establishments with greater ex-ante country and firm exposure to the 2022 energy price shock did not differentially increase non-LCT hiring with the onset of the 2022 energy crisis.

TABLE 11. PRE/POST CRISIS RESULTS REPLACING DEPENDENT VARIABLE WITH NON-LCT JOB POSTINGS

	Dep var: Total non-LCT job ads (IHS transformation)		
	(1)	(2)	(3)
Post-February 2022 × Country exposure	-0.177		-0.184
	(0.401)		(0.401)
Post-February 2022 × Country exposure × Firm exposure		-0.033	0.109
		(0.313)	(0.067)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	No	No	Yes
Observations	1,982,647	1,982,647	1,982,647
Adjusted R-squared	0.781	0.781	0.781

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) < 0.10, (**) < 0.05, and (***) < 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from Q2 2021 to Q4 2022 (with singleton observations automatically dropped). Dependent variable is inverse hyperbolic sine of total non-LCT-related job ads by establishment in month. Country exposure measure is ratio of total energy use from imported natural gas in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). See text for further details.

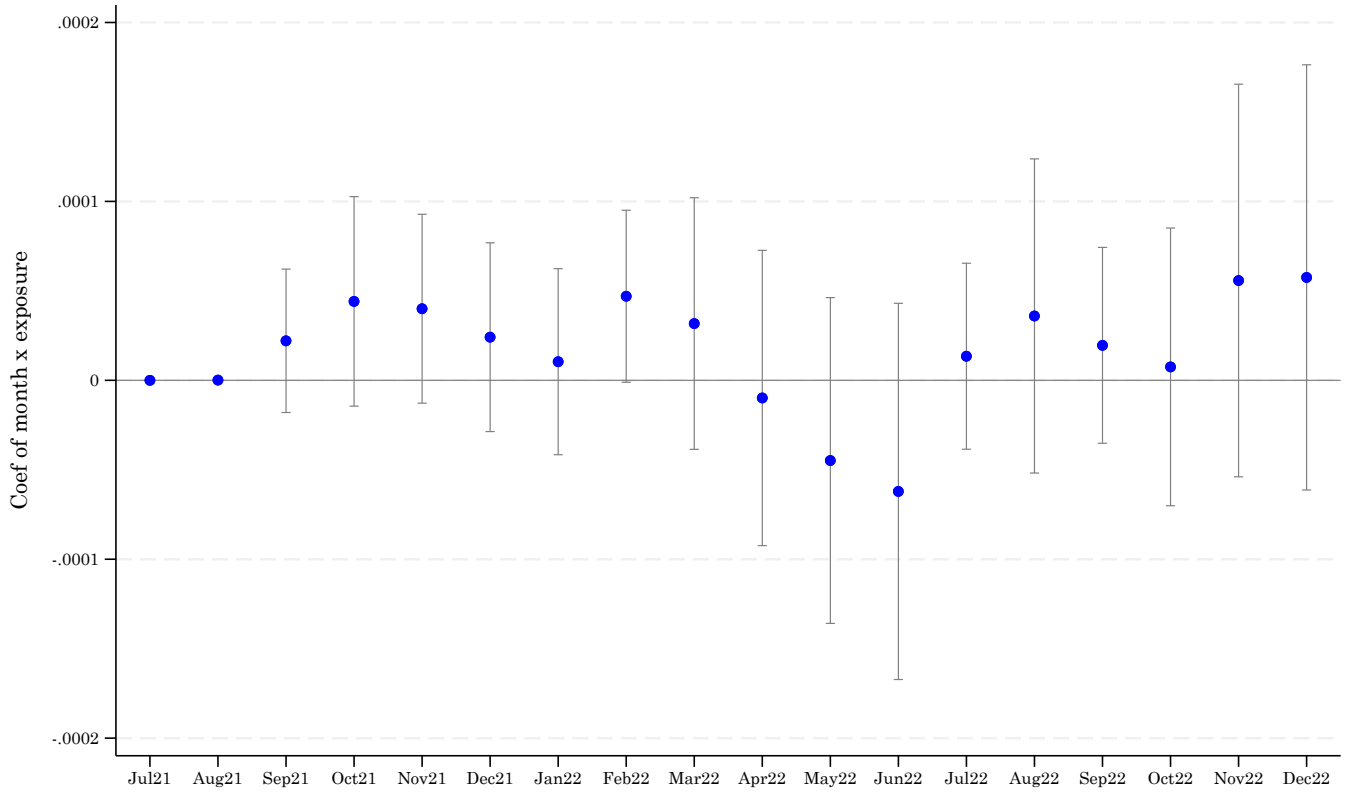


Figure 15: Placebo test: Establishment-level event study replacing dependent variable with non-LCT job postings

Notes: This figure displays the estimated coefficients and 95% confidence intervals of the interaction between each year-month and the interaction of ex-ante energy import dependence and energy intensity from Equation (4). Point estimates from the events studies shows the change in the number of non-LCT-related job ads posted by an establishment each month from July 2021 to December 2022. Regressions include year-month and establishment fixed effects. Standard errors are clustered by country. Further details in text.

4.4.8 Alternative specifications

This section includes a several alternative specifications repeating the same pre/post February 2022 regressions as in Equation 3. Regression results are shown in Table 12 for the baseline specifications with country exposure based on natural gas import dependence. Column (1) is the estimation of a linear probability model with the dependent variable an indicator for whether the establishment posted any LCT-related job ads in a given month. We find that the probability that an establishment posted a LCT-related job ad after February 2022 increased by 75.7 percentage points if their firm had a one-standard deviation higher baseline energy intensity. Column (2) is the estimation of a log-linear model, with the dependent variable as the log number of LCT-related job ads posted by an establishment in a given month. The number of observations in this regression is substantially smaller than in Column (1) and our baseline specification because it excludes a large number of observations for which an establishment did not post any LCT job ads. Column (3) is a Poisson pseudo-maximum likelihood estimation with the dependent variable as the number of LCT-related job ads posted by an establishment in a month.[13] For the Columns (2) and (3) specifications there is no significant differential increase in LCT hiring after February 2022 by establishments of firms with greater ex-ante energy intensity in countries with higher ex-ante dependence on imported natural gas. This suggests that the extensive margin of LCT-related hiring was the most responsive to the 2022 energy price shock among more-exposed establishments. This is reasonable since often only a single new hire is required for an establishment to adopt LCTs (for example, in the case of a manufacturing plant that hires a sustainability officer to spearhead and enact various energy efficiency measures throughout its operations).

[13]The number of observations in this regression is again much smaller than our baseline because many are automatically excluded on account of being either singletons or separated by a fixed effect [Correia, 2015].

TABLE 12. PRE/POST CRISIS RESULTS WITH ALTERNATIVE SPECIFICATIONS

	Dep var: LCT job ad measures		
	DV: I(ads)	DV: ln(ads)	PPML - DV: ads
	(1)	(2)	(3)
Post-February 2022 × Country exposure	0.086***	0.711***	1.893**
	(0.027)	(0.237)	(0.844)
Post-February 2022 × Country exposure × Firm exposure	0.024**	-0.506	-0.843
	(0.009)	(0.357)	(1.354)
Year-month FE	Yes	Yes	Yes
Establishment FE	Yes	Yes	Yes
Post-Feb '22 x Firm Exposure	Yes	Yes	Yes
Observations	1,982,647	89,046	399,621
Adjusted R-squared	0.444	0.574	

Note: Standard errors clustered at the country level in parentheses. Levels of significance denoted by (*) $<$ 0.10, (**) $<$ 0.05, and (***) $<$ 0.01. Sample is firm establishments (defined by a firm-country-region triplet) with monthly data spanning from Q2 2021 to Q4 2022 (with singleton observations automatically dropped). Dependent variable in column (1) is indicator for whether establishment posted any LCT-related job ads in each month; in column (2) is . Country exposure measure is ratio of total energy use from imported natural gas in 2019. Firm exposure is energy intensity, calculated as fuel and SHEC consumption of the firm divided by its sales (both in 2020). See text for further details.

5. Conclusion

This paper uses a rich and high-frequency dataset of scraped online job postings and earnings calls transcripts from 35 countries to construct proxy measures for the diffusion of a comprehensive range of LCTs across regions, industries, occupations, and countries from 2014 to 2022. It follows a growing literature that infers the spread of new technologies through their footprint in the demand for new tasks or skills in the text of job postings (e.g. Acemoglu et al. [2022], Goldfarb et al. [2023]) and mentions in the quarterly earnings calls of the world's largest firms, in a similar vein to Bloom et al. [2021].

It creates a comprehensive list of keywords relating to LCTs by building on the European Patent Office (EPO)'s Y02 classification of patents related to 'climate change mitigation technologies', hand-extracting all technology-related nouns from the titles and descriptions of these patent classifications. It then classifies job postings as being LCT-related if they mention any of these LCT keywords or their close synonyms in the text. We additionally use a dataset of the transcripts from quarterly shareholder earnings calls meetings of publicly listed firms, constructing an analogous measure of the extent to which publicly listed firms are discussing LCTs in their shareholder meetings.

