COVID-INDUCED ECONOMIC UNCERTAINTY, TASKS, AND OCCUPATIONAL DEMAND

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Covid-induced Economic Uncertainty, Tasks, and Occupational Demand*

Sotiris Blanas† Rigas Oikonomou‡

Abstract

In this paper, we provide novel evidence of the impact of Covid-induced economic uncertainty on the relative demand for different occupations in the US, according to a wide range of occupational characteristics. We conduct the analysis using monthly online job postings data at the occupation-US state level in January 2020 – December 2020 together with data on fixed occupational characteristics and monthly measures of economic uncertainty in the US, which are apportioned to occupation-state pairs based on pre-Covid country-wide occupational employment shares. The analysis reveals that Covid-induced economic uncertainty increased the relative demand for occupations with relatively high non-routine cognitive analytical, non-routine cognitive interactive, and non-routine manual task content – especially when these are also non-essential, as well as occupations that have both relatively high non-routine cognitive analytical and social or interaction task content. This evidence is consistent with the secular phenomenon of routine-biased technological change resulting in job polarisation and the growing complementarity between analytical and social tasks, but also with its episodic aspect implying its acceleration during recessions. Additional evidence, however, shows that Covid-induced economic uncertainty decreased the relative demand for customer-oriented occupations (e.g. food service, personal care and service) and increased the relative demand for essential or contact-intensive occupations with relatively high routine manual or routine cognitive task content, as well as occupations that are both contact-intensive and essential or service-oriented (e.g. healthcare practice and support, protective service, community and social service). This evidence is rationalised by idiosyncratic features of the pandemic shock (e.g. major health crisis, social distancing, lockdown). Further research in this direction could help us to understand whether these effects are temporary or long-lasting.

Keywords: Occupational demand; Occupational characteristics; Tasks; Online Job Postings; Covid-induced economic uncertainty; Covid-19; Pandemic

JEL Classification: E32, J23, J24, J63, O33

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1 Introduction

The Covid-19 pandemic outbreak in early 2020 has led to a global health emergency and the imposition of restrictive measures (e.g. strict lockdowns, domestic and international travel restrictions and bans, social distancing, isolation, contact-tracing) for the containment of the rapid spread of the virus (Ferguson et al., 2020; Gupta et al., 2020). The upheaval in the labour markets around the globe was imminent and at massive scale, and has persisted to a large extent since then. The nascent literature examining the labour market implications of the Covid-19 shock has provided some first robust evidence on its unequal effects on the employment, earnings and hiring rates of workers with different demographic or other characteristics (e.g. Adams-Prassl et al., 2020; Baylis et al., 2021; Mongey et al., 2021; Forsythe et al., 2020).

Our goal in this paper is to advance further this literature by conducting the first comprehensive analysis on the effects of the Covid-19 shock on the relative demand for occupations, according to a broad set of characteristics such as routine intensity, service-orientedness, physical contact intensity, and essentiality. To this end, we exploit monthly data from Burning Glass Technologies (BGT) on online job postings of two-digit (SOC) occupations in all fifty-one US states over January 2020 – December 2020 and data on occupational characteristics from various sources.[1] Importantly, in addition to shedding light upon how the Covid-19 shock has shifted the occupational composition of US labour demand, the analysis allows us to reflect upon these shifts in relation to labour market trends that were persistent in the US and other advanced economies in recent decades and until before the pandemic outbreak, most notably, job polarisation.[2]

We start the analysis by documenting that the ratio of the country-wide number of online job postings to total US population declined sharply in the months of the first lockdown (March–April), recovered only partially and exhibited small fluctuations when the lockdown was lifted (May–October), and plummeted again during the second lockdown (November–December).[3] We, then, document that although the per capita number of online job postings

[1] The main advantage of online job postings data is that they provide real-time information about future labour demand.

[2] This term has been coined to describe the decrease in employment of occupations with relatively high routine task content, which lie in the middle of the wage distribution, relative to the employment of occupations with relatively high non-routine cognitive task content and occupations with relatively high non-routine manual task content, which lie in the high and low end, respectively, of the wage distribution (e.g. Autor et al., 2003; Acemoglu & Autor, 2011).

[3] Sharp declines in online job postings in March–April 2020 for the US and other countries have also been

of all occupations under consideration declined sharply during the first lockdown, there were important differences in their trends in the subsequent months. As a consequence, the shares of online job postings of some occupations increased (e.g. community and social service; healthcare practice; healthcare support), while those of other occupations decreased (e.g. management; business and financial; legal; arts and entertainment; sales; food preparation and service). Alongside these trends, we show that occupations differ substantially in the intensity or status of the characteristics under consideration.

In order to investigate whether and how the Covid-19 shock has contributed to the aforementioned shifts in the occupational composition of US labour demand, we regress the share of online job postings of each occupation-state pair on the interaction between a measure of Covid-induced economic uncertainty and a variable for a certain occupational characteristic. We focus on economic uncertainty as it is a key driving force of firms' hiring decisions amid the Covid-19 shock. To capture it empirically, we rely on the monthly news-based and composite Economic Policy Uncertainty (EPU) indices of Baker et al. (2016), and alternatively, on the monthly sales revenue and employment growth uncertainty indices of the Survey of Business Uncertainty (SBU).[4] As these are country-level measures, we apportion them to occupation-state pairs according to the pre-Covid (2019) share of employment of each pair in country-wide employment of the respective occupation.[5] We estimate the specification by OLS while controlling for unobserved differences across occupation-state pairs (e.g. initial demographics, human capital) by including occupation-state dummies, and for common time-varying shocks (e.g. FED and federal government policies) by including month dummies.[6]

reported by other studies (e.g. Forsythe et al., 2020; Hensvik et al., 2021).

[4]Similarly to postings of job vacancies, the main advantage of these measures of economic uncertainty is that they are forward-looking, while the SBU measures have the extra advantage of capturing the subjective beliefs of managers about the short-run prospects of their businesses and the aggregate economy. For a detailed account of the latter measures and the associated survey, see Altig et al. (2020). Intuitively, Covid-induced economic uncertainty, measured by either the EPU or the SBU indices, moved in opposite directions with respect to online job postings per capita: it spiked during the first lockdown (March–April), after which it declined but remained at high levels relative to the pre-pandemic months, and picked up slightly again during the second lockdown (November–December). Relatedly, Baker, Bloom, Davis, & Terry (2020) have shown that these uncertainty measures can explain a large fraction of the drop in US GDP witnessed during the first months of the pandemic outbreak.

[5]Information on the latter variable is drawn from the US Bureau of Labour Statistics (BLS).

[6]We claim that the OLS estimates are unlikely to suffer from the simultaneity bias for the following reasons. Due to the size of the US economy, it is highly unlikely that changes in the number of online job postings of a given occupation-state pair can contribute to country-wide economic uncertainty. Also, the country-wide employment shares of occupation-state pairs are held constant in a year that precedes the highly unpredictable Covid-19 shock, while the variables capturing occupational characteristics are also time-invariant. To address a possible omitted variable bias in the estimates due to differences in the type of anti-Covid measures adopted across US states or in the timing of their imposition or relaxation, we perform a robustness check in which we replace the month dummies with dummies for state-month pairs.

The econometric analysis reveals that Covid-induced economic uncertainty impacted differentially the relative demand for occupations with different characteristics in the US. In particular, Covid-induced economic uncertainty increased the relative demand for occupations with relatively high non-routine cognitive analytical, non-routine cognitive interactive, and non-routine manual task content –especially, when these occupations are also non-essential (e.g. architecture and engineering; education). It also increased the relative demand for occupations that have both relatively high non-routine cognitive analytical and social or interaction task content (e.g. managerial). By contrast, it decreased the relative demand for non-essential or less contact-intensive occupations with relatively high routine intensity (e.g. office and administrative support). These findings are in accord with existing evidence showing that the secular phenomenon of routine-biased technological change (RBTC) has led to job polarisation (e.g. Autor et al., 2003; Spitz-Oener, 2006; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Goos et al., 2014), as well as with its episodic aspect pointing to the acceleration during recessions of the adoption of new technologies undertaking routine tasks (Hershbein & Kahn (2018); Jaimovich & Siu, 2020). In addition, the last two findings are consistent with existing evidence on the link between RBTC and the growing complementarity between analytical and social tasks (Borghans et al. (2014); Weinberger (2014); Deming, 2017).

Interestingly, however, we derive additional findings that are seemingly at odds with the job polarisation phenomenon and likely explained within the new setting that has been generated since the onset of the Covid-19 shock. That is, a setting dominated by a major health crisis and restrictive measures (e.g. social distancing, lockdown) aiming at restraining the rapid spread of the virus. According to these findings, Covid-induced economic uncertainty decreased the relative demand for customer-oriented occupations (e.g. food preparation and service; personal care and service; non-essential salespersons). In recent decades and until before the pandemic hit, such occupations had experienced relative employment gains, partly because they were, and still are, less amenable to offshoring and automation. Also, Covid-induced economic uncertainty increased the relative demand for essential or contact-intensive occupations with relatively high routine manual or routine cognitive task content, for occupations that are both essential and contact-intensive, and those that are both contact-intensive and service-oriented. These effects are likely to be particularly driven by healthcare practice and support, protective service, and community and social service occupations. Whether these effects are temporary or will persist in the post-Covid era, remains to be explored in future research.

Related literature The novel empirical evidence of this paper contributes to four streams of literature. First, our focus on identifying the differential effects of the Covid-19 shock on the demand for different occupations, and subsequently, to consider the routine and non-routine task content of occupations and their degrees of customer- and service-orientedness is motivated by the influential literature providing evidence on job polarisation and its determinants. In turn, a set of findings that we derive are consistent with key evidence of two streams of this literature. In particular, one stream shows that routine-biased technological change (RBTC) and offshoring are major drivers of job polarisation (Autor et al., 2003; Spitz-Oener, 2006; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Goos et al., 2014). RBTC also partly explains why cognitive analytical and cognitive interactive tasks have become increasingly complementary since the 1980s, as Borghans et al. (2014), Weinberger (2014), and Deming (2017) have shown using US data. In fact, machines have starting undertaking some cognitive analytical tasks, while social interaction is, at least up to now, a prerogative of humans (Autor, 2015). Another stream of this literature establishes a link between RBTC and job polarisation during recessions. Using data for the US, Hershbein & Kahn (2018) show that skill requirements in online job postings increased in Metropolitan Statistical Areas (MSAs) that were disproportionately hit by the Great Recession (2007–2009), that this effect persisted through 2015, and that it was correlated with a surge in capital investments, both at the MSA and firm levels. Relatedly, Jaimovich & Siu (2020) show that employment losses in routine occupations in the US since the early 1980s have been primarily observed during recessions, and that the lack of employment recovery in these occupations accounts almost entirely for the jobless recoveries in the aggregate.

Our approach to consider in the analysis additional occupational characteristics, most notably, physical contact intensity, tele-work potential, and essentiality, is influenced by the burgeoning stream of literature studying the labour market implications of the Covid-19 shock. To our knowledge, this paper is the first to conduct a comprehensive analysis of the differential effects of this shock on the demand for different occupations, according to wide range of occupational characteristics. In doing so, it enriches this stream of literature by deriving a set of findings that, as mentioned earlier, are consistent with evidence on job polarisation, but also another set of findings that are at odds with it, and can rather be rationalised by idiosyncratic features of the pandemic shock (e.g. major health crisis, social distancing, lockdown).

Using data from real-time surveys conducted in the US, UK, and Germany in March and April 2020, Adams-Prassl et al. (2020) document smaller job losses in the latter country, which are attributed to its firmer labour market institutions such as the short-time work schemes that were well-established in the country pre-Covid. They also show that job and earnings losses in the three countries were higher for workers with temporary work arrangements and those with relatively limited tele-work potential. Disproportionate losses were also incurred by female and non-college-graduate workers in the US and UK, but not in Germany. In a seminar vein, using data for Canada, Baylis et al. (2021) find larger employment losses for women in the first part of the Covid-19 pandemic outbreak due to their larger concentration in high viral risk occupations, and for the less educated workers due to their lower tele-work potential. Using data from the US Current Population Survey, Cortes & Forsythe (2020) find that the Covid-19 shock has exacerbated inequalities, with the low-educated, younger, and female workers, and those of Hispanic origin experiencing larger increases in job losses and larger decreases in hiring rates. Similar evidence is also provided by Montenovo et al. (2020). Further on the US, Mongey et al. (2021) find that jobs with low tele-work potential and those with high physical proximity requirements, which were more likely to be filled by workers with relatively low education and income, suffered relatively large employment losses, but not those that are also essential.[7]

Using data on online job postings from Burning Glass Technologies, Forsythe et al. (2020) report a collapse of over 40% in the number of job vacancies in the US by April 2020. However, they also find that essential retail and nursing maintained or decreased slightly their job posting levels. The simultaneous rise in unemployment insurance claims made by workers in such occupations points to a great deal of churn in the US labour market. The latter is consistent with the evidence provided by Barrero et al. (2020) on realised and predicted job reallocation in the US since the onset of the Covid-19 shock. A collapse of similar magnitude in the number of job vacancies is also reported for Sweden by Hensvik et al. (2021), who exploit relevant data from the country's largest online job board. The authors also provide evidence on job reallocation, with labour market searches shifting towards occupations that have been hit less severely by the pandemic.[8] Exploiting rich online job postings data

[7]Large increases in employment losses during the Covid-19 shock have been reported by several other studies (Bartik et al., 2020; Hassan et al., 2020; Cajner et al., 2020; Coibion et al., 2020; Bick & Blandin, 2021).

[8]A similar shift in labour market searches has been identified for the US by Marinescu et al. (2021), with the use of data from Glassdoor, and Bernstein et al. (2020), with the use of data from a job board focused on tech companies (Angel-List Talent).

from LinkUp, Campello et al. (2020) show that new-hiring cuts during the Covid-19 shock were more pronounced for high-skill jobs, smaller or credit-constrained firms, highly-unionised industries, and low-income areas.