It finds that there was a rapid increase in LCT-related hiring in 2022, particularly in the second half. Using a subset of the data for 16 advanced economies for which online job postings data is available since 2014, it finds that growth in LCT-related hiring was very modest from 2014 to 2019, rose modestly thereafter, and accelerated rapidly in 2022. LCT-related hiring increased by three-quarters from under 1 percent of all online job postings at the end of 2021 to 1.7 percent by the end of 2022. For the full dataset of 35 countries, there was a similar pattern of only modest growth from 2019 to 2021 and then rapid growth in 2022.

Rapid growth in LCT-related hiring occurred in three quarters of the countries and regions studied, although was strongest in Europe. The rate of growth in the share of jobs related to LCTs in 2022 relative to 2021 was highest in France, Germany, Luxembourg, and Australia. The only countries in the sample where the share of LCT-related hiring in 2022 was not at least 25 percent higher than in 2021 were Belgium (where there was a large increase in 2021), the Netherlands, Singapore, and Canada. In the USA, the share of job postings related to LCTs increased by 37 percent, from 0.39 percent in 2021 to 0.54 percent in 2022.

Four groups of LCTs had particularly large increases from 2021 to 2022: those related to renewable energy, new energy vehicles, improved thermal performance, and electrical generation and storage. In particular, of the nearly one million more LCT job postings in 2022 compared to 2021, nearly three quarters were related to just seven LCTs: electric vehicles, renewable energy - general (mentions of 'alternative', 'clean', or 'renewable' energy), solar energy, insulation, ev charging, heat pumps, and wind energy. There were 3.3 times as many electric vehicle job postings in 2022 as in 2021, and 2.3 times as many electric vehicle charging job postings, for example. The 2022 growth in LCT-related job postings was concentrated in the manufacturing, electricity and heat supply, and construction industries.

Mentions of LCTs in shareholder earnings calls transcripts also rapidly increased in 2022, although growth started somewhat earlier than for job postings. The share of earnings calls mentioning LCTs started to increase rapidly in the first quarter of 2021, following steady but modest growth since 2014. Growth in LCT mentions in earnings calls was also driven by renewable energy, electric vehicles, solar energy, ev charging, energy storage, and wind energy.

It explores the role of the 2022 global energy crisis and, particularly, the Russian invasion in Ukraine, in driving this increase in LCT-related hiring. It examines whether there was a differential increase in LCT-related hiring after the energy crisis started in the firms most

exposed to the rise in energy prices, due to their *ex-ante* energy intensity and being located in countries with a higher dependence in 2019 on imports of natural gas or fossil fuels.

It finds that establishments in countries with greater dependence on imported natural gas differentially increased their LCT-related job postings after the crisis following the invasion in February 2022. In addition, within exposed countries, establishments with a higher energy intensity also saw a relative increase in LCT-related postings. These effects materialized in March 2023 and increased in magnitude towards the end of the year. This increase in LCT-related hiring was strongest for jobs related to energy generation technologies.

Taken together, the evidence in this paper suggests that the diffusion of low-carbon technologies accelerated around the world in 2022, with a central role of the clean energy transition. This acceleration occurred across a wide range of regions, countries, industries and occupations, with potentially wide-ranging implications. The results suggest that the global energy crisis played an important role in triggering this accelerated diffusion. The declining supply, and increased prices of natural gas and other fossil fuels appear to have spurred the heightened deployment of low-carbon technologies, particularly those related to energy generation, suggesting that energy prices play an important role in triggering low-carbon innovation. Further research will be required to disentangle the detailed mechanisms through which the energy crisis affected LCT diffusion.

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A. Appendix

A.1 BGT Job postings data coverage

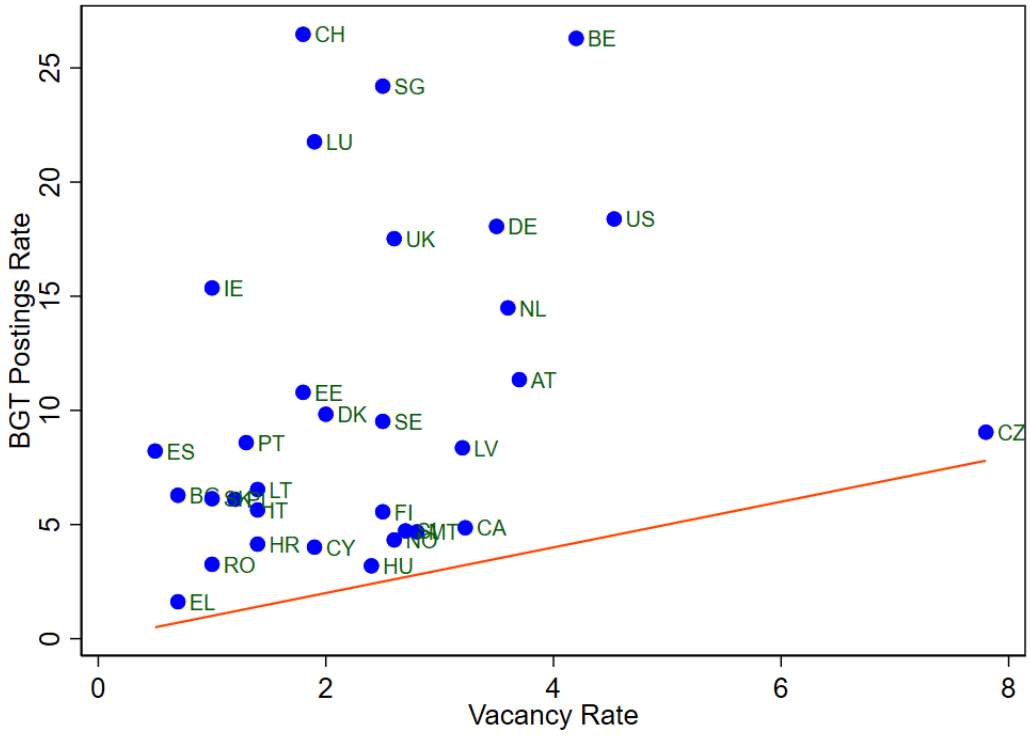


Figure A1: Estimated BGT over/under coverage by country, 2019

This figure compares for each country the 2019 vacancy rate (number of vacancies as a share of total employment plus vacancies), as calculated by national statistical agencies (in some cases, as an average of quarterly or monthly vacancy rate, to a 'BGT postings rate' (calculated as the total number of postings as a share of total employment plus total number 45 degree line in red. There is no comparable vacancy rate data for France, Australia, and New Zealand.

TABLE A1. COUNTRIES WITH FIRST YEAR IN DATASET AND TOTAL ADVERTS

Country	Region	Year	LCT Adverts ('000s)	Total Adverts ('000s)
Australia	Pacific	2014	46.4	5327.3
Austria	Western Europe	2014	63.1	5947.7
Belgium	Western Europe	2014	289.5	18392.2
Bulgaria	Eastern Europe	2019	1.5	918.8
Canada	North America	2014	115.8	9081.1
Croatia	Eastern Europe	2019	2.1	585.5
Cyprus	Southern Europe	2019	.4	90.9
Czech Republic	Eastern Europe	2019	6.8	2606.1
Denmark	Northern Europe	2014	117.1	3596.8
Estonia	Northern Europe	2019	.4	379.3
Finland	Northern Europe	2019	6.8	860.9
France	Western Europe	2014	709.5	54431.3
Germany	Western Europe	2014	940.1	82080
Greece	Southern Europe	2019	1.7	364.6
Hungary	Eastern Europe	2019	27	1093.1
Ireland	British Isles	2019	20.4	1971.4
Italy	Southern Europe	2014	172	10153.8
Latvia	Northern Europe	2019	1	427.4
Lithuania	Northern Europe	2019	1.6	648.6
Luxembourg	Western Europe	2014	14.4	861.2
Malta	Southern Europe	2019	.7	65.2
Netherlands	Western Europe	2014	176.3	13714.1
New Zealand	Pacific	2014	6.1	1159.7
Norway	Northern Europe	2014	32.2	1016
Poland	Eastern Europe	2019	133	6363.5
Portugal	Southern Europe	2019	33.9	2013.5
Romania	Eastern Europe	2019	16.5	1342.3
Singapore	Pacific	2014	99.5	8369.5
Slovakia	Eastern Europe	2019	4.2	761.6
Slovenia	Eastern Europe	2019	1	297
Spain	Southern Europe	2019	239.8	5301.9
Sweden	Northern Europe	2019	93.7	2987.2
Switzerland	Western Europe	2014	240.2	13116.8
USA	North America	2014	3074.6	309985
United Kingdom	British Isles	2014	763.5	76723

Notes: This table shows the total number of job postings related to each technology across all countries based on whether data for that country begins in 2014 or 2019.