The final stream of literature to which our paper relates studies non-labour-market outcomes of economic uncertainty induced by the Covid-19 shock. Baker, Bloom, Davis, & Terry, 2020 estimate that half of the predicted US output contraction during the months of 2020 was accounted for by Covid-induced economic uncertainty, as measured by the stock market volatility (VIX), the news-based Economic Policy Uncertainty (EPU), and the Survey of Business Uncertainty (SBU) indices. In addition, Baker, Bloom, Davis, & Terry (2020) show that investments in tangible and intangible capital are extremely responsive to EPU, most likely due to their irreversible nature and the relatively high associated sunk costs. There is also evidence on the unprecedented impact of the Covid-19 shock on the stock market (Baker, Bloom, Davis, Kost, et al., 2020; Leduc & Liu, 2020). Our paper emulates this group of studies in using the EPU and SBU measures in order to capture Covid-induced economic uncertainty. Unlike these studies, however, it is the first paper that does so with the aim to identify its labour market implications and, in particular, its implications for occupational demand.

Layout of the paper In Section 2, we describe the different datasets that we rely on and the construction of variables. We also present the main trends of online job postings and measures of economic uncertainty in the US during the Covid-19 shock, as well as the patterns of occupations by occupational characteristic. In Section 3, we give a detailed account of the econometric model and the identification strategy, while in Section 4, we present and rationalise the main results and perform some robustness checks. In Section 5, we highlight the key conclusions drawn from the main results and indicate some promising avenues for future research.

2 Data and stylised facts

In this section, we describe the online job postings data that we employ throughout the empirical analysis, the variables capturing a broad range of occupational characteristics, and the variables capturing economic uncertainty induced by the Covid-19 pandemic outbreak.

2.1 Online job postings

The monthly online job postings data for the US cover the period January 2020 – December 2020 and have been assembled, compiled and made publicly available by Burning Glass Technologies (henceforth, BGT).[9] BGT collects millions of job postings from close to 40,000 online sources, such as job boards, employer sites, newspapers, and public agencies, to name a few. The publicly available version of the dataset includes the monthly count of online job postings by geographic area (i.e., country-wide, US state) and occupation. The fifty-one US states are identified by their unique two-letter ISO codes. Occupations are identified by their two-digit 2010 Standard Occupational Classification (SOC) codes. The dataset also includes information, originally drawn from the US Census, on the monthly population of the whole country and each US state in 2019. The key advantage of using online job postings data is that they offer a point-in-time measure of labour demand and at a finer-grained (i.e., two-digit occupation) level than relevant surveys do. Equally importantly, job vacancy postings are inherently forward-looking, capturing the intention of firms to develop new employment relationships in the short- to medium-run.[10]

Panel (a) of Figure 1 shows the monthly variation in the total number of online job postings per capita in the US over January 2020 – December 2020.[11] In April, when the disease was spreading fast and lockdown and social distancing measures were in effect, online job postings per capita declined steeply, to 0.69% from 1.08% and 1.06% in January and February and roughly 1.04% in March.[12] They partially bounced back in May and June and fluctuated slightly until October –when lockdown measures had been lifted, declined sharply in November –when the second wave of the pandemic broke out– albeit much less than in April, and declined slightly further in December. Importantly, as evident in Panel (b), the

[9] Note that although the Covid-19 crisis continued through 2021, BGT has made publicly available only the data for 2020.

[10] Thus, they are indicative of the subjective perceptions firms have about the short- and longer-run prospects of their idiosyncratic overall performance, the performance of their industry, and the aggregate economy. On the downside, such data may miss part of labour demand as not all jobs postings are advertised online, while employers may advertise multiple job vacancies in a single posting. For instance, job vacancy postings tend to cover a disproportionately high number of higher-skilled occupations (e.g. Hershbein & Kahn, 2018). Be that as it may, online job postings data should be viewed as complementary to survey data, rather than their substitutes. In fact, as Dalton et al. (2020) show, BGT's online job postings data are very much aligned with those collected by the US Bureau of Labor Statistics through the Job Opening and Labor Turnover Survey (JOLTS).

[11] This is calculated as the ratio of the country-wide number of online job postings to aggregate US population.

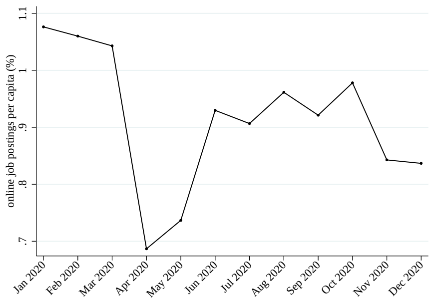
[12] This translates to a 37% decline in the online job postings per capita between January and April. A decline of 40% in the number of online job postings in the US has been reported by Forsythe et al. (2020), who also use BGT data. A decline of a similar magnitude has also been reported for Sweden by Hensvik et al. (2021), based on data from the country's major online job board.

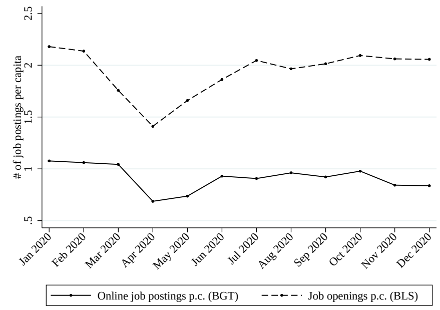
trend exhibited by online job postings per capita bears a very close resemblance to the trend of the total number of monthly job vacancies to population ratio, calculated based on the JOLTS data. In addition to the similar trends, the BGT data at our disposal have a relatively high degree of representativeness, as online job openings account for at least half of the official number of job openings for each month of 2020. These facts are consistent with the evidence of Dalton et al. (2020) on the alignment between BGT and JOLTS data and confirm BGT's high standards of online job postings data collection and processing. In addition, although we by no means disregard the possibility of idiosyncratic factors having contributed to the aforementioned trend of US online job postings per capita, it is noteworthy that we obtain very similar trends for all the other countries that are available in the BGT dataset, namely, Australia, Canada, New Zealand, Singapore and the UK. The similarities in the trends is particularly evident in Feb 2020 – May 2020, that is, immediately before, during, and towards the end the first wave of the Covid-19 pandemic (Figure B1).[13]

Albeit informative about how US labour demand evolved in the months of 2020, Panels (a) and (b) of Figure 1 mask the possible heterogeneity in the demand for different occupations over that period. Indeed, Panels (a)–(v) of Figure 2 reveal that although there was hardly any two-digit (2010 SOC) occupation that did not experience a precipitous decline in its online job postings per capita during the first wave of the pandemic (March 2020 – May 2020), there were remarkable differences along this dimension in the subsequent months. In particular, the online job postings per capita of a relatively small number of occupations were mostly on an increasing trend, especially, during the second wave of the pandemic (healthcare practice; community and social service; protective service; farming, fishing, and forestry; production). Also, a couple of occupations (healthcare support; transportation and material moving) had higher online job postings per capita in the second half of 2020 than in January of the same year (i.e., pre-Covid) and despite small declines in these during the second wave of the pandemic. By contrast, the online job postings per capita of the rest of the occupations recovered only partly around May–June –when the lockdown measures had been lifted, increased further or fluctuated slightly through October, before falling precipitously again as of November due to the second wave of the pandemic.

[13]Note that we do not include the additional countries in the analysis due to lack of or incomplete data on country-wide employment shares of occupation-geographic area pairs. As we will explain in Section 3 for the US case, if we were to include the additional countries, we would need these data in order to apportion the country-level economic uncertainty measures to each occupation-area pair.

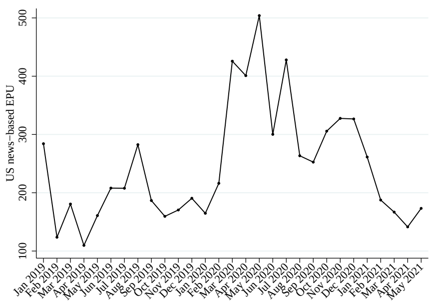
Figure 1: Job postings per capita and Covid-induced economic uncertainty in the US

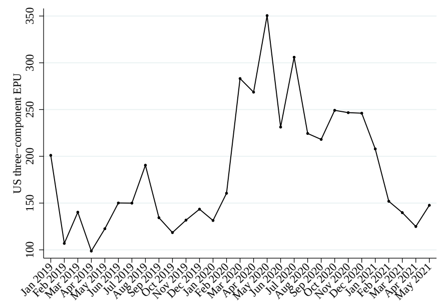




(a) Online job postings per capita

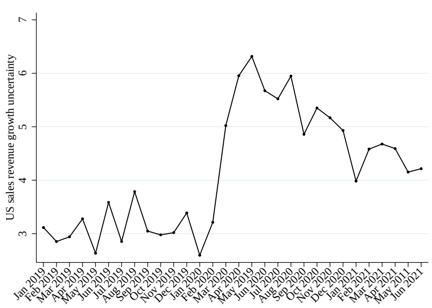
(b) Online (BGT) Vs Total (BLS JOLTS)

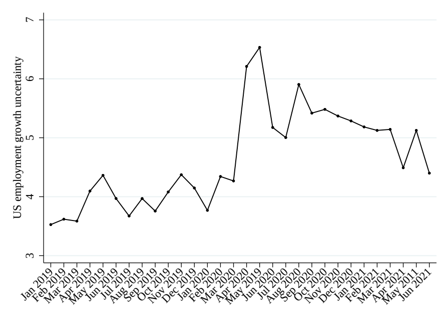




(c) News-based EPU

(d) Composite EPU





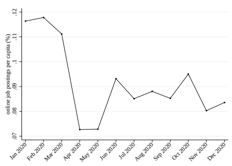
(e) Sales revenue growth uncertainty

(f) Employment growth uncertainty

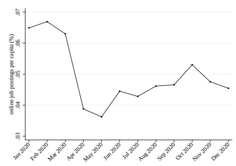
Notes: Panel (a) displays the monthly variation in the online job postings per capita in the US in January 2020 – December 2020. Panel (b) displays the line of Panel (a) along with the monthly variation in the total number of monthly job vacancies to population ratio in January 2020 – December 2020. Panels (c) and (d) display the monthly variation in US news-based and composite EPU measures in January 2019 – May 2021. Panels (e) and (f) display the monthly variation in the sales revenue and employment growth uncertainty measures in the US in January 2019 – June 2021.

Source: Online job postings per capita in Panels (a) and (b): Authors' calculations based on online job postings data of Burning Glass Technologies (BGT). Total job vacancies per capita in Panel (b): Authors' calculations based on job vacancy data of the US Bureau of Labor Statistics (BLS)'s Job Openings and Labor Turnover Survey (JOLTS). EPU measures in Panels (c) and (d): https://www.policyuncertainty.com/; see particularly Baker et al. (2016). SBU measures in Panels (e) and (f): Atlanta FED, University of Chicago Booth School of Business, Stanford University; see particularly Altig et al. (2020).

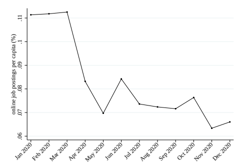
Figure 2: Job postings per capita in the US by two-digit (SOC) occupation



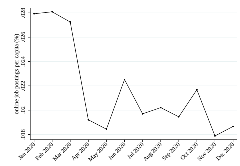
(a) Management



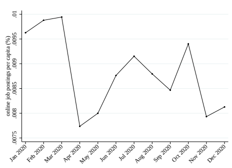
(b) Business & Financial



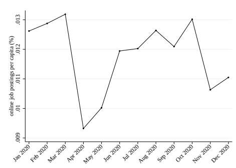
(c) Computer & Mathematical



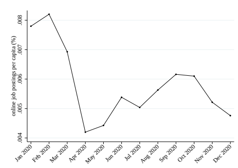
(d) Architecture & Engineering



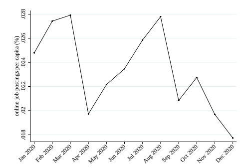
(e) Life, Physical, & Social Science



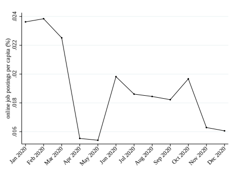
(f) Community & Social Service



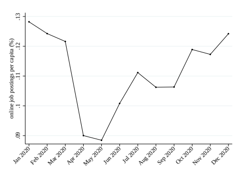
(g) Legal



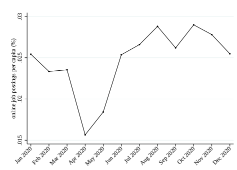
(h) Education, Training, & Library



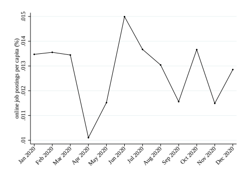
(i) Arts, Design, Entertainment, Sports, Media



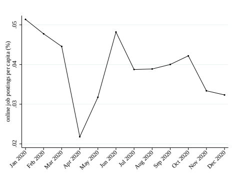
(j) Healthcare Practitioners & Technical



(k) Healthcare Support

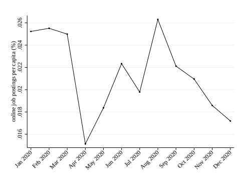


(l) Protective Service

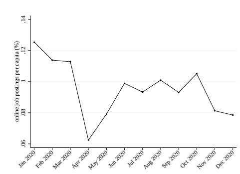


(m) Food Preparation & Service

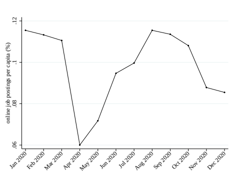
(n) Building Cleaning & Maintenance



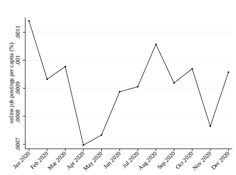
(o) Personal Care & Service



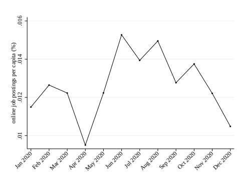
(p) Sales & Related



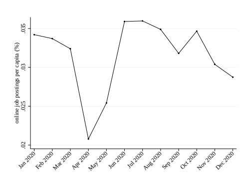
(q) Office & Administrative Support



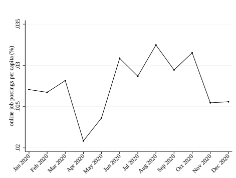
(r) Farming, Fishing, & Forestry



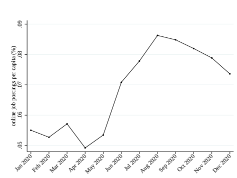
(s) Construction & Extraction



(t) Installation, Maintenance, & Repair



(u) Production

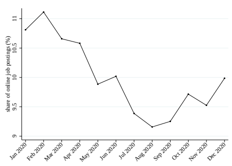


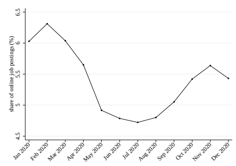
(v) Transportation & Material Moving

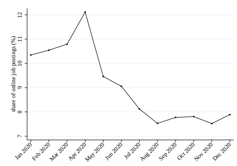
Notes: Monthly variation in the ratio of the number of online job postings of each two-digit (2010 SOC) occupation in the US to the total US population in January 2020 – December 2020.

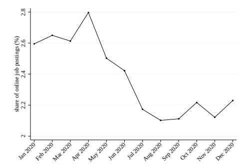
Source: Authors' calculations based on online job postings data of Burning Glass Technologies (BGT).

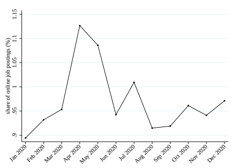
Figure 3: Share of job postings in the US by two-digit (SOC) occupation

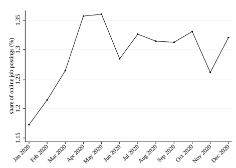

(a) Management

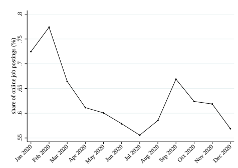

(b) Business & Financial

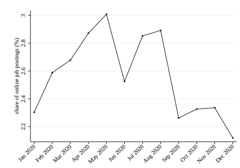

(c) Computer & Mathematical

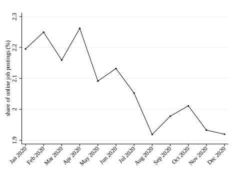

(d) Architecture & Engineering

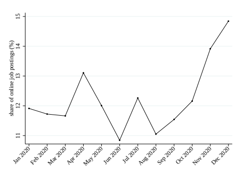

(e) Life, Physical, & Social Science

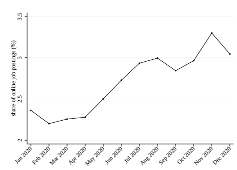

(f) Community & Social Service

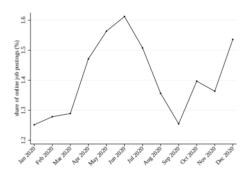

(g) Legal

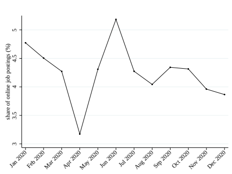

(h) Education, Training, & Library

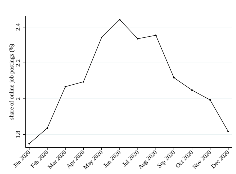

(i) Arts, Design, Entertainment, Sports, Media

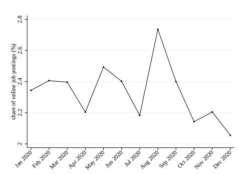

(j) Healthcare Practitioners & Technical

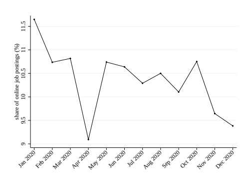

(k) Healthcare Support

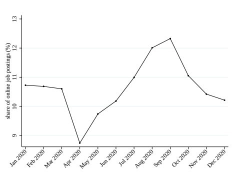

(l) Protective Service

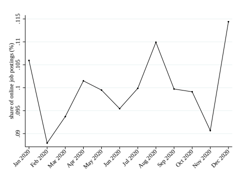

(m) Food Preparation & Service

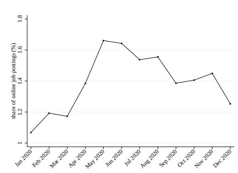

(n) Building Cleaning & Maintenance

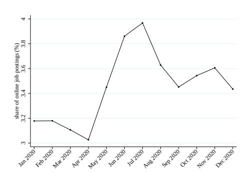

(o) Personal Care & Service

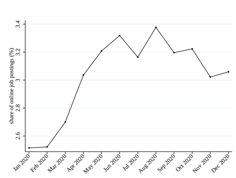

(p) Sales & Related

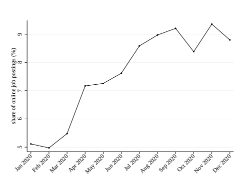

(q) Office & Administrative Support


(r) Farming, Fishing, & Forestry


(s) Construction & Extraction


(t) Installation, Maintenance, & Repair


(u) Production


(v) Transportation & Material Moving

Notes: Monthly variation in the share of the number of online job postings of each two-digit (2010 SOC) occupation in the US in the total number of online job postings in the US in January 2020 – December 2020.
Source: Authors' calculations based on online job postings data of Burning Glass Technologies (BGT).

The aforementioned trends had important implications for the occupational composition of labour demand, as indicated by the evolution of the shares of online job postings of occupations over the months of 2020 in Panels (a)–(v) of Figure 3.[14] With respect to January 2020 (pre-Covid shock), community and social service, healthcare practice, healthcare support, protective service, farming, fishing and forestry, production, transportation and material moving, life, physical and social science, and construction and extraction occupations gained higher shares in the total number of online job postings. These gains naturally translate to losses for the rest of the occupations.

2.2 Variables for occupational characteristics

The salient heterogeneity in the evolution of the absolute and relative demands for different occupations during the Covid-19 pandemic outbreak suggests that different occupational characteristics might have contributed to it. For instance, the higher shares of online job postings of community and social service and healthcare practice and support occupations may be attributed to the fact that such occupations, despite their relatively high physical contact requirements, are essential during a pandemic. By contrast, other occupations that are contact-intensive but not essential experienced declines in their shares of online job postings (e.g. personal care and service, food service, arts and entertainment). In addition, it is by now well understood that occupational characteristics such as routine intensity explain the secular declines in the relative employment of such occupations due to routine-biased technological change (RBTC) and offshoring (Autor et al., 2003; Autor & Dorn, 2013; Goos et al., 2014), as well as the RBTC-induced declines in their relative employment during economic downturns (e.g. Jaimovich & Siu, 2020).

In order to be able to make an in-depth investigation of how occupational characteristics influenced firms' hiring strategies during the Covid-19 pandemic outbreak, we construct variables capturing a wide range of occupational characteristics. To save on space, we relegate to Appendix Section A.1 the full description of the data sources and how all measures are constructed and give here a rather brief account. For each two-digit (2010 SOC) occupation, we construct measures of: non-routine cognitive analytical, non-routine cognitive interactive, non-routine manual, routine manual, and routine cognitive task content using the data of Au-

[14] These are calculated as the shares of online job postings of occupations in the country-wide number of online job postings.

tor et al. (2003); social, coordination, and interaction task content and degrees of customer- and service-orientedness using the data of Deming (2017); physical contact intensity using the data of Leibovici et al. (2020); and tele-work potential as constructed by Dingel & Neiman (2020) using ONET data (benchmark) or manually (alternative). As the original measures are available at more disaggregated occupation levels, we aggregate these up to the two-digit (2010 SOC) level by calculating their unweighted means.[15]

In line with evidence of the extant literature, occupations such as computer science and mathematical, architecture and engineering, and life, physical and social science have relatively high non-routine cognitive analytical and interactive task content, while managerial occupations are among those that have simultaneously relatively high social, coordination, and interaction task content. Construction and extraction, transportation, protective service, and building cleaning occupations have relatively high non-routine manual task content, while healthcare practice and support are among the occupations with relatively high routine manual and routine cognitive task content. These occupations along with personal care and service, sales, community and social care, and protective service occupations also have relatively high degrees of customer- and service-orientedness (see Tables B1 and B2). Not surprisingly, healthcare support and practice, food preparation and service, and personal care and service are the most contact-intensive occupations (column (3) of Table B3), while computer science and mathematical, education, training and library, legal, business and financial, and managerial occupations have relatively high tele-work potential (columns (4) and (5) of Table B3).

Finally, to construct a dummy variable indicating whether an occupation is essential or not, we use the data of Mongey et al. (2021) and classify an occupation as essential if its employment share in essential industries is at least 60%. Under this approach, the following occupations are labeled as essential: community and social service; healthcare practice; healthcare support; protective service; farming, fishing, and forestry; production; transportation and material moving. As some retail occupations play an essential role amid a pandemic (e.g. salespersons in grocery stores), we also label sales and related occupations as essential in the benchmark version of the dummy variable. In an alternative version, we treat this occupation as non-essential (see columns (1) and (2), respectively, of Table B3).[16]

[15]Calculating the unweighted medians produces very similar measures.

[16]Note that the threshold set by Mongey et al. (2021) for the identification of essential occupations is 75%. We abstract from doing so, as we would have to exclude from the list occupations that are to a large extent essential amid a pandemic: community and social service, production, and transportation and material moving.

2.3 Covid-induced economic uncertainty

In order to capture the effect of the Covid-19 shock on firms' hiring strategies, we use a comprehensive measure of economic uncertainty. Our baseline measure is the news-based Economic Policy Uncertainty (EPU) index of Baker et al. (2016) for the US.[17] Alongside the baseline measure, we draw information on the composite US EPU index.[18] The base value of the EPU measures is equal to 100. Hence, deviations above (below) this value imply that uncertainty is above (below) average.

Panels (c) and (d) of Figure 1 display the monthly variation in the news-based and composite measures of EPU in the US over January 2019 – May 2021.[19] Economic uncertainty in 2019 and January 2020 was above average, with the two measures fluctuating within the ranges of 100–300 and 100–200, but low relative to economic uncertainty in February 2020 – December 2020. In fact, between February and March, when the spread of the Covid-19 virus started having the features of a pandemic, economic uncertainty rose sharply (the news-based EPU increased from 216 to 426 and the composite EPU increased from 161 to 283). Although it declined slightly in April, it rose again in May and reached its peak by that month. Between June and August –when lockdown and other restrictive measures had been lifted or relaxed, it fluctuated at lower levels, which were still higher than the pre-pandemic ones, and was again on a rising trend as of October, when the second wave of the pandemic hit the country. It is only in February 2021 when economic uncertainty went down to its pre-pandemic levels and remained at such levels in the next few months. The striking differences in the level of economic uncertainty in the US between the months marked by the Covid-19 crisis and those that preceded it likely suggest that the rising economic uncertainty in 2020 was induced primarily by this shock, rather than other idiosyncratic factors.[20]

For instance, in order for meat and diary products produced by individuals in farming occupations to reach the final consumer, they have to be transported to the relevant store for sale. This implies that the services of individuals in transportation occupations (e.g. truck driver) and production occupations (e.g. butcher) are indispensable parts of the supply chain.

[17]For this particular country, the news-based EPU is also available by individual policy area, namely: health policy, fiscal policy, government spending, tax policy, monetary policy, national security, entitlement programmes, regulation, financial regulation, trade policy, and sovereign debt and currency management. For a detailed account of the construction of these measures, see Appendix Section A.4 and Baker et al. (2016).

[18]One of the components of this measure is the news-based EPU. For details about the concept of this measure and the steps taken for its construction, see Appendix Section A.4.

[19]We have included the values of EPU in all months of 2019 and the first five months of 2021 in order to have measures of comparison when discussing the evolution of EPU over the months of 2020. The same logic applies to the rest of the figures that display the values of variables for months that are adjacent to those of 2020.

[20]The EPU measures for different policy areas exhibited very similar trends in 2020 except for trade policy uncertainty that was on a declining path overall (Panels (a)–(k) of Figure B2). The latter is a reversal of the rise

In addition, we use alternative measures of economic uncertainty, whose construction is predicated upon US firms' probabilistic expectations about their sales revenue and employment growth four quarters ahead, rather than upon information from US newspapers. Information on firms' subjective expectations is originally collected through the Survey of Business Uncertainty (SBU), which is conducted jointly by the Atlanta FED, Stanford University, and the University of Chicago Booth School of Business.[21] As shown in Panels (e) and (f) of Figure 1, the measures of sales revenue and employment growth uncertainty exhibited very similar trends in the months of 2020 to those of the EPU measures. The consistency in the trends of EPU and SBU measures in the months of 2020 is extra evidence on their capacity to capture Covid-induced economic uncertainty.[22]

In sum, the descriptive statistics analysis reveals that online job postings and economic uncertainty moved in opposite directions during the Covid-19 pandemic outbreak: two slumps and a moderate recovery in the per capita number of online job postings coincided with equivalent spikes and a moderate decline in the measures of economic uncertainty. In addition, there is a great deal of qualitative and quantitative heterogeneity in the variation of online job postings per capita and share of online job postings across occupations, and substantial differences across occupations in certain characteristics. Our goal in the econometric analysis is to identify the differential effects of Covid-induced economic uncertainty on the demand

in trade policy uncertainty since the revision of US trade policy by the Trump administration and the initiation of the so-called US-China "trade war". Not surprisingly, the largest spikes in March and April corresponded to uncertainty about health policy: the relevant EPU rose from roughly 155 in February to 771 in March to 1031 in April. Nevertheless, the sizeable spikes in uncertainty about other policy areas clearly demonstrates the numerous negative economic side-effects of the Covid-19 pandemic outbreak. Health-related EPU also rose slightly in December, amid the second wave of the Covid-19 pandemic. In that month, the most sizeable spikes are observed for EPU related to entitlement programmes (e.g. unemployment insurance, welfare state benefits) aiming at (partly) compensating for the job and income losses incurred by individuals since the onset of the crisis, and to debt and currency management as a result of the expansionary fiscal measures coupled with public revenue losses. By contrast, the EPU for other policy areas declined in that month. Given the universality of the shock, we would also expect to observe similar trends in economic uncertainty at the global level and in other individual countries. We show that this was indeed the case by plotting the Global EPU measure and the unweighted mean of EPU measures of individual countries other than the US from January 2019 to May 2021 (Panels (a) and (b) of Figure B3). Information on these EPU measures is retrieved from the same source as for the US measures. The individual countries for which we calculate the unweighted average are: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Korea, Netherlands, Russia, Spain, Singapore, UK, Sweden, and Mexico.