A.2 Occupation and industry crosswalks

The data on online job postings from BGT includes information about the industry and occupation of the job posting, as shown in the charts in Section 3. In order to compare diffusion of LCTs by industry and occupation across countries, all postings were reclassified into two internationally-harmonized classifications provided by the International Labour Organization (ILO). This section describes the data sources and processes used to crosswalk from national industry and occupation classifications into these internationally-harmonized ILO classifications.

A.2.1 Industry crosswalks

Postings in the BGT data are provided in several different national industrial classifications, which were re-classified to the International Standard Industrial Classification of All Economic Activities (ISIC) Rev. 4 at the one-digit 'Section' level using crosswalks published by national statistical agencies. Table A2 lists the national industry classifications for each country in the BGT data (note all European countries used the same classification), with the crosswalks included in the footnote, as well as the share of all job postings for that country that were successfully re-classified at the one-digit ISIC level.

Crosswalks published by national statistical agencies were used to assign each job posting into an ISIC 2-digit sector, however these only link ISIC codes to the most-granular level of the original industry classification (e.g. six-digit NAICS 'national industry' codes or 4-digit ANZSIC 'Classes'). This is problematic because a portion of the job postings with a non-missing industry are only identified at a higher-level industry aggregation than is included in the crosswalks (e.g. 5- or 4-digit NAICS5, NAICS4; ANSIC Divisions; etc.). In order to link these postings to an ISIC Sector, a probabilistic approach, taking advantage of the hierarchical nature of all these industry classifications, was used. The original industry codes (at whatever level of aggregation they are identified) were matched to ISIC 2-digit Sectors based on whichever ISIC Sector has the largest share of the disaggregated industry in the concordance. So, for example, 4-digit NAICS ('NAICS4') group 3364 ('Aerospace product and parts manufacturing') was corresponded to ISIC Section 30 ('Manufacture Of Other Transport Equipment') because five of the six different NAICS6 industries that are 'under' this NAICS4 (336411, 336412, 336413, etc.) corresponded to ISIC 4-digit codes in the ISIC Sector 30 (one NAICS6 industry corresponded to ISIC Sector 28). If ISIC Sector shares of the disaggregated industries were equal, then whichever ISIC Sector is numbered first on the list of ISIC Sectors (e.g. "12" over "34") was used.

In order to minimize any potential errors from this probabilistic crosswalking process, all analyses are only at the more aggregated level of one-digit ISIC Sections rather than two-digit ISIC Sectors.

A.2.2 Occupation crosswalks

Postings in the BGT data are provided in several different national occupation classifications, which were re-classified to the International Classification of Occupations (ISCO) at the three-digit 'Minor Groups' level using crosswalks published by national statistical agencies. Table A3 lists the national occupation classifications for each country in the BGT data (note all European countries used the same classification), with the crosswalks included in the footnotes, as well as the share of all job postings for that country that were successfully re-classified at the three-digit ISCO level. The vast majority of postings that could not be re-classified were because there was no information included about the occupation of that job posting, rather than that it was not possible to match the occupation code as described in a national occupational classification to a three-digit ISCO code.

For several countries there are multiple occupations in national occupational classification that match to multiple three-digit ISCO codes ('ISOC3'). These cases were dealt with based on the official guidance from the UK Office of National Statistics to assign the value by UK SOC (eg. employment counts) to the ISCO3 50/50 or (in one case) 40/60.[14] In similar cases

[14] SOC2010 to ISCO08 mapping, UK Office of National Statistics,

TABLE A2. INDUSTRY RE-CLASSIFICATION BY COUNTRY

Country	Classification in BGT data	% of postings classified to ISIC
Australia	Australian and New Zealand Standard Industrial Classification (ANZSIC), 2006[a]	99.8
Canada	North American Industry Classification System (NAICS) 2017[b]	99.9
European countries	European Statistical classification of economic activities (NACE) Rev. 2 [c]	100
New Zealand	Australian and New Zealand Standard Industrial Classification (ANZSIC), 2006[d]	99.9
Singapore	Singapore Standard Industrial Classification (SSIC) Version 2018[e]	40.1
United Kingdom	UK Standard Industrial Classification[f]	52.9
United States	North American Industry Classification System (NAICS) 2017[g]	73.1

Notes: This table lists the national industrial classification that the BGT data is provided in and the share of all job postings that were successfully crosswalked to the one-digit ISCO classification, over the entire period for which data is available for each country (from either 2014 or 2019 until 2022).

[a]ANZSIC 2006 - ISIC Rev. 4 Correspondence Table, Australian Bureau of Statistics, https://www.abs.gov.au/ausstats/abs@.nsf/PrimaryMainFeatures/1292.0.55.005?OpenDocument

[b]NAICS2017US to ISIC Rev. 4 Correspondence Table, United Nations Statistics Division, https://unstats.un.org/unsd/classifications/Econ/isic

[c]One-digit NACE industries are synonymous with one-digit ISIC codes. The European Commission, https://ec.europa.eu/eurostat/web/nace/overview

[d]ANZSIC 2006 - ISIC Rev. 4 Correspondence Table, Australian Bureau of Statistics, https://www.abs.gov.au/ausstats/abs@.nsf/PrimaryMainFeatures/1292.0.55.005?OpenDocument

[e]SSIC 2015 (Version 2018) - ISIC Rev. 4 Correspondence Table, Government of Singapore, https://www.singstat.gov.sg/-/media/files/standards_and_classifications/industrial_classification/ssic2015-v2018-isic-4-correspondence.ashx

[f]One-digit UK SIC industries are synonymous with one-digit ISIC codes. UK Office for National Statistics, https://www.ons.gov.uk/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities/uksic2007

[g]NAICS2017US to ISIC Rev. 4 Correspondence Table, United Nations Statistics Division, https://unstats.un.org/unsd/classifications/Econ/isic

TABLE A3. OCCUPATION RE-CLASSIFICATION BY COUNTRY

Country	Classification in BGT data	% of postings classified to ISCO
Australia	Australian and New Zealand Standard Classification of Occupations (ANZSCO) Version 1.2[a]	89.6
Canada	2010 Standard Occupational Classification (SOC)[b]	87.7
European countries	European Skills, Competences, Qualifications and Occupations (ESCO)[c]	100
New Zealand	Australian and New Zealand Standard Classification of Occupations (ANZSCO) Version 1.2[d]	88.0
Singapore	Singapore Standard Occupational Classification (SSOC) Version 2018[e]	86.8
United Kingdom	UK Standard Occupational Classification (SOC) 2010[f]	98.6
United States	US Standard Occupational Classification (SOC) 2010[g]	86.5

Notes: This table lists the national occupational classification that the BGT data is provided in and the share of all job postings that were successfully crosswalked to the one-digit ISCO classification, over the entire period for which data is available for each country (from either 2014 or 2019 until 2022).

[a]ANZSCO v1.2 correspondence to ISCO-08, Australian Bureau of Statistics, https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1220.02013,%20Version%201.2?OpenDocument

[b]BGT data for Canada used the US SOC rather than the Canadian National Occupational Classification (NOC).

[c]Three-digit ESCO occupations are synonymous with three-digit ISCO codes. The European Commission, https://esco.ec.europa.eu/en/classification/occupation_main

[d]ANZSCO v1.2 correspondence to ISCO-08, Australian Bureau of Statistics, https://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/1220.02013,%20Version%201.2?OpenDocument

[e]A correspondence table from the SSOC Version 2020 to ISCO was-08 was used in conjunction with a correspondence table from SSOC Version 2018 to SSOC Version 2018, both available from: Government of Singapore, https://www.singstat.gov.sg/standards/standards-and-classifications/ssoc

[f]SOC2010 to ISCO08 mapping, UK Office of National Statistics, https://www.ons.gov.uk/file?uri=/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2010/ug201002soc2010toisco08v2_tcm77-283163.xls

[g]ISCO-08 x SOC 2010 Crosswalk, Bureau of Labor Statistics, https://www.bls.gov/soc/ISCO_SOC_Crosswalk.xls

for the United States, Canada, Australia, New Zealand, and Singapore, a probability-weighted crosswalk was used. In these cases, a proportion x of the job postings in the origin country occupation matched to multiple ISOC3 codes was assigned to each of the ISCO3 codes, where the proportion x is the share of job postings in each of these ISCO3 occupations across the UK, Germany, France, Netherlands, and Austria from 2014 to 2022.

https://www.ons.gov.uk/file?uri=/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc201
283163.xls

A.3 Keywords and technologies

TABLE A4. TECHNOLOGIES BY TOTAL ADVERTS ('000S) FOR EACH COUNTRY COHORT

Technology	Adverts, 2014 Cohort	Adverts, 2019 Cohort
renewable energy - general	1251899	52936
solar energy	949983	106386
insulation	897789	22746
electric vehicles	760565	33006
wind energy	453197	25715
biofuels	318828	16397
heat pumps	294966	31276
nuclear	286201	2659
ev charging	217866	12221
energy storage	203581	17401
smart grids	130888	6342
led lamps	99341	47098
reactive power compensation	90453	480
solid waste management	86303	2415
decentralized energy	75768	4395
cogeneration systems	70443	2705
smart metering	67542	1145
hybrid vehicles	60294	5412
geothermal	52439	364
hydropower	49640	3522
bio plastics	48642	11942
hybrid energy systems	42405	4157
switched-mode power supplies	40121	148927
energy recovery	39699	929
carbon capture	36194	1184
biopackaging	30521	1264
compact fluorescent lamps	25250	93
combined cycle power plant	24903	797
presence detection sensors	23221	1418
absorption cooling	22869	127
solar applications	21511	154
high voltage dc link	14372	1601
integrated gassification combined cycle	13667	2
roof garden systems	13550	213
demand response systems	10602	23549
energy efficient lighting - general	9096	96
induction heating	5083	72
energy efficient heating - general	4603	87
energy from the sea	4519	719
superconducting elements	3735	155
flexible ac transmission systems	2228	185
induction cooking	1993	70
energy efficient computing	1661	19
active power filtering	1159	12
halogen lamps	384	14
discharge lamp	285	7

Notes: This table shows the number of LCT-related and total job postings over the entire time for which there is data for each country from 2014 or 2019 until 2022.