[21]For detailed information about the survey and the SBU measures, see Altig et al. (2020) and https://www.atlantafed.org/research/surveys/business-uncertainty.

[22]Naturally, the measures of sales revenue and employment growth expectations exhibited opposite trends (Panels (a) and (b) of Figure B4). Also, there are strong and highly statistically significant correlations between the main (i.e., news-based) EPU measure and the other measures of economic uncertainty under consideration. The magnitudes of the correlations are: 97% (composite EPU), 92% (Global EPU), 89% (Global EPU PPP), 86% (cross-country mean of EPU), 86% (cross-country median of EPU), 53% (SBU sales revenue growth uncertainty), 73% (SBU employment growth uncertainty), -61% (SBU sales revenue growth expectations), and -43% (SBU employment growth expectations).

for occupations that have pre-Covid occupational structure of US states and a wide range of occupational characteristics.

3 Econometric model

In order to study the impact of Covid-induced economic uncertainty on the relative demand for occupations with different characteristics, we estimate the following specification:

$$\begin{aligned} OJP_{ost} = \alpha_{os} + \alpha_t + \beta_{EPU_{ost}} * EPU_{ost} + \beta_{EPU_t,char} * EPU_t * char_o \\ + \beta_{EPU_{ost},char} * EPU_{ost} * char_o + \epsilon_{ost} \end{aligned} \tag{1}$$

where OJP_{ost} is the share of online job postings of occupation o in US state s in month t of the year 2020. The specification includes occupation-US state fixed effects, which account for time-invariant unobserved heterogeneity across occupation-state pairs, such as initial differences in the demographics, human capital, and real disposable income of individuals. It also includes month fixed effects, which account for time-varying shocks to all occupation-state pairs, namely, the aggregate business cycle, the loosening of US FED's monetary policy and expansion of quantitative easing programmes, and the US federal government's fiscal and labour market policies (e.g. CARES act).

The month dummies also capture the onset of the Covid-19 shock and the timings of the imposition and relaxation of the associated restrictive measures, albeit not their severity. However, as shown in Section 2.3, a critical aspect of the Covid-19 shock is the elevated economic uncertainty, which is likely to have impacted the hiring decisions of firms. For this reason, we incorporate in the specification our baseline measure of Covid-induced economic uncertainty, namely, the news-based EPU in the US (EPU_t). To apportion this measure to each occupation-state pair, we multiply it by the share of employment of occupation-state pair os in country-wide employment of occupation o in 2019: $EPU_{ost} = EPU_t * \frac{E_{os,2019}}{E_{oUS,2019}}$. Information on occupation-state-level employment for 2019 is drawn from the US Bureau of Labour Statistics (BLS). By interacting this variable with a variable for a certain occupational characteristic, we obtain the main term of interest of the specification ($EPU_{ost} * char_o$). The relevant coefficient estimate, $\beta_{EPU_{ost},char}$, captures the differential effect of Covid-induced economic uncertainty on the relative demand for a given occupation in a given US state, according to its pre-Covid country-wide occupational employment share and the intensity or status of a certain characteristic (e.g. service-orientedness, physical contact, essentiality). As common in the empirical literature, we facilitate the economic interpretation of this coefficient estimate by standardising the relevant variable, so that its mean equals zero and its standard deviation equals one. We also include EPU_{ost} and $EPU_t * char_o$ in the specification, as these are components of the interaction term that are not captured by the fixed effects. Unobserved factors impacting the demand for occupation o in US state s in month t are captured by the error term, ϵ_{ost}.

Eq. 1 is estimated by OLS. The coefficient estimates of the main explanatory variables are unlikely to be subject to a simultaneity bias for the following reasons. The country-wide employment share of occupation-state pairs is held constant and its values correspond to a year that precedes that highly unpredictable Covid-19 shock. Although the time-varying country-wide EPU could impact the share of online job postings of an occupation in a certain US state, it is highly unlikely, especially due to the size of the US economy, that the expansion or contraction of online job postings of an occupation in a given state has the potential to feedback into country-wide economic uncertainty. As for the variables capturing different occupational characteristics, these are by construction time-invariant and thus, cannot be determined by monthly changes in the online job postings of an occupation-state pair. Given the sets of fixed effects in the main specification, a possible threat to the identification strategy may stem from policy shocks to US states (e.g. adoption of different anti-Covid policies and measures, time differences in the imposition or relaxation of anti-Covid measures). To address the possibility of an omitted variable bias in the specifications, we conduct a robustness exercise in which we replace the month fixed effects with state-month fixed effects.

4 Econometric results

4.1 Covid-induced EPU and occupational demand

We kick-off the econometric analysis by identifying the effects of Covid-induced economic uncertainty on the absolute and relative occupational demand in US states without accounting for differences across occupations in the intensity or status of a given characteristic. To this end, we estimate Eq. 1 by OLS after dropping $EPU_t * char_o$ and $EPU_{ost} * char_o$ and focusing on the interpretation of the coefficient estimate of EPU_{ost}. As the dependent variable, we use the log of the number of online job postings or the number of online job postings per capita of occupation-state pairs, which measure absolute occupational demand, or the share of online job postings of occupation-state pairs, which measures relative occupational demand. The results are shown in columns (1) and (4), (2) and (5), and (3) and (6), respectively, of Panel A of Table 1. The main explanatory variable in the first three columns is constructed based on the main (i.e., news-based) EPU, while in the last three columns, it is constructed based on the composite EPU. In all six columns, the relevant coefficient estimate is negative and statistically significant at 1% or 5%. This suggests that occupations in US states that were more exposed to Covid-induced economic uncertainty experienced disproportionate declines in the log of their number of online job postings, their online job postings per capita, and their shares of online job postings. That is, the elevated uncertainty and the ensuing reluctance or incapacity of firms to proceed to new hires hit disproportionately occupations in US states that were over-represented at country level pre-Covid. In terms of size, the coefficient estimates suggest that an increase of one standard deviation in the exposure of the average occupation-state pair to Covid-induced economic uncertainty decreased the number of online job postings per capita by 0.49 or 0.56 percentage points (columns (2) and (5)) and the share of online job postings by 0.12 or 0.074 percentage points (columns (3) and (6)).[23]

In additional estimations, we confirm the robustness of the results to using different measures of economic uncertainty for the construction of the main explanatory variable. In particular, we use the Global EPU or Global EPU PPP (columns (1)–(3) and (4)–(6) of Panel B of Table 1), the mean or median of EPU across countries other than the US (columns (1)–(3) and (4)–(6) of Panel A of Table C1), the SBU sales revenue or employment growth uncertainty (columns (1)–(3) and (4)–(6) of Panel C of Table 1), and the SBU sales revenue or employment growth expectations (columns (1)–(3) and (4)–(6) of Panel B of Table C1). In all cases, the estimations yield very similar results qualitatively. By and large, though, using the alternative economic uncertainty measures yields even stronger negative effects of Covid-induced economic uncertainty on occupation-state pairs that had higher country-wide occupational

[23]Very similar results are obtained when we re-estimate the equations in columns (2) and (3) of Panel A using the news-based EPU by policy area (e.g. health, fiscal, monetary) for the construction of the main explanatory variable. In particular, we identify disproportionately negative effects on the per capita number of online job postings and the share of online job postings of occupation-state pairs by Covid-induced uncertainty in all economic areas except for trade policy and debt and currency management. Trade policy uncertainty impacted positively the per capita number of online job postings, while it exerted no statistically significant effect on the share of online job postings. Debt and currency management uncertainty exerted no statistically significant effects on either the per capita number of online job postings or the share of online job postings (Panels (a) and (b) of Figure C1).

employment shares pre-Covid. For instance, an increase of one standard deviation in the exposure of the average occupation-state pair to Covid-induced economic uncertainty (based on SBU employment growth uncertainty) decreased the number of online job postings per capita by 1 percentage point (column (5) of Panel C of Table 1), while an increase of one standard deviation in the exposure of the average occupation-state pair to Covid-induced economic uncertainty (based on the cross-country median EPU) decreased the number of online job postings per capita by 0.23 percentage points (column (5) of Panel A of Table C1).[24]

Table 1: Covid-induced economic uncertainty and occupational demand

Panel A: US news-based and composite EPU						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	log # of OJP	OJP p.c.	OJP share	log # of OJP	OJP p.c.	OJP share
EPU_{ost} (main)	-0.017***	-0.0049***	-0.0012***			
	[0.005]	[0.0004]	[0.0003]			
EPU_{ost} (alt)				-0.017**	-0.0056***	-0.00074*
				[0.007]	[0.0005]	[0.0004]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.987	0.929	0.953	0.987	0.929	0.953
Panel B: Global EPU						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	log # of OJP	OJP p.c.	OJP share	log # of OJP	OJP p.c.	OJP share
Global EPU_{ost}	-0.021**	-0.0081***	-0.0014***			
	[0.009]	[0.0007]	[0.0005]			
Global EPU_{ost} PPP				-0.022**	-0.0086***	-0.0014***
				[0.009]	[0.0007]	[0.0005]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.987	0.929	0.953	0.987	0.929	0.953
Panel C: US sales revenue and employment growth uncertainty						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	log # of OJP	OJP p.c.	OJP share	log # of OJP	OJP p.c.	OJP share
SBU_{ost} (sales gr. unc.)	-0.011	-0.0060***	-0.00028			
	[0.008]	[0.0006]	[0.0005]			
SBU_{ost} (emp. gr. unc.)				-0.035***	-0.010***	-0.00068
				[0.01]	[0.0008]	[0.0006]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.987	0.929	0.953	0.987	0.930	0.953

Notes: OLS estimations with robust standard errors in all columns of all panels. Two-digit (SOC) occupation-US state and month fixed effects are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

[24]To remove any remaining concerns over the capacity of the EPU measures to capture Covid-induced economic uncertainty, we also conduct the following exercise. Instead of using their values for the months of 2020, we use their values for the corresponding months of the year before (2019) while maintaining the 2020 values for the outcome variable. If the principal driver of economic uncertainty in the months of 2020 were not the Covid-19 shock, but other factors that were very similar to those having contributed to economic uncertainty in the months of 2019 (when the Covid-19 shock hadn't hit yet), then this exercise should yield very similar results qualitatively to those Table 1. We find that this is not actually the case: the coefficient estimates that we obtain from these estimations are positive, rather than negative as in the main estimations, and are mostly statistically significant at 1% (Panels C and D of Table C1 and Panels (c) and (d) of Figure C1).

4.2 Accounting for occupational characteristics

As highlighted in Section 2.2, occupations differ substantially in the intensity or status of certain characteristics and this source of heterogeneity can potentially shape the effects of Covid-induced economic uncertainty on their relative demand. Therefore, we now proceed to the core of the analysis by estimating Eq. 1, with the share of online job postings of occupation-state pairs as the dependent variable. In these estimations, our main focus is on the interpretation of the coefficient estimate of $EPU_{ost} * char_o$. We first consider the measures of non-routine cognitive analytical, non-routine cognitive interactive, non-routine manual, routine manual, and routine cognitive task content of occupations that we have created using the relevant data of Autor et al. (2003) (columns (1)–(5) of Panel A of Table 2). These occupational characteristics have been widely used in the stream of literature providing evidence on job polarisation. However, the Covid-19 pandemic outbreak and the associated restrictive measures (e.g. lockdown, social distancing) have generated a new setting to which additional occupational characteristics are likely to be at least as pertinent. Therefore, we also consider the measures of customer- and service-orientedness, physical contact intensity, and tele-work potential that we have created using the relevant data of Deming (2017), Leibovici et al. (2020), and Dingel & Neiman (2020), respectively, as well as the essential status of occupations that we identify using the relevant data of Mongey et al. (2021) (columns (1)–(5) of Panel B of Table 2).

Same as in the previous section, the negative and significant coefficient estimates of EPU_{ost} in columns (1)–(3) of Panel A and column (3) of Panel B suggest that Covid-induced economic uncertainty exerted disproportionately negative effects on the relative demand for occupations in US states that had higher country-wide occupational employment shares pre-Covid. However, the coefficient estimates of the main interaction term of interest, $EPU_{ost} * char_o$, suggest that positive effects were actually exerted on the relative demand for occupations that have relatively high non-routine cognitive interactive task content (column (2) of Panel A), non-routine manual task content (column (3) of Panel A), or physical contact intensity (column (3) of Panel B). The first two effects are consistent with existing evidence pointing to job and skill polarisation (e.g. Autor et al., 2003; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Michaels et al., 2014; Blanas, 2021). The third effect is likely explained by the context created by the Covid-19 shock, as individuals in some contact-intensive occupations –most notably, healthcare practice and support– are in the front line to tackle the major health crisis that this shock has brought about.

Table 2: Covid-induced economic uncertainty and relative occupational demand

Panel A: Cognitive analytical/interactive, non-routine manual, routine cognitive/manual					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
EPU_{ost}	-0.0025**	-0.0017***	-0.0023***	-0.0014	-0.00068
	[0.001]	[0.0004]	[0.0004]	[0.002]	[0.0005]
EPU_t * cogn. analytical	-0.00025				
	[0.0004]				
EPU_{ost} * cogn. analytical	0.0014				
	[0.001]				
EPU_t * cogn. interactive		0.000020			
		[0.0003]			
EPU_{ost} * cogn. interactive		0.00086**			
		[0.0004]			
EPU_t * non-routine manual			0.0020***		
			[0.0004]		
EPU_{ost} * non-routine manual			0.0019**		
			[0.0008]		
EPU_t * routine manual				0.00013	
				[0.0006]	
EPU_{ost} * routine manual				0.00027	
				[0.002]	
EPU_t * routine cognitive					0.00093***
					[0.0002]
EPU_{ost} * routine cognitive					-0.00059
					[0.0004]
Observations	13,464	13,464	13,464	13,464	13,464
R^2	0.953	0.953	0.954	0.953	0.953
Panel B: Customer/Service-orientedness, physical contact intensity, tele-work, essential					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
EPU_{ost}	0.0011	-0.0016	-0.0061***	0.00040	-0.0022***
	[0.001]	[0.001]	[0.002]	[0.0007]	[0.0003]
EPU_t * customer	-0.0022***				
	[0.0004]				
EPU_{ost} * customer	-0.0022**				
	[0.001]				
EPU_t * service		-0.00042			
		[0.0003]			
EPU_{ost} * service		0.00048			
		[0.001]			
EPU_t * contact			0.00033		
			[0.0006]		
EPU_{ost} * contact			0.0050***		
			[0.002]		
EPU_t * tele-work				-0.00028	
				[0.0004]	
EPU_{ost} * tele-work				-0.0020***	
				[0.0007]	
EPU_t * essential					-0.00032
					[0.0004]
EPU_{ost} * essential					0.0020***
					[0.0005]
Observations	13,464	13,464	13,464	13,464	13,464
R^2	0.954	0.953	0.953	0.953	0.953

Notes: OLS estimations with robust standard errors in all columns of both panels. Two-digit (SOC) occupation-US state and month fixed effects are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

In addition, while the effect on the relative demand for essential occupations is positive, that on the relative demand for non-essential occupations is negative (column (5) of Pane B). This result is likely explained by the the need for unhampered provision of essential goods and services (e.g. groceries, healthcare) by individuals in some occupations amid a major health crisis and the imposition of unconventional restrictive measures (e.g. lockdown, social distancing). The negative and significant coefficient estimates of the main interaction term in columns (1) and (4) of Panel B suggest that Covid-induced economic uncertainty exerted disproportionately negative effects on the relative demand for occupations with relatively high degree of customer-orientedness and those with relatively high tele-work potential. The first of the two effects is likely driven by customer-oriented occupations that were hit particularly hard by the imposition of restrictive measures (e.g. food service, personal care and service). Albeit surprising, similar evidence to the second effect has been provided by Forsythe et al. (2020). This effect likely suggests that, due to the elevated uncertainty and low expected demand (Baker, Bloom, Davis, & Terry, 2020), firms were reluctant or incapable of prioritising the hiring of new employees who can perform a relatively large fraction of their tasks from distance. Finally, the effects on the relative demand for occupations with relatively high routine manual or routine cognitive task content, and for service-oriented occupations are statistically insignificant (columns (4) and (5) of Panel A and column (2) of Panel B).

Importantly, the results of this section are robust to the use of the alternative measures of occupational characteristics (Panels A and B of Table C2). Specifically, we aggregate the measures of Autor et al. (2003), Deming (2017), and Leibovici et al. (2020) up to the two-digit (2010 SOC) level by calculating the unweighted median of their values, rather than the unweighted mean, which is the benchmark. As an alternative measure of tele-work potential, we use the manual version of Dingel & Neiman (2020). To account for the fact that some occupations in the sales and related occupation category are not essential (e.g. salesperson in apparel store), we use the alternative dummy variable for the essential status of occupations, which labels this occupation category as non-essential. In a second robustness check, we use the measures of the abstract (non-routine cognitive), non-routine manual, and routine task content that we create using the data of Autor & Dorn (2013).[25] The estimation results obtained bear a very close resemblance to those of the main analysis (Table C3). In an additional check, we ensure that the estimates are not spuriously driven by time-varying shocks to US states, most notably, differences in the type of anti-Covid measures or the

[25] For the construction of these measures, see Appendix Section A.1.

timing of their introduction or removal by incorporating dummies for US state-month pairs in lieu of month dummies (Table C4).

From the analysis in Table 2, we conclude that while some of our findings are consistent with the main findings and associated rationale of the extant literature on routine-biased technological change (RBTC) and job polarisation, other findings are novel and can primarily be rationalised by the conditions generated by the Covid-19 pandemic outbreak. To be able to get more insights about these, we consider in the remaining sections of the econometric analysis different pairwise combinations of occupational characteristics.

4.2.1 The joint role of non-routine cognitive analytical and interactive tasks

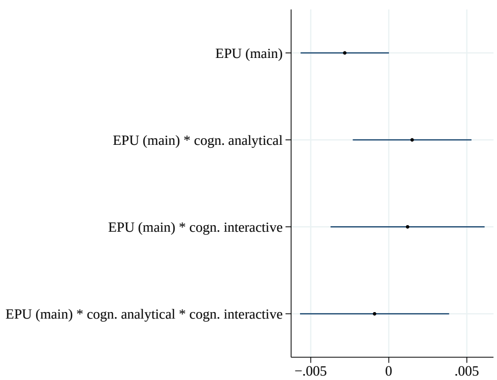
Building upon the literature on RBTC and job polarisation, Deming (2017) has shown that over 1980–2010 occupations that have both relatively high non-routine cognitive analytical and non-routine cognitive interactive task content experienced the largest gains in employment shares, followed by occupations that have relatively high non-routine cognitive interactive task content and relatively low non-routine cognitive analytical task content. These gains translated to relatively large employment share losses for occupations with both relatively low non-routine cognitive analytical and interactive task content and relatively small losses for occupations with relatively high non-routine cognitive analytical task content but relatively low non-routine cognitive interactive task content. Evidence on the increasing complementarity between cognitive analytical and cognitive interactive tasks has also been uncovered by Borghans et al. (2014) and Weinberger (2014). The underlying rationale is that machines (e.g. computers, robots, AI) do not only undertake an increasing range of routine tasks, but also of non-routine cognitive analytical tasks. By contrast, non-routine cognitive interactive tasks are largely shielded from automation (Autor, 2015).

Motivated by this evidence, we incorporate in the equation of column (1) of Table 2 a triple interaction term, which is the multiplication of the main interaction term by the measure of non-routine cognitive interactive task content, based on the relevant data of Autor et al. (2003), or the measure of the social, coordination, or interaction task content, based on the relevant data of Deming (2017).[26] The estimation results are displayed in Panels (a)–(d) of Figure 4. Although the effect of Covid-induced economic uncertainty on the relative demand

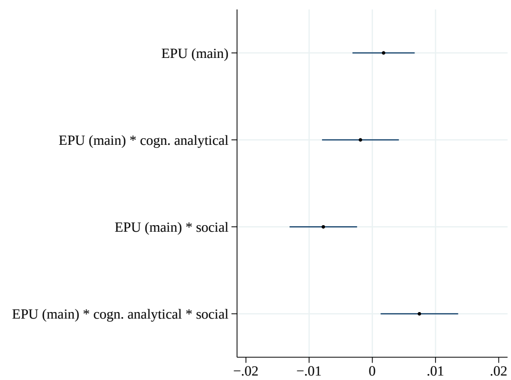
[26]These specifications also include the interactions of the country-level EPU with individual characteristics and pairwise combinations of these. This applies to all the specifications with triple interaction terms that follow. Their coefficient estimates are not disclosed for the sake of exposition.

for occupations with both relatively high non-routine cognitive analytical and interactive or coordination task content is statistically insignificant (Panels (a) and (c)), we identify positive and statistically significant effects on the relative demand for occupations that have both relatively high non-routine analytical and social or interaction task content (Panels (b) and (d)). Hence, similarly to the 1980–2010 period examined by Deming (2017), we show that the joint role of analytical and interactive tasks was also crucial in shaping the relative demand for occupations amid the Covid-19 pandemic outbreak.

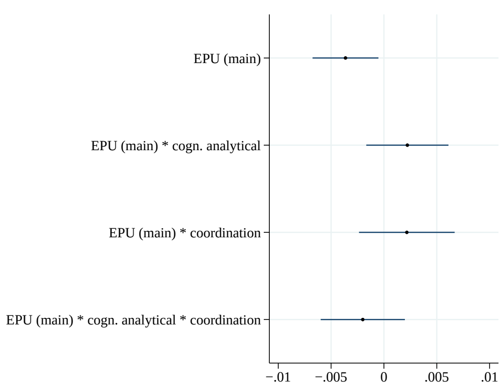
Figure 4: The joint role of non-routine cognitive analytical and interactive tasks



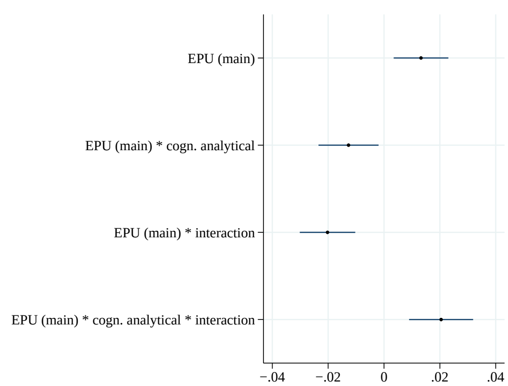
(a) Cognitive interactive



(b) Social



(c) Coordination



(d) Interaction

Notes: OLS estimations with robust standard errors and two-digit (SOC) occupation-US state and month fixed effects in all panels. These specifications also include the interactions of the country-level EPU with individual characteristics and pairwise combinations of these. Their coefficient estimates are not disclosed for the sake of exposition.

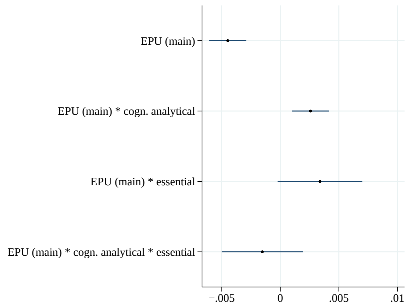
4.2.2 The joint role of occupational characteristics and essential status

Given the essential role of some occupations during the pandemic outbreak and the subsequent lockdowns, we consider next the joint role of the main occupational characteristics with the essential status of occupations. To this purpose, we re-estimate the equations in columns (1)–(5) of Panel A and columns (1)–(3) of Panel B of Table 2 after multiplying their main interaction terms by the dummy variable indicating whether an occupation is essential or not. The results are shown in Figure 5.

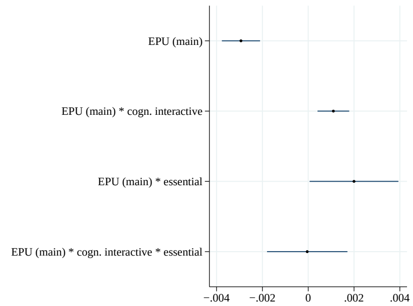
Covid-induced economic uncertainty exerted positive effects on the relative demand for non-essential occupations with relatively high non-routine cognitive analytical, non-routine cognitive interactive, and non-routine manual task content (Panels (a)–(c)). By contrast, it impacted positively (negatively) the relative demand for (non-)essential occupations with relatively high routine manual or routine cognitive task content (Panels (d) and (e)). Although the effects on the relative demand for non-essential occupations are in line with the existing evidence on job polarisation, the effects on the relative demand for the essential routine-intensive occupations are not. Instead, the latter are most likely accounted for by the health emergency and the ensuing rising relative demand for healthcare practice and support occupations that have in fact relatively high routine manual and routine cognitive task content (see columns (4) and (5) of Table B1). They may also be accounted for by production occupations that also have relatively high routine manual and routine cognitive task content and some of these (e.g. butchers, grocery store staff, warehouse workers) played a critical role for the unhampered supply of essential products (e.g. food) to consumers amid the Covid-19 shock and, especially, the lockdowns.

In addition, Covid-induced economic uncertainty impacted positively the relative demand for occupations that are both essential and contact-intensive (Panel (g)). This effect sheds more light on the result in column (3) of Table 2 and is most likely explained by the rising relative demand for healthcare practice and support and protective service occupations, which are both essential amid a pandemic crisis and require intensive physical contact (see columns (1)–(4) of Table B3). By contrast, there are no statistically significant effects of Covid-induced economic uncertainty on the relative demand for essential customer- or service-oriented occupations (Panels (f) and (h)).