TABLE A5. TECHNOLOGIES BY TOTAL ADVERTS IN 2019-22 SAMPLE

Agg Tech Group	Technology	Adverts
Generation	renewable energy - general	818377
Generation	solar energy	609761
Vehicles	electric vehicles	552301
Energy-use	insulation	498234
Generation	wind energy	224974
Generation	heat pumps	187078
Generation	biofuels	174286
Energy-use	switched-mode power supplies	171962
Vehicles	ev charging	171350
Generation	energy storage	154429
Generation	nuclear	128873
Consumer	led lamps	77021
Energy-use	smart grids	70634
Generation	decentralized energy	56643
Waste & materials	solid waste management	53838
Generation	cogeneration systems	37726
Vehicles	hybrid vehicles	35730
Generation	reactive power compensation	35335
Waste & materials	bio plastics	34186
Energy-use	smart metering	32175
Generation	hydropower	28711
Energy-use	demand response systems	27956
Generation	geothermal	26160
Generation	hybrid energy systems	26072
Energy-use	carbon capture	23721
Energy-use	energy recovery	23295
Waste & materials	biopackaging	23119
Consumer	compact fluorescent lamps	16879
Energy-use	presence detection sensors	16851
Generation	solar applications	13503
Consumer	absorption cooling	12385
Generation	combined cycle power plant	10622
Generation	high voltage dc link	8455
Energy-use	roof garden systems	8068
Consumer	energy efficient lighting - general	3588
Consumer	energy efficient heating - general	2641
Consumer	induction heating	2549
Generation	energy from the sea	2513
Generation	superconducting elements	2135
Generation	flexible ac transmission systems	1564
Consumer	induction cooking	1394
Consumer	energy efficient computing	920
Generation	active power filtering	634
Generation	integrated gassification combined cycle	537
Consumer	halogen lamps	163
Consumer	discharge lamp	67

Notes: This table shows the number of job postings related to each technology, with the aggregate technology group listed, across all countries since 2019

TABLE A6. TOP 25 FASTEST-GROWING TECHNOLOGIES

Technology	CAGR, 2014-22 (%)	Share of all LCT Adverts (%)
decentralized energy	34.12	.456
presence detection sensors	33.32	.148
ev charging	32.38	1.312
switched-mode power supplies	31.9	.302
solid waste management	29.97	.532
electric vehicles	28.78	4.826
energy storage	28.59	.984
biopackaging	27.06	.171
bio plastics	24.89	.236
carbon capture	22.43	.222
induction cooking	21.71	.007
compact fluorescent lamps	20.76	.096
roof garden systems	19.87	.048
energy recovery	19.67	.202
flexible ac transmission systems	19.58	.01
renewable energy - general	18.78	5.599
heat pumps	17.9	1.336
demand response systems	16.85	.032
solar energy	16.46	3.566
hybrid vehicles	15.68	.221
solar applications	15.45	.059
hydropower	14.04	.202
led lamps	13.91	.416
cogeneration systems	13.9	.286
hybrid energy systems	13.68	.149

Notes: This table shows the growth rate of the 25 fastest-growing technologies since 2014, in the 16 countries with data starting that year, as well as the share of all LCT-related job postings that are related to these technologies.

TABLE A7. TOP 30 KEYWORDS IN JOB ADVERTS AND EARNINGS CALLS

Keyword	Technology	Job postings	Keyword	Technology	Earnings Calls
insulation	insulation	479329	renewable energy	renewable energy - general	6866
renewable energy	renewable energy - general	400428	electric vehicles	electric vehicles	4198
renewable energies	renewable energy - general	177345	hydrogen	hydrogen	3741
electric car	electric vehicles	162595	clean energy	renewable energy - general	3124
power factor	switched-mode power supplies	139943	electric vehicle	electric vehicles	3098
heat pump	heat pumps	108087	alternative energy	renewable energy - general	1815
wind energy	wind energy	104025	insulation	insulation	1644
emitting diode	led lamps	101993	energy storage	energy storage	1639
solar array	solar energy	99907	ethanol	biofuels	1631
electric engine	electric vehicles	85628	biomass	biofuels	1624
electric vehicle	electric vehicles	84868	solar power	solar energy	1411
electric vehicles	electric vehicles	83424	wind farms	wind energy	1386
clean energy	renewable energy - general	77439	carbon capture	carbon capture	1328
reactive power	reactive power compensation	74416	wind power	wind energy	1261
pv system	solar energy	71780	solar panels	solar energy	1152
solar powered	solar energy	70690	nuclear power	nuclear	1042
biomass	biofuels	68232	solar energy	solar energy	1034
charging station	ev charging	66120	fuel cell	hydrogen	957
solar energy	solar energy	60445	biofuels	biofuels	835
nuclear power	nuclear	59806	hydropower	hydropower	792
waste sorting	solid waste management	59456	electric cars	electric vehicles	771
wind turbine	wind energy	58491	combined cycle	combined cycle power plant	769
biogas	biofuels	58432	charging stations	ev charging	712
wind power	wind energy	57778	wind turbines	wind energy	692
pv solar	solar energy	55676	biofuel	biofuels	690
wind park	wind energy	52851	cogeneration	cogeneration systems	686
energy storage	energy storage	51855	biodiesel	biofuels	667
photovoltaic solar	solar energy	51829	ev charging	ev charging	628
wind farms	wind energy	42986	fuel cells	hydrogen	607
smart metering	smart metering	40900	geothermal	geothermal	600

Notes: This table shows the 30 technology-related keywords with the highest number of mentions in job postings and earnings calls, across all 35 countries in the data. Note that for non-english job postings, mentions of non-english keywords are counted as the english translated keyword.

A.4 BGT-FactSet matching procedure

Prior the matching process began, we established four distinct variations of the company names present in both the FactSet and BGT datasets, taking into account any possible differences that could hinder company identification. Subsequently, we conducted an *exact* matching analysis using these different name variations in a predetermined order. Specifically, we first matched company names using Variation N°1, followed by Variation N°2, and so on. It's worth noting that we removed previously matched companies from the BGT dataset before moving on to the next variation to avoid matching the same company twice.

TABLE A8. **VARIATIONS OF COMPANY NAMES TO CONDUCT MATCHING**

Variation	Description
1	Lower-case company name. No changes or deletion of any special character or symbol.
2	Lower-case company name. Punctuation marks and special symbols dropped.
3	Punctuation marks-free, lower-case company name. Company suffixes (Ltd., Corp., LLC, etc.) removed (whole word and abbreviation).
4	Punctuation marks-free, lower-case company name. International company suffixes (AG, B.V., Oy, etc.) removed (whole word and abbreviation).

Additionally, we also considered that a fuzzy matching was necessary even after conducting the exact matching because of variations in spelling or punctuation that could cause an exact match to fail, leading to an incomplete or inaccurate match. Thus, to ensure a more thorough and comprehensive analysis, a fuzzy matching was performed using company names with Variation N°2, utilizing the TF-IDF and Levenshtein distance methods to account for such variations in the text.

Once the results of the two matching processes were obtained and put together, we dropped the duplicated matches from the combined results based on entity characteristics from FactSet using the following criteria:

1. Keep the FactSet Entity that is incorporated in the same country as the BGT country, if there is only one of these among all of the possible FactSet ID values for the duplicated BGT firm-country pair.
2. For still unidentified duplicates, we keep the FactSet Entity of a duplicated company with the highest average annual sales (if info available).
3. For still unidentified duplicates, we keep the FactSet Entity of a duplicated company with the oldest founding year.
4. For still unidentified duplicates, we keep the FactSet Entity that is not a subsidiary.
5. If after all of these steps, we still couldn't identify the correct duplicate, we proceed to identify those duplicated BGT firm-country pairs that belong to the same entity from the relationship dataset (i.e., the parent company), and create an artificial affiliate that captures the duplicated entities within a country. For example, if there is a 'Google Germany' company name in BGT, and it has a match with 'Google Germany Ltd.' and 'Google Germany Inc.' in FactSet, we create the artificial affiliate as 'Google Germany' in FactSet, and keep that instead of 'Google Germany Ltd.' and 'Google Germany Inc.'.