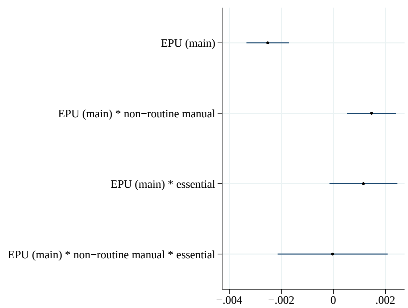
Figure 5: The joint role of occupational characteristics and essential status



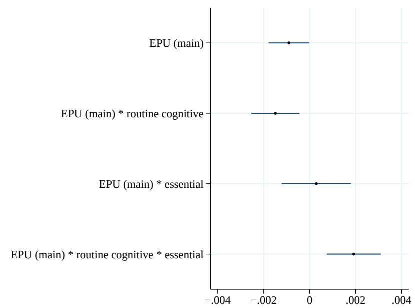
(a) Cognitive analytical



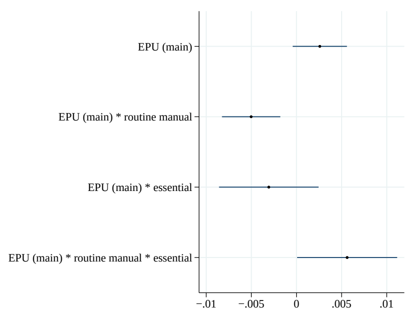
(b) Cognitive interactive



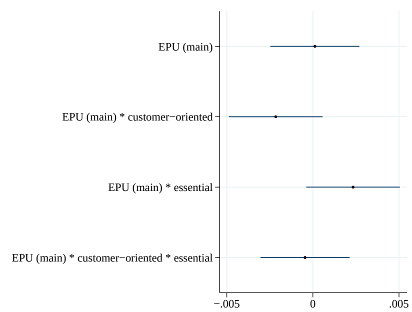
(c) Non-routine manual



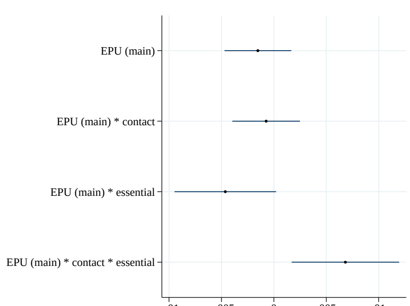
(d) Routine cognitive



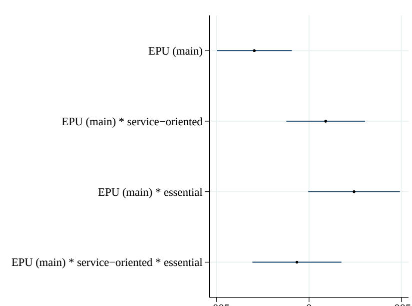
(e) Routine manual



(f) Customer orientedness



(g) Physical contact intensity



(h) Service orientedness

Notes: OLS estimations with robust standard errors and two-digit (SOC) occupation-US state and month fixed effects in all panels. These specifications also include the interactions of the country-level EPU with individual characteristics and pairwise combinations of these. Their coefficient estimates are not disclosed for the sake of exposition.

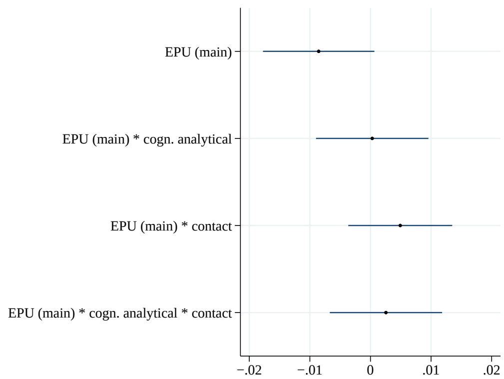
4.2.3 The joint role of occupational characteristics and physical contact intensity

Since the onset of the Covid-19 pandemic outbreak, working in physical contact or close proximity to others has become a major issue leading to the adoption of social-distancing practices. In order to better understand the implications of this phenomenon for occupational demand, we now look into the joint role of the main occupational characteristics and physical contact intensity. We do so by re-estimating the equations in columns (1)–(5) of Panel A and column (2) of Panel B of Table 2 after multiplying their main interaction terms by the measure of physical contact intensity. The results of these estimations are shown in Figure 6.

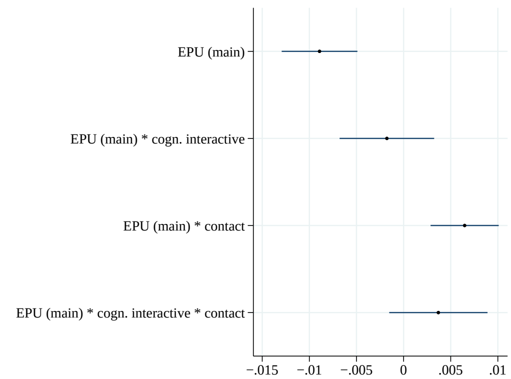
While Covid-induced economic uncertainty exerted no statistically significant effects on the relative demand for contact-intensive occupations with relatively high non-routine cognitive analytical and interactive task content (Panels (a) and (b)), it exerted a negative and significant effect on the relative demand for contact-intensive occupations with relatively high non-routine manual task content and a positive and significant effect on the relative demand for less contact-intensive occupations with relatively high non-routine manual task content (Panel (c)). The two effects are novel and add new insights about how occupational demand during the Covid-19 shock might have changed with respect to the recent pre-Covid period, which was largely marked by the job polarisation phenomenon. Specifically, in the the pre-Covid period the relative demand for low-paying service occupations (e.g. waiters, hairdressers, plumbers) increased as their tasks were largely shielded from offshoring and automation due to their relatively high physical contact intensity and non-routine manual task content. By contrast, the identified effects during the Covid-19 shock are most likely explained by the declining demand for occupations such as food service and arts and entertainment, which are both contact-intensive and have relatively high non-routine manual task content, as well as by the rising demand for occupations such as farming, fishing, and transportation, which are less-contact intensive, but have relatively high non-routine manual task content (see column (3) of Tables B1 and B3).

What is more, Covid-induced economic uncertainty exerted positive (negative) effects on the relative demand for (less) contact-intensive occupations that have relatively high routine manual or routine cognitive task content, or high degree of service-orientedness (Panels (d)–(f) of Figure 6). Again, these findings point to important changes in the occupational composition of US labour demand compared to the recent pre-Covid period. While the negative effects are consistent with the relative employment contraction in the recent pre-Covid period of less

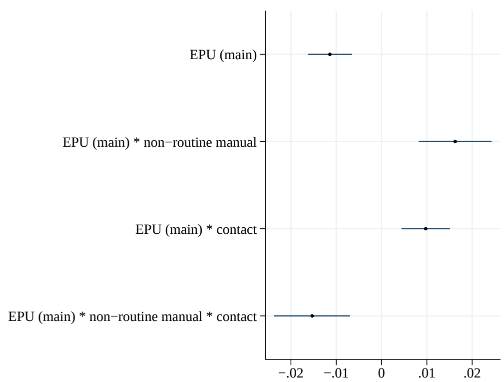
Figure 6: The joint role of occupational characteristics and physical contact intensity



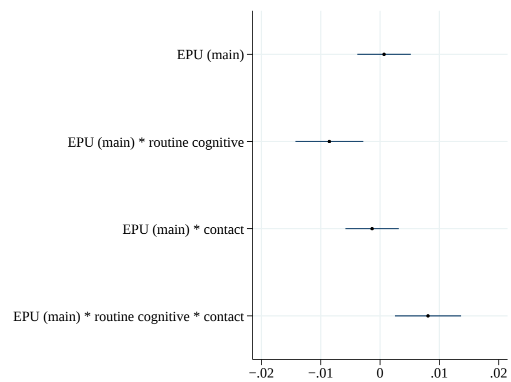
(a) Cognitive analytical



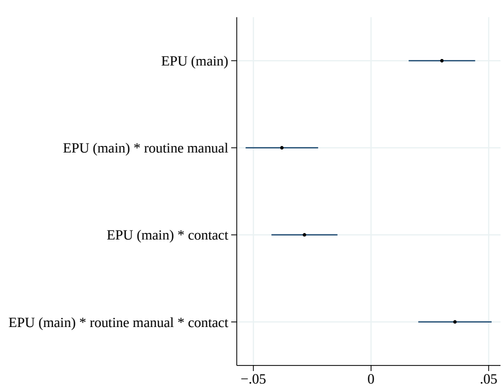
(b) Cognitive interactive



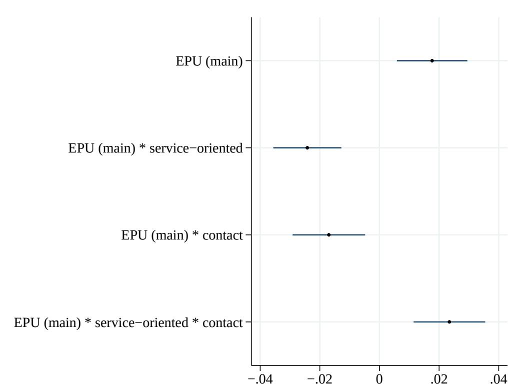
(c) Non-routine manual



(d) Routine cognitive



(e) Routine manual



(f) Service orientedness

Notes: OLS estimations with robust standard errors and two-digit (SOC) occupation-US state and month fixed effects in all panels. These specifications also include the interactions of the country-level EPU with individual characteristics and pairwise combinations of these. Their coefficient estimates are not disclosed for the sake of exposition.

contact-intensive occupations that have relative high routine manual or cognitive task content (e.g. production and assembly line staff, administrative and clerical staff), the positive effects are most likely explained by the increase in the relative demand for community and service, healthcare practice and support, protective service, and essential sales occupations. Indeed, all these occupations are highly contact-intensive and have relatively high routine manual or cognitive task content, or high degree of service-orientedness (see columns (4)–(5) of Table B1, column (5) of Table B2, and column (3) of Table B3).

5 Conclusion

The Covid-19 shock has caused large-scale upheaval in the labour markets around the world, including in the US, but the adverse consequences are likely to have been borne disproportionately by some individuals, occupations, and sectors. This paper is the first to conduct a comprehensive analysis on the effects of Covid-induced economic uncertainty on the relative demand for occupations that differ in a broad range of characteristics. The period that we examine covers all months (January–December) of 2020, which were marked by the onset of the Covid-19 pandemic outbreak, the rapid spread of the virus across and within countries, and the imposition of restrictive measures for its containment (e.g. two strict lockdowns, domestic and international travel restrictions or bans, social distancing). To conduct the analysis, we combine monthly online job postings data at the occupation-US state level with data on fixed occupational characteristics and monthly data on measures of economic uncertainty in the US (Economic Policy Uncertainty, Survey Business Uncertainty). We apportion the latter measures to occupation-state pairs according to their pre-Covid (2019) country-wide occupational employment shares.

From the analysis, we obtain results that are consistent with the secular phenomenon of RBTC leading to "job polarisation" (e.g. Autor et al., 2003; Autor & Dorn, 2013) and stronger complementarity between analytical and social tasks (Borghans et al. (2014); Weinberger (2014); Deming, 2017), but also with its episodic aspect implying its acceleration during recessions (Hershbein & Kahn, 2018). Specifically, we find that Covid-induced economic uncertainty increased the relative demand for occupations with relatively high non-routine cognitive analytical, non-routine cognitive interactive, and non-routine manual task content. These effects hold particularly for occupations that are also non-essential. Positive effects are also identified on the relative demand for occupations that have both relatively high non-routine cognitive analytical and social or interaction task content.

Importantly, though, additional findings are rationalised by the peculiarity of the Covid-19 shock, that is, the major health crisis and restrictive measures (e.g. lockdown, social distancing) that it has brought about. In particular, we find that Covid-induced economic uncertainty decreased the relative demand for customer-oriented occupations (e.g. food preparation and service, personal care and service), while it increased the relative demand for essential or contact-intensive occupations with relatively high routine manual or routine cognitive task content, as well as occupations that are both essential and contact-intensive and those that are both contact-intensive and service-oriented (e.g. healthcare practice and support, protective service, community and social service).

Whether the latter effects are temporary or will lead to structural shifts in the occupational composition of US labour demand remains an open question and will depend on various factors. For instance, tele-presence has become common since the onset of the pandemic and tele-work is now viewed as a conventional human resource practice that will likely continue even after the pandemic ends (Barrero et al., 2021). This is also evident by the rising patent applications in the US between January 2020 and September 2020 for digital technologies that prop-up tele-work, such as tele-presence software and equipment (Bloom et al., 2021). Tele-presence is a form of automation (Mindell, 2015), and firms –especially, the relatively large ones that can incur more easily the sunk costs of irreversible investments– might have already shifted disproportionately their capital investments towards other more costly automation technologies (e.g. industrial robots, Artificial Intelligence systems). If this is indeed the case, then the increasingly automation-intensive future may arrive sooner than previously anticipated and will determine accordingly the occupational composition of labour demand in the US and other countries (Autor & Reynolds, 2020). This is an intriguing research topic and merits in-depth investigation.

Another factor to consider is the de-densification of cities that started with the pandemic and was facilitated by the adoption of tele-work practices (Ramani & Bloom, 2021). Until before the pandemic hit, large cities were attractors of talented individuals in high-paying occupations (e.g. managerial, business and financial, computer science, architecture and engineering, legal) and highly-innovative sectors (e.g. ICT, pharmaceuticals, biotechnology), who were concentrated in them in order to benefit from agglomeration effects. Their physical presence in large cities boosted the demand for local services such as food preparation and service, security, cleaning, entertainment, and recreation (Moretti, 2012). This is the main reason for the increase in the demand for the latter occupations relative to middle-paying ones that were more amenable to automation and offshoring (Autor & Dorn, 2013). The ongoing pandemic shock reversed this trend and if this reversal becomes permanent in the post-pandemic era, it can have profound implications for the occupational composition of labour demand in the medium- to long-run. This is definitely another topic which is worth shedding light upon.

Although anti-Covid vaccines have become available by now, there are large differences in inoculation rates both across and within countries, while new variants of the virus have been spreading around the globe.[27] As the pandemic is still in full swing and the time horizon of its end is unclear, we have to continue to closely monitor its economic and labour market effects. Insights such as those derived from this analysis could be particularly useful to policy makers in the US and other countries and prompt them to design and implement ambitious medium- to long-term plans that could mitigate the adverse labour market effects of the ongoing pandemic shock and prepare the workforce for the new state that will emerge after the end of the current state of emergency.

[27]Check, for instance: https://www.nytimes.com/interactive/2021/world/covid-vaccinations-tracker.html.

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Appendix

A Data and variables

A.1 Variables for occupational characteristics

Occupational task content measures of Autor et al. (2003) By relying on the fourth (1977) edition of the US Department of Labor's Dictionary of Occupational Titles (DOT), the authors create measures of the non-routine cognitive analytical, non-routine cognitive interactive, non-routine manual, routine manual, and routine cognitive task content of 330 occupations in 1980.[28] As occupations are identified by their occ1990dd codes, we first map these codes to two-digit 2010 SOC codes according to the US IPUMS CPS (see Appendix Section A.2), and then calculate the unweighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Table B1).