6. We drop every duplicate we cannot identify using this criteria ($\approx 1\%$ of the dataset).

A.5 Comparing job postings to alternative diffusion measures

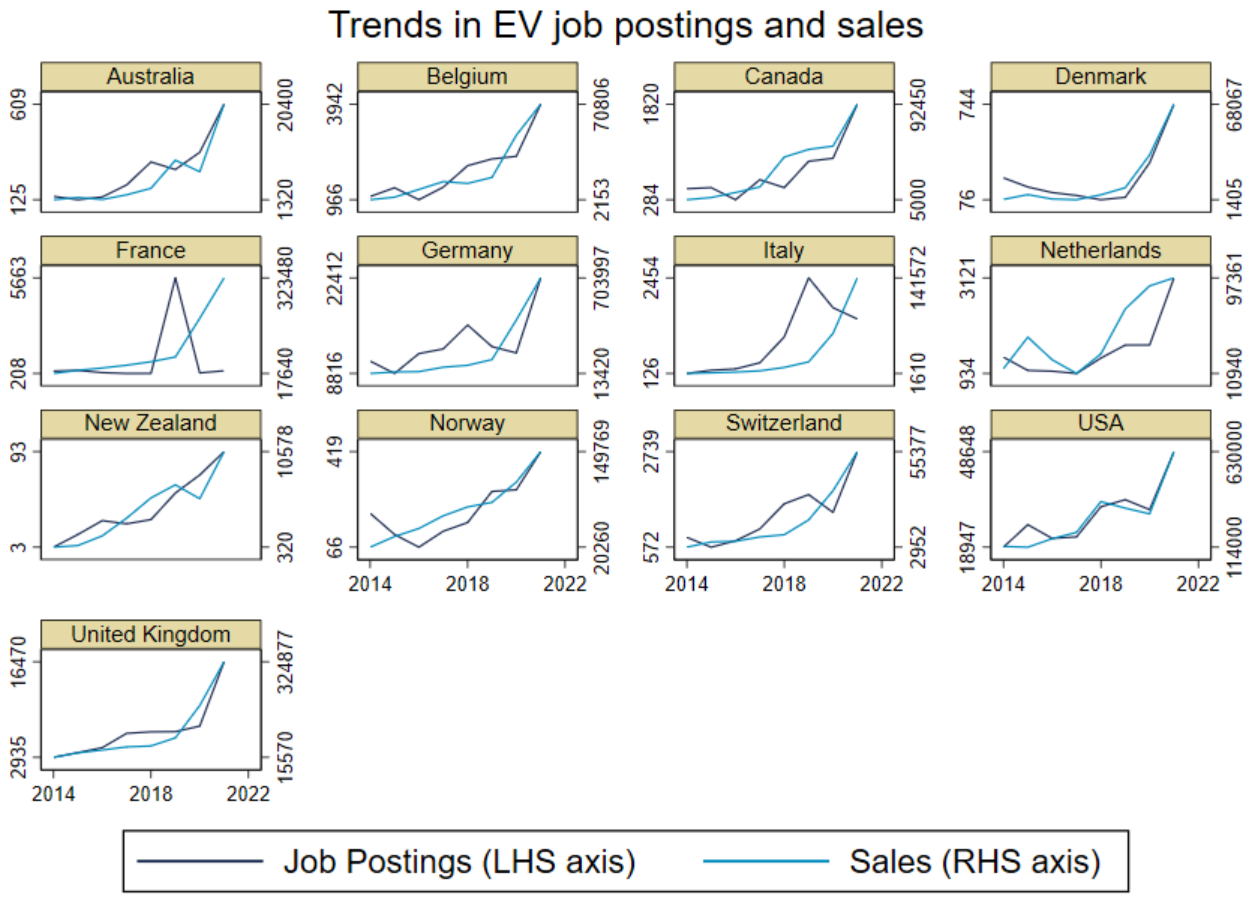


Figure A2: Comparison of EV Job postings and Sales

Notes: Displays annual trends in the number of all online job postings related to electric vehicles and EV sales in all countries with available data. EV job postings are for the following technologies: "electric vehicles", "hybrid vehicles", and "new energy vehicles - general". EV sales data are from the IEA and include battery and plug-in hybrid buses, cars, trucks, and vans.

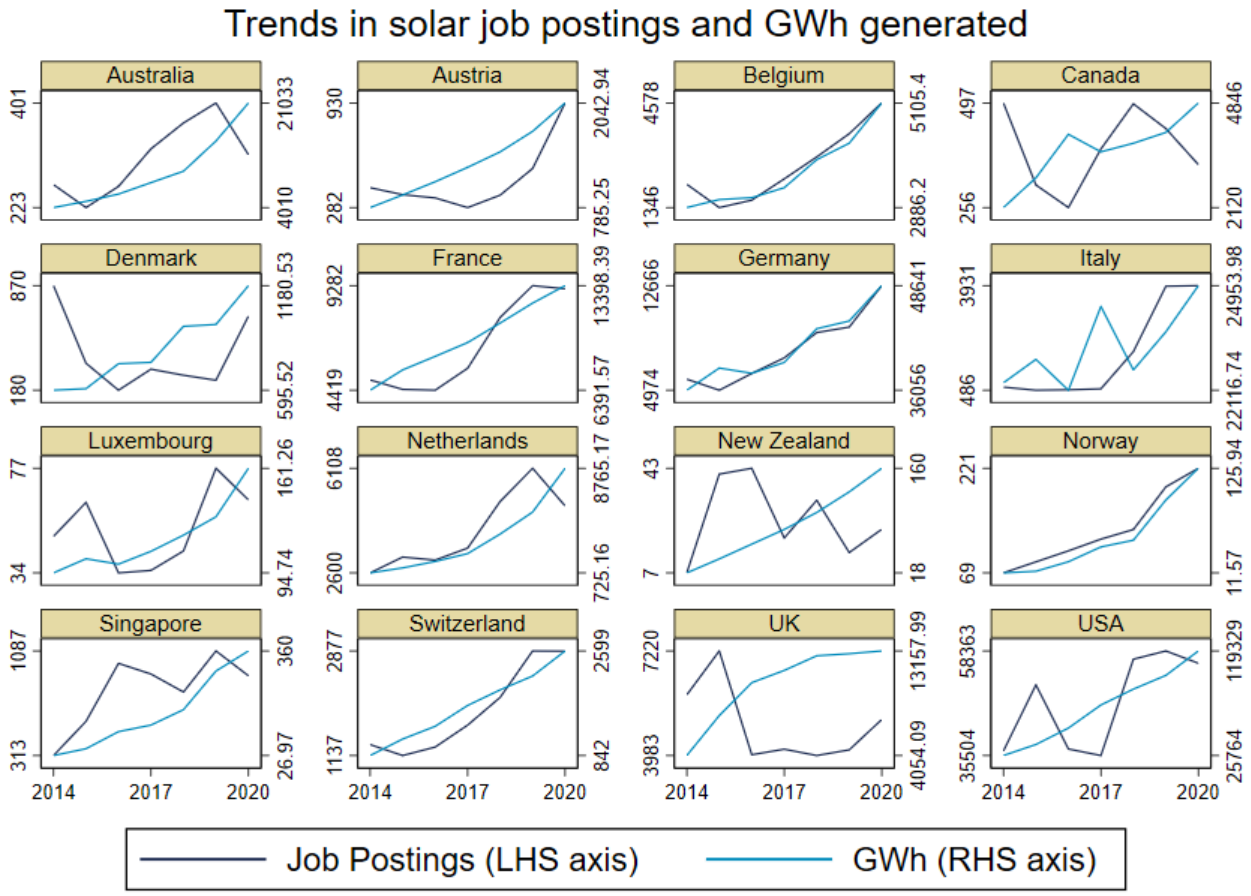


Figure A3: Comparison of Solar Job postings and GwH Generated

Notes: Displays annual trends in the number of all online job postings related to solar energy and GWh generated in all countries with available data. Energy generation data are from IRENA.