Occupational task content measures of Autor & Dorn (2013) The authors create measures of the abstract (i.e., non-routine cognitive), non-routine manual, and routine task content of 330 occupations in 1980.[29] Occupations are identified by their occ1990dd codes. Therefore, we first assign two-digit 2010 SOC codes to occ1990dd codes as indicated by the US IPUMS CPS (see Appendix Section A.2), and then calculate the unweighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Table B4).

Occupational task content measures of Deming (2017) The author creates task content measures for different O*NET 1998 occupations by considering tasks that pertain to the DOT category of non-routine cognitive interactive tasks (social, coordination, interaction), the degree of customer orientedness, and the degree of service orientedness (e.g. provision of care).[30] As all measures range between 1 (lowest) and 7 (highest), the author re-scales these measures so that they range between 0 and 10. In order to produce scores at the two-digit SOC level, we first map O*NET occupation codes to two-digit 2010 SOC codes. We do so by using sequentially the crosswalk between O*NET codes and occ1990 codes, the crosswalk between occ1990 codes and occ1990dd codes, and the crosswalk between occ1990dd codes and two-digit SOC codes. The first two crosswalks are provided by Deming (2017), while the third crosswalk is the one that we have created based on US IPUMS CPS and described above.[31] Then, we calculate the unweighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Table B2).

[28] Non-routine cognitive analytical tasks are those requiring quantitative reasoning, non-routine cognitive interactive tasks are those requiring direction, control and planning, and non-routine manual tasks are those requiring eye-hand-foot coordination. Routine manual tasks are those requiring finger dexterity, while routine cognitive tasks are those requiring setting limits, tolerances or standards.

[29] For the construction of these measures, they aggregate the respective original task scores of Autor et al. (2003): non-routine cognitive analytical and non-routine cognitive interactive; non-routine manual; routine manual and routine cognitive.

[30] For the precise O*NET definition of each type of task, see Appendix Section A.3.

[31] There is a more than 99% match between O*NET 1998 and occ1990 codes and a perfect match between occ1990 and occ1990dd codes.

Essential occupations à la Mongey et al. (2021) We identify essential occupations using the data of Mongey et al. (2021). After obtaining information on employment in two-digit occupations from the Occupational Employment Statistics Survey (OES) 2018, the authors calculate the employment share of each occupation in essential industries. To identify essential industries, they rely on the relevant four-digit NAICS industry classification of Kane & Tomer (2021). We label an occupation as essential if its employment share in essential industries is at least equal to 60%. Under this methodology, the following occupations are labeled as essential: community and social service; healthcare practice, healthcare support; protective service; farming, fishing, and forestry; production; transportation and material moving. As some retail occupations are also deemed as essential (e.g. salespersons in grocery stores), we also label sales and related occupations as essential in the benchmark version of the dummy variable. In the alternative version, we treat this occupation as non-essential (see columns (1) and (2), respectively, of Table B3).

Physical contact intensity measures of Leibovici et al. (2020) The authors create a physical contact intensity index for four-digit 2010 SOC occupations by combining individual-level data from the 2017 American Community Survey with information from O*NET on the extent to which an occupation requires a worker to perform job tasks in close physical proximity to other people. A score is assigned to each possible answer, whose aggregation yields the contact intensity index.[32] Using the contact intensity scores for four-digit 2010 SOC occupations, we then calculate the unweighted mean across these by two-digit 2010 SOC occupation.

Tele-work measures of Dingel & Neiman (2020) By relying on O*NET questions related to the capacity of workers in different occupations to tele-work, the authors calculate the fraction of tasks of 8-digit 2010 SOC occupations that can be performed from distance. As a result, the occupation-specific tele-work measure ranges between zero and one, with zero values implying that not a single task can be performed from distance and unit values implying that all tasks can be performed from distance. Alternatively, the authors assign manually 0, 0.5 or 1 to each 6-digit 2010 SOC code. Calculating the unweighted mean of these measures across 8-digit and 6-digit SOC codes, respectively, by the corresponding two-digit SOC code, we obtain tele-work measures at the occupation level considered in our analysis. The scores are displayed in columns (5) and (6) of Table B3.

A.2 Concordance between occ1990dd and two-digit SOC

The correspondence of occ1990dd codes to two-digit 2010 SOC occupation titles according to the US IPUMS CPS is listed below:

Management (3–37); Architecture and Engineering (43–59); Computer and Mathematical

[32]The possible answers and associated scores in parentheses are: "I don't work near other people (beyond 100 ft.)" (0); "I work with others but not closely (e.g., private office)" (25); "Slightly close (e.g., shared office)" (50); "Moderately close (at arm's length)" (75); "Very close (near touching)" (100).

(64–68); Life, Physical, and Social Science (69–83, 166, 173); Healthcare Practitioners and Technical (84–106, 203–208); Education, Training, and Library (113–165); Community and Social Service (174–176); Legal (178, 179, 234); Arts, Design, Entertainment, Sports, and Media (183–200); Sales and Related (243–253, 256–290); Business and Financial Operations (253–256); Office and Administrative Support (303–391); Protective Service (415–427); Food Preparation and Service (434–444); Healthcare Support (445–447); Building and Grounds Cleaning and Maintenance (448–455); Personal Care and Service (456–469); Farming, Fishing, and Forestry (473–498); Installation, Maintenance, and Repair (503–549); Construction and Extraction (558–617, 865, 869); Production (628–699); Transportation and Material Moving (803–859).

A.3 Definitions of different types of tasks in Deming (2017)

Social The measure of social task content of an occupation is the average of four variables: 1) social perceptiveness (defined as "being aware of others' reactions and understanding why they react the way they do"); 2) coordination ("adjusting actions in relation to others' actions); 3) persuasion ("persuading others to approach things differently"); and 4) negotiation ("bringing others together and trying to reconcile differences").

Coordination The measure of coordination task content of an occupation is the average of two variables: 1) coordinating work and activities of others (defined as "coordinating members of a work group to accomplish tasks"); and 2) developing and building teams ("encouraging and building mutual trust, respect, and cooperation among team members").

Interaction The measure of interaction task content of an occupation is calculated as the average of four variables: 1) interpreting the meaning of information to others (defined as "translating or explaining what information means and how it can be understood or used to support responses or feedback to others"); 2) communicating with other workers ("providing information to supervisors, fellow workers, and subordinates"); 3) communicating with persons outside the organization ("representing the organization to customers, the public, government, and other external sources"); and 4) establishing and maintaining relationships ("developing constructive and cooperative working relationships with others").

Customer-oriented The degree of customer-orientedness of an occupation corresponds to tasks requiring knowledge of principles and processes for providing customer and personal services, including needs assessment techniques, quality service standards, alternative delivery systems, and customer satisfaction evaluation techniques.

Service-oriented The degree of service-orientedness of an occupation is the average of two variables: 1) assisting and caring for others (defined as "providing assistance or personal care to others"); and 2) service orientation ("actively looking for ways to help people").

A.4 Economic policy uncertainty

A.4.1 News-based index

For the US, the news-based Economic Policy Uncertainty (EPU) index is a measure of the monthly frequency of articles in ten leading national newspapers (e.g. New York Times, Boston Globe) that contain at least one keyword from each of the following groups: "economic" or "economy" (group 1); "uncertain" or "uncertainty" (group 2); "congress", "deficit", "Federal Reserve", "legislation", "regulation", "White House" (group 3). As the number of articles may vary across newspapers, the monthly frequency is normalised by the total count of articles in the corresponding newspaper and month. The data and methodology can be found at: https://www.policyuncertainty.com/. According to the authors, the index aims at capturing uncertainty about *who* will make economic policy decisions, *what* economic policy actions will be undertaken and *when*, and the *economic effects* of policy actions (or inaction) – including uncertainties related to the economic ramifications of "non-economic" policy matters, e.g., military actions. Also, the index aims at capturing both *near-term* concerns (e.g. when will the Fed adjust its policy rate) and *longer-term* concerns (e.g. how to fund entitlement programs). For the construction of the EPU by policy area, the authors combine the keywords in groups 1–3 with keywords that are relevant to each individual policy area.

The keywords by policy area are:

Healthcare: health care, Medicaid, Medicare, health insurance, malpractice Tort reform, malpractice reform, prescription drugs, drug policy, food and drug administration, FDA, medical malpractice, prescription drug act, medical insurance reform, medical liability, part D, affordable care act, Obamacare.

Fiscal policy: Anything covered by "Taxes" or "Government Spending & Other".

Taxes: taxes, tax, taxation, taxed.

Government spending and other: government spending, federal budget, budget battle, balanced budget, defense spending, military spending, entitlement spending, fiscal stimulus, budget deficit, federal debt, national debt, Gramm-Rudman, debt ceiling, fiscal footing, government deficits, balance the budget.

Monetary policy: Federal Reserve, the FED, money supply, open market operations, quantitative easing, monetary policy, fed funds rate, overnight lending rate, Bernanke, Volker, Greenspan, central bank, interest rates, FED chairman, FED chair, lender of last resort, discount window, European Central Bank, ECB, Bank of England, Bank of Japan, BOJ, Bank of China, Bundesbank, Bank of France, Bank of Italy.

National Security national security, war, military conflict, terrorism, terror, 9/11, defense spending, military spending, police action, armed forces, base closure, military procurement, saber rattling, naval blockade, military embargo, no-fly zone, military invasion.

Entitlement Programs: entitlement program, entitlement spending, government entitlements, social security, Medicaid, medicare, government welfare, welfare reform, unemployment insurance, unemployment benefits, food stamps, AFDC, TANF, WIC program, disability insurance, part D, OASDI, Supplemental Nutrition Assistance Program, Earned Income Tax Credit, EITC, head start program, public assistance, government subsidized housing.

Regulation: Anything covered by "Financial Regulation" and truth in lending, union rights, card check, collective bargaining law, national labor relations board, NLRB, minimum wage, living wage, right to work, closed shop, wages and hours, workers compensation, advance notice requirement, affirmative action, at-will employment, overtime requirements, trade adjustment assistance, Davis-Bacon, equal employment opportunity, EEO, OSHA, antitrust, competition policy, merger policy, monopoly, patent, copyright, federal trade commission, FTC, unfair business practice, cartel, competition law, price fixing, class action, healthcare lawsuit, Tort reform, tort policy, punitive damages, medical malpractice, energy policy, energy tax, carbon tax, cap and trade, cap and tax, drilling restrictions, offshore drilling, pollution controls, environmental restrictions, clean air act, clean water act, environmental protection agency, EPA, immigration policy.

Financial Regulation: banking (or bank) supervision, Glass-Steagall, TARP, thrift supervision, Dodd-Frank, financial reform, commodity futures trading commission, CFTC, house financial services committee, basel, capital requirement, Volcker rule, bank stress test, securities and exchange commission, sec, deposit insurance, FDIC, FSLIC, OTS, OCC, FIRREA.

Trade Policy: import tariffs, import duty, import barrier, government subsidies, government subsidy, WTO, World Trade Organization, trade treaty, trade agreement, trade policy, trade act, Doha Round, Uruguay Round, GATT, dumping.

Sovereign Debt and Currency Crises: sovereign debt, currency crisis, currency crash, currency devaluation, currency revaluation, currency manipulation, euro crisis, Eurozone crisis, european financial crisis, european debt, asian financial crisis, asian crisis, Russian financial crisis, Russian crisis, exchange rate.

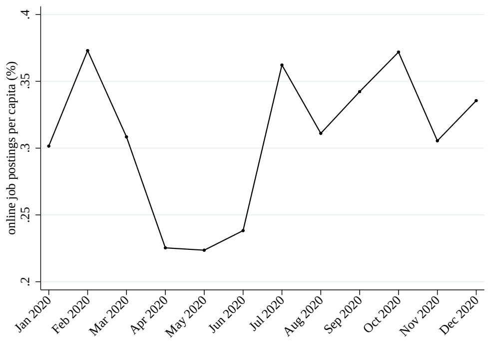
A.4.2 Composite index

The composite Economic Policy Uncertainty (EPU) index consists of three components. The first component is the news-based EPU. The second relies on tax code expiration data retrieved from reports of the Congressional Budget Office (CBO) that compile lists of temporary federal tax code provisions. Temporary tax measures can capture the uncertainty facing firms and households as they can be extended with very short or no prior notice. The third component relies on data on disagreements about economic forecasts that are retrieved from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The level of disagreement is measured empirically as the dispersion in the quarterly forecast of individuals for one year in the future about three variables that are directly influenced by government policy: CPI, purchases of goods and services by state and local governments, and purchases of goods and services by the federal government.

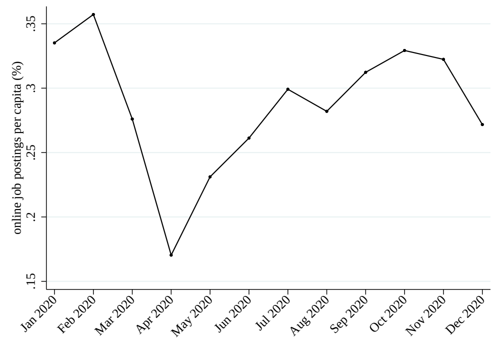
For the construction of the composite (three-component) EPU measure, Baker et al. (2016) take the following steps. First, they normalise each component by its own standard deviation prior to January 2012. Then, they calculate the weighted average of the three components using weights of 1/2 on the first component (i.e., news-based EPU), 1/6 on the second component (i.e., based on temporary tax measures), and 1/6 on the two sub-components of the third component (i.e., based on disagreement about the CPI forecast and disagreement about the federal/state/local purchases forecast).