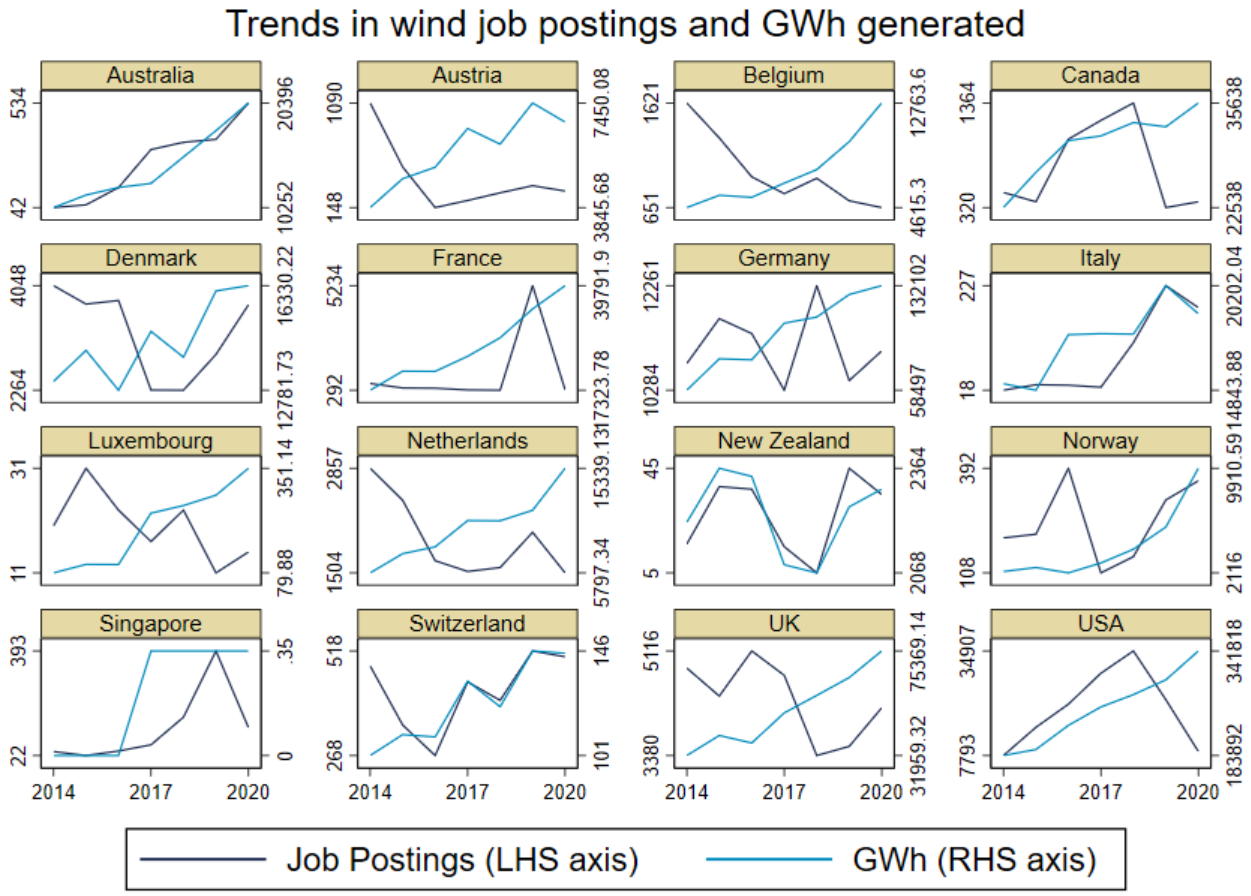
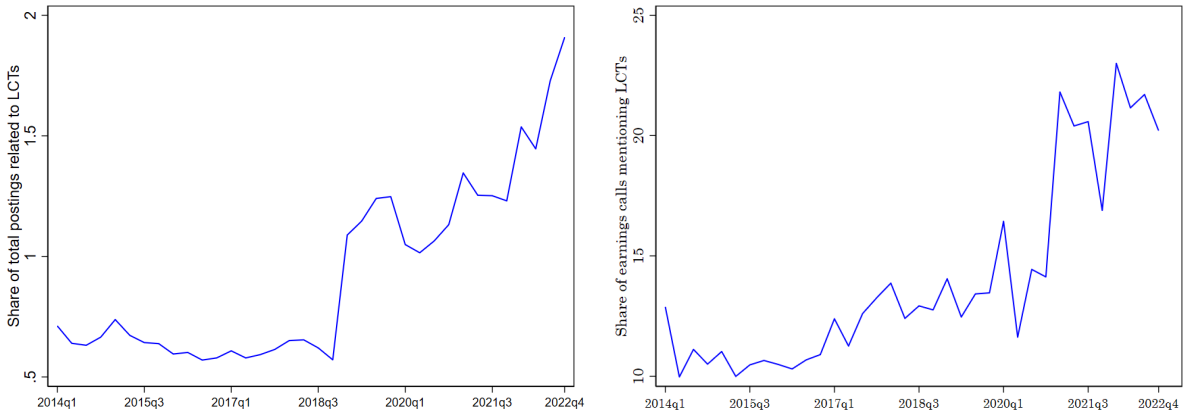


Figure A4: Comparison of Wind Job postings and GwH Generated

Notes: Displays annual trends in the number of all online job postings related to wind energy and GWh generated in all countries with available data. Energy generation data are from IRENA.

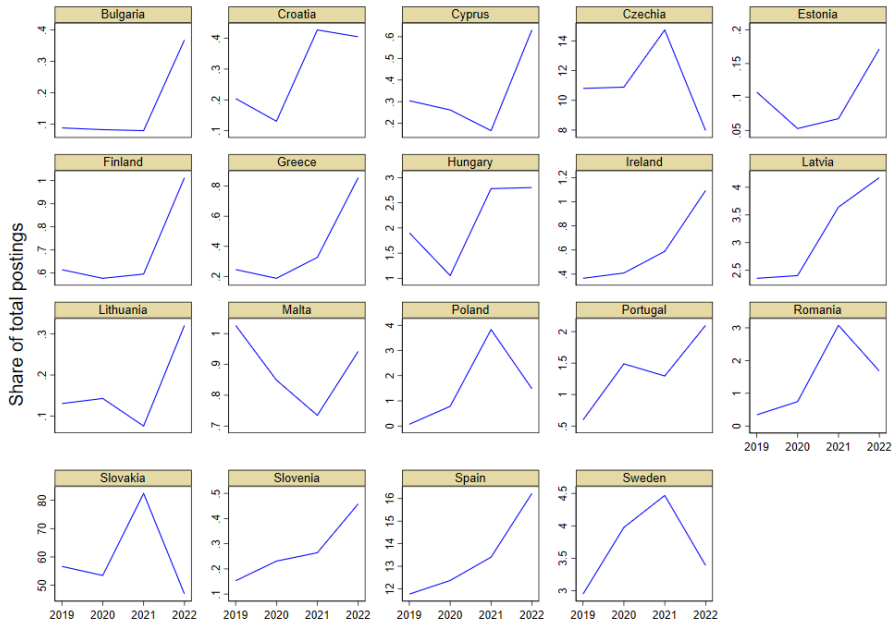
A.6 Additional Descriptive Results



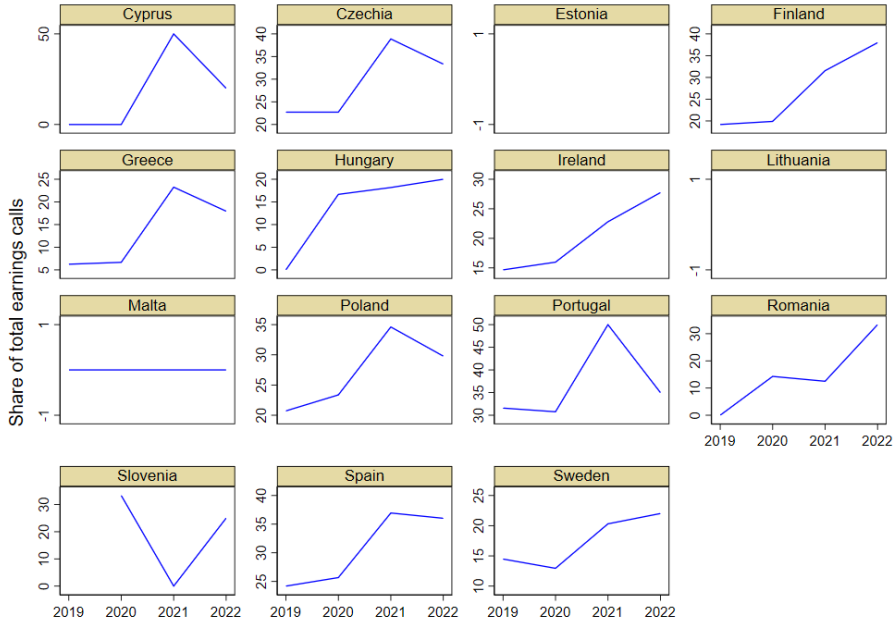
(a) Job postings (b) Earnings calls

Figure A5: Share of LCT-related job postings and earnings calls

Notes: Panel (a) displays the share of all online job postings in all 35 countries that mention LCTs. Panel (b) displays the share of all quarterly earnings calls of publicly listed firms that mention LCTs



(a) Job postings



(b) Earnings calls

Figure A6: Share of LCT-related job postings and earnings calls by country for 2019 cohort

Notes: Panel (a) displays the share of all online job postings that mention LCTs by year, for 19 countries with data starting in 2019. Panel (b) displays the share of all quarterly earnings calls of publicly listed firms in these countries that mention LCTs.

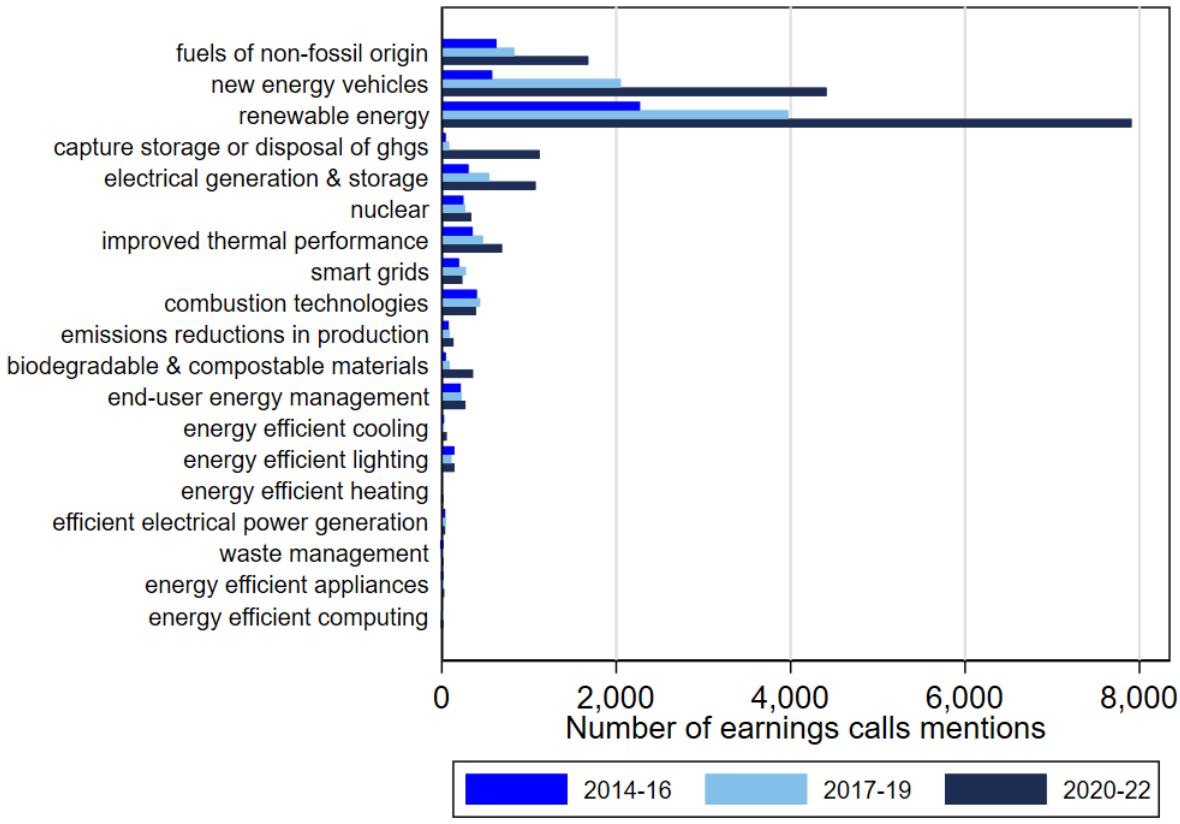
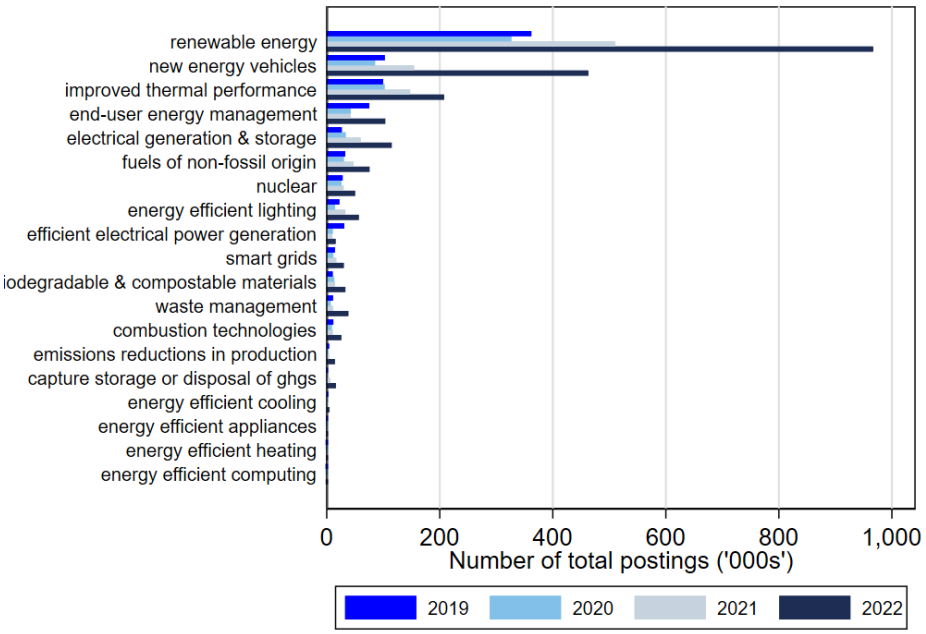
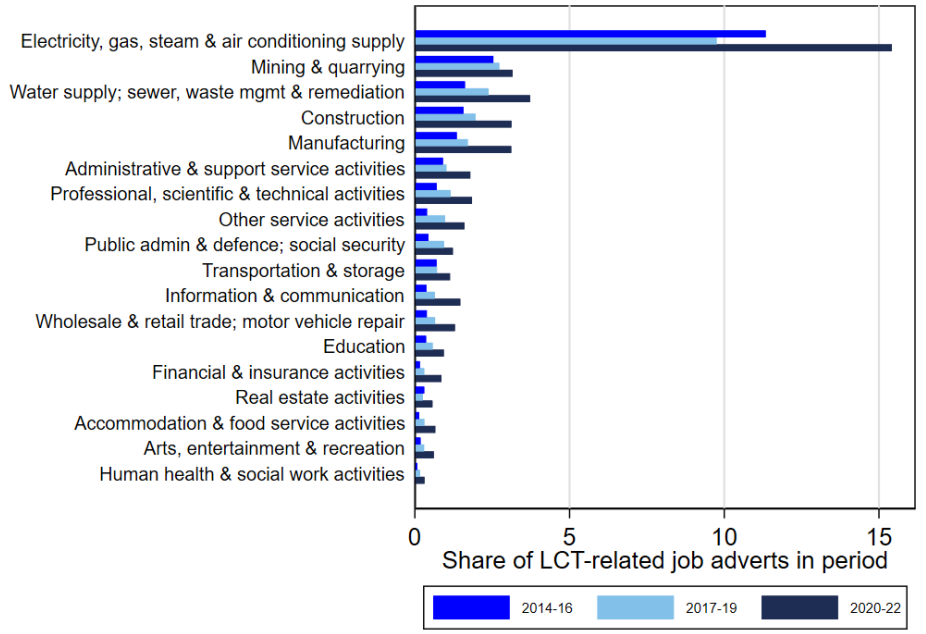


Figure A7: Number of earnings calls mentioning LCTs by Technology Group

Notes: This figure displays the number of quarterly earnings calls of publicly listed firms that mention LCTs in each Technology Group, across the 16 countries with data since 2014.