B Additional descriptive statistics

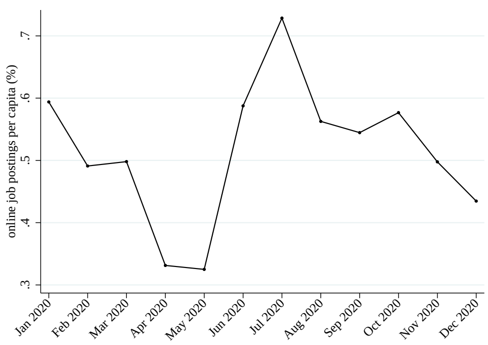
Figure B1: Online job postings per capita in other countries



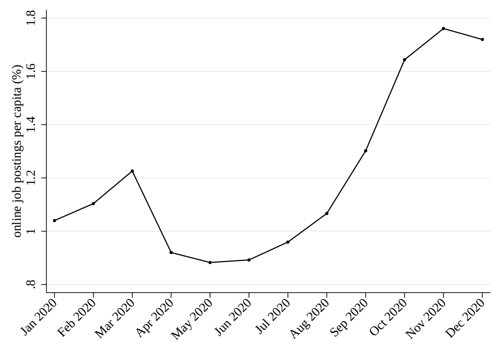
(a) Australia



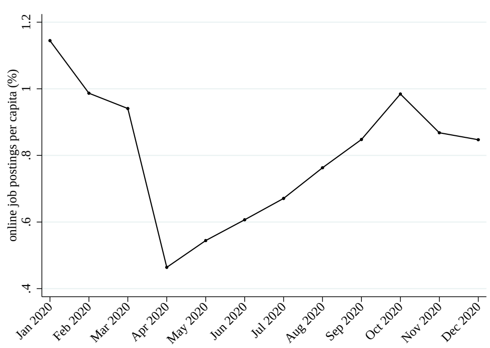
(b) Canada



(c) New Zealand



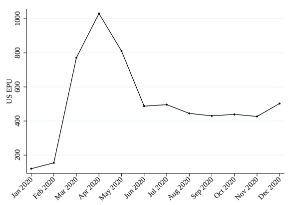
(d) Singapore



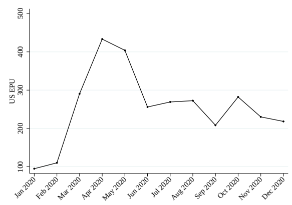
(e) United Kingdom

Notes: Monthly variation in ratios of number of online job postings in Australia, Canada, New Zealand, Singapore and the United Kingdom to the respective nationwide population in January 2020 – December 2020.
Source: Authors' calculations based on online job postings data of Burning Glass Technologies (BGT).

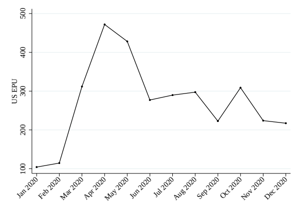
Figure B2: US EPU by policy area



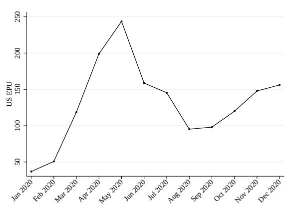
(a) Health policy



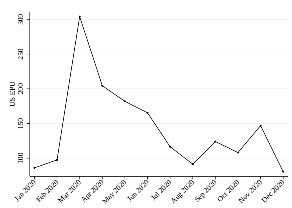
(b) Fiscal policy



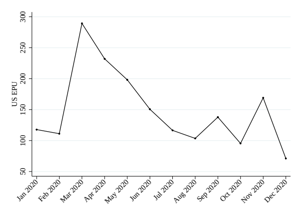
(c) Tax policy



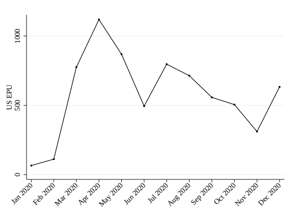
(d) Government policy



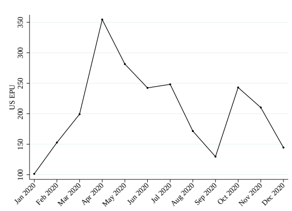
(e) Monetary policy



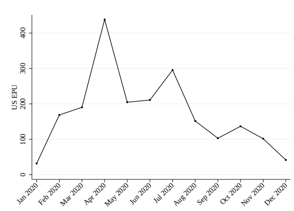
(f) Security policy



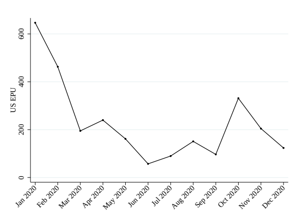
(g) Entitlement programmes



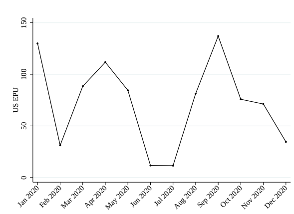
(h) Regulation



(i) Financial regulation



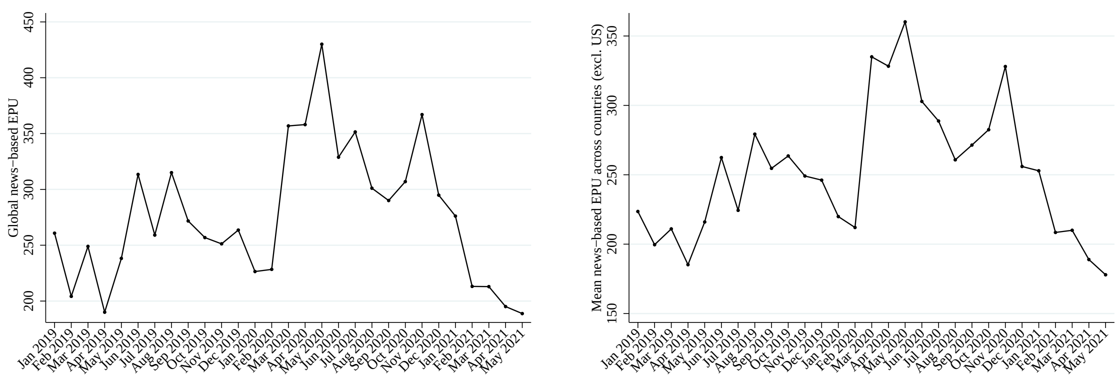
(j) Trade policy



(k) Debt and currency crisis

Notes: Monthly variation in US (news-based) EPU measure by policy area in January 2020 – December 2020. *Source*: https://www.policyuncertainty.com/; see particularly Baker et al. (2016).

Figure B3: Global EPU and EPU in countries other than the US

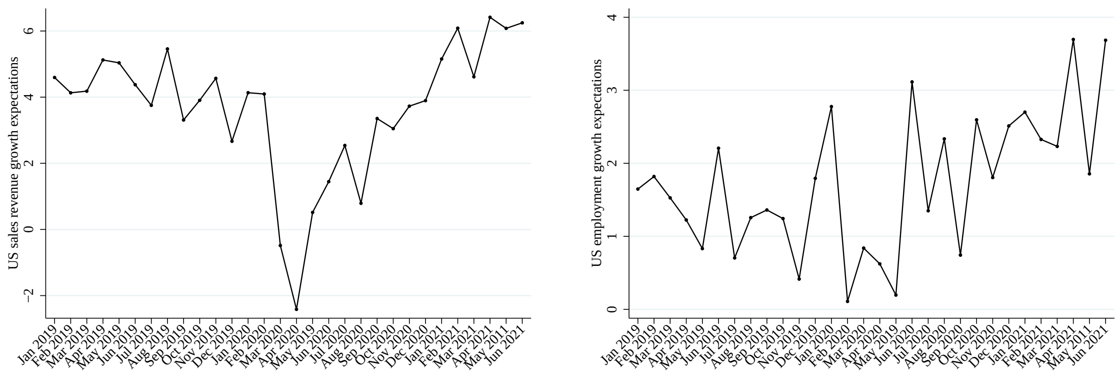


(a) Global

(b) Cross-country mean, excl. US

Notes: Monthly variation in the (news-based) Global EPU measure and the unweighted average of (news-based) EPU measures for a group of countries other than the US in January 2019 – May 2021. The group of countries comprises: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Korea, Netherlands, Russia, Spain, Singapore, UK, Sweden, and Mexico.
Source: https://www.policyuncertainty.com/; see particularly Baker et al. (2016).

Figure B4: Business expectations in the US



(a) Sales revenue growth expectations

(b) Employment growth expectations

Notes: Monthly variation in the sales revenue and employment growth expectation measures in the US in January 2019 – June 2021.

Source: Atlanta FED, University of Chicago Booth School of Business, Stanford University; see particularly Altig et al. (2020).

Table B1: Autor et al. (2003) task content scores by (two-digit SOC) occupation

Two-digit (SOC) occupation code & title	Non-routine			Routine	
	cognitive analytical	cognitive interactive	manual	manual	cognitive
11 Management	5.40	6.71	0.49	2.78	2.24
13 Business and Financial Operations	4.76	2.73	0.02	3.06	1.05
15 Computer and Mathematical	7.90	4.72	0.71	2.58	4.90
17 Architecture and Engineering	8.49	6.75	1.02	4.68	7.76
19 Life, Physical, and Social Science	7.94	4.80	0.71	3.88	5.29
21 Community and Social Service	5.61	4.30	0.16	2.54	0.23
23 Legal	4.47	3.18	0.06	2.89	3.65
25 Education, Training, and Library	4.78	5.28	1.33	3.49	0.56
27 Arts, Design, Entertainment, Sports, and Media	3.83	2.82	1.92	4.43	3.28
29 Healthcare Practitioners and Technical	5.92	2.97	1.09	5.60	4.37
31 Healthcare Support	3.69	0.38	0.79	4.77	6.26
33 Protective Service	1.66	1.24	2.30	2.48	0.87
35 Food Preparation and Service	1.73	0.37	1.10	2.84	1.51
37 Building and Grounds Cleaning and Maintenance	1.81	1.27	2.21	2.97	4.22
39 Personal Care and Service	2.20	1.34	0.93	3.72	1.65
41 Sales and Related	3.91	2.18	0.67	3.74	2.18
43 Office and Administrative Support	2.87	0.79	0.20	4.07	5.82
45 Farming, Fishing, and Forestry	2.44	2.98	2.44	3.17	2.88
47 Construction and Extraction	2.64	0.36	3.15	4.29	8.41
49 Installation, Maintenance, and Repair	3.78	0.43	1.63	4.91	8.82
51 Production	3.53	0.79	0.99	4.54	8.76
53 Transportation and Material Moving	1.62	1.47	3.70	2.82	3.10

Notes: For the calculation of the scores by two-digit 2010 SOC occupation, we rely on Autor et al. (2003)'s 1980 measures of the non-routine cognitive analytical, non-routine cognitive interactive, non-routine manual, routine manual, and routine cognitive task content of 330 occupations (identified by their occ1990dd codes). First, we map occ1990dd codes to two-digit 2010 SOC codes according to the US IPUMS CPS (see Appendix Section A.2) and then, we calculate the simple average of the measures across occ1990dd codes by the corresponding two-digit SOC code.
Source: Authors' calculations based on data of Autor et al. (2003).

Table B2: Deming (2017) task content scores by (two-digit SOC) occupation

Two-digit (SOC) occupation code & title	Social	Coordination	Interaction	Customer-oriented	Service-oriented
11 Management	6.18	4.81	7.12	6.02	3.55
13 Business and Financial Operations	6.43	2.15	6.43	6.94	3.65
15 Computer and Mathematical	3.79	1.81	6.20	2.08	1.86
17 Architecture and Engineering	5.32	6.30	7.81	3.56	2.44
19 Life, Physical, and Social Science	4.37	3.20	7.37	3.35	2.86
21 Community and Social Service	6.71	4.72	7.59	7.09	8.66
23 Legal	5.22	2.54	6.56	5.20	3.06
25 Education, Training, and Library	4.93	4.09	6.95	5.12	6.27
27 Arts, Design, Entertainment, Sports, and Media	3.51	2.79	5.10	3.77	1.89
29 Healthcare Practitioners and Technical	4.52	2.94	6.34	6.74	6.97
31 Healthcare Support	3.26	1.26	4.80	5.49	6.79
33 Protective Service	4.37	2.15	5.08	7.15	5.61
35 Food Preparation and Service	1.55	1.35	3.75	7.17	4.21
37 Building and Grounds Cleaning and Maintenance	3.05	2.67	3.65	4.68	2.97
39 Personal Care and Service	2.42	1.56	4.20	8.38	5.39
41 Sales and Related	4.45	2.58	6.03	8.71	4.19
43 Office and Administrative Support	2.20	1.43	4.16	5.40	3.38
45 Farming, Fishing, and Forestry	1.94	1.86	3.32	2.47	1.44
47 Construction and Extraction	1.15	1.03	1.72	1.62	1.02
49 Installation, Maintenance, and Repair	1.40	1.18	2.58	2.94	1.71
51 Production	1.11	1.14	1.80	1.24	0.99
53 Transportation and Material Moving	2.07	1.77	3.16	4.00	2.20

Notes: For the calculation of the scores by two-digit 2010 SOC occupation, we rely on Deming (2017)'s task content measures. The author creates such measures for different O*NET 1998 occupations by considering tasks that pertain to the DOT category of non-routine cognitive interactive tasks (social, coordination, interaction, customer-oriented), and the DOT category of non-routine manual tasks (service-oriented). The precise O*NET definition of each type of task are shown in Appendix Section A.3. The author re-scales all measures so that they range between 0 and 10. In order to produce scores at the two-digit SOC level, we first map O*NET occupation codes to two-digit 2010 SOC codes. We do so by using sequentially the crosswalk between O*NET codes and occ1990 codes, the crosswalk between occ1990 codes and occ1990dd codes, and the crosswalk between occ1990dd codes and two-digit SOC codes. We then calculate simple averages of the measures across occ1990dd codes by the corresponding two-digit SOC