(a) Number of LCT-related job postings by technology group

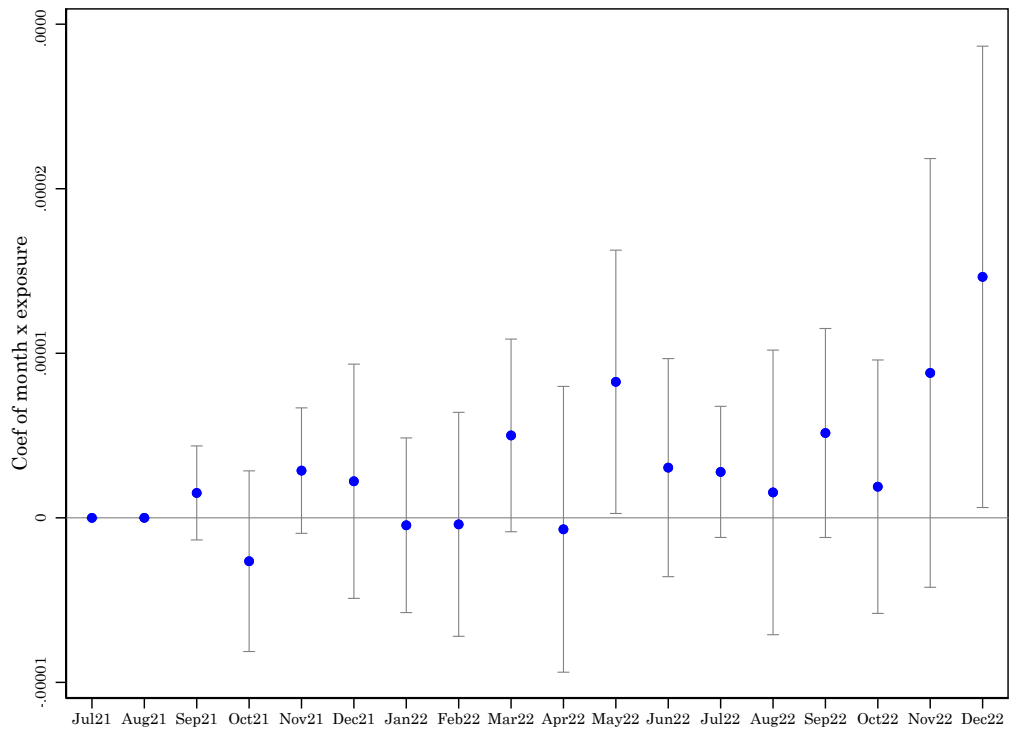


(b) Share of LCT-related job postings by ISIC section

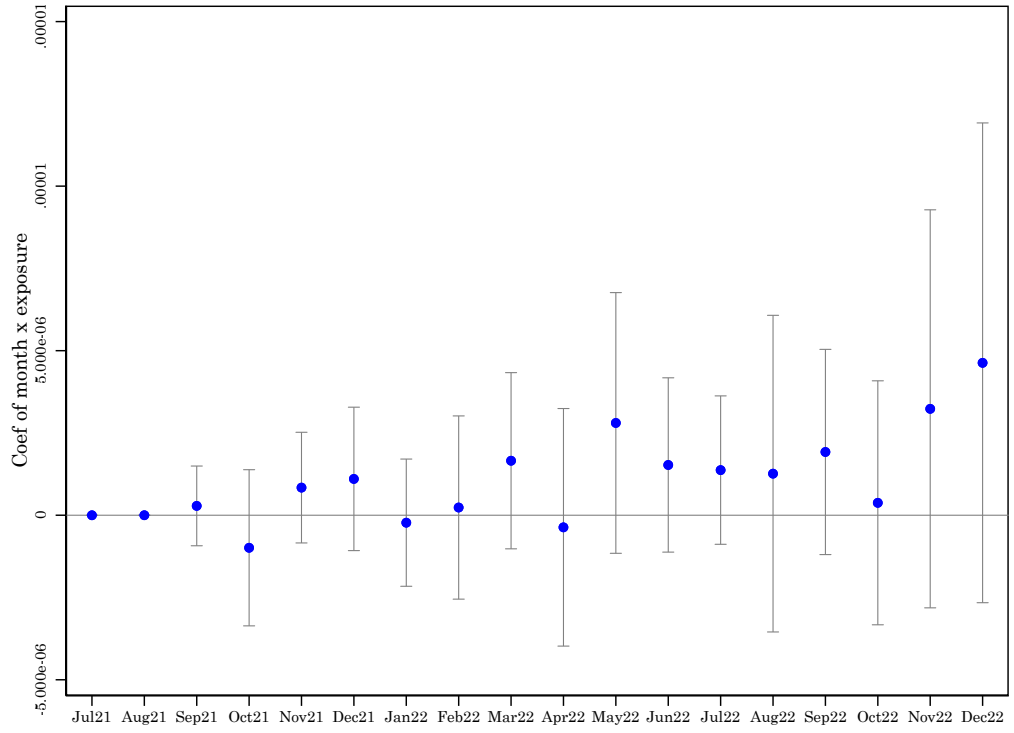
Figure A8: LCT-related job postings by technology and industry

Notes: Panel (a) displays the total number of online job postings in all 35 countries for each LCT category in each time period. Panel (b) displays the share of LCT-related job postings by 1 digit ISIC section.

A.7 Additional Regression Results



(a) Natural gas import dependence and energy intensity



(b) Fossil fuel import dependence and energy intensity

Figure A9: Establishment-level event study regression (country x firm exposure), controlling for main effects

Notes: This figure displays the estimated coefficients and 95% confidence intervals of the interaction between each year-month and the interaction of ex-ante energy import dependence and energy intensity from Equation (4). Point estimates from the events studies show the change in the number of LCT-related job ads posted by an establishment each month from July 2021 to December 2022. Regressions control for the main effects interactions between each year-month and ex-ante energy import dependence and between each year-month and ex-ante firm energy intensity and also include year-month and establishment fixed effects. Standard errors are clustered by country. Further details in text.

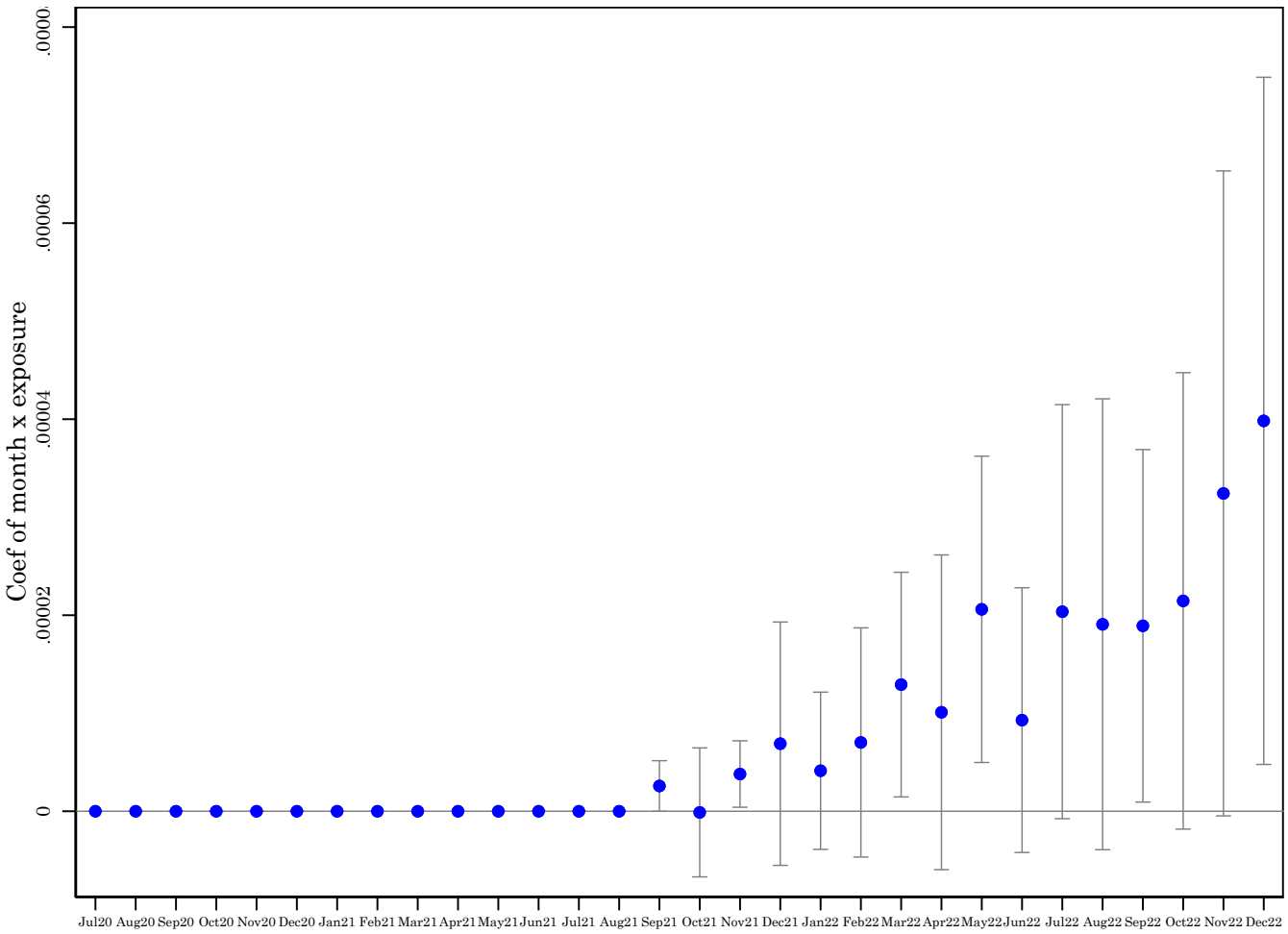


Figure A10: Extended pre-period event study of LCT job postings on exposure based on country natural gas import dependence and firm energy intensity

Notes: This figure displays the estimated coefficients and 95% confidence intervals of the interaction between each year-month and the interaction of ex-ante energy import dependence and energy intensity from Equation (4). Point estimates from the events studies show the change in the number of LCT-related job ads posted by an establishment each month from July 2021 to December 2022. Regressions include year-month and establishment fixed effects. Standard errors are clustered by country. Further details in text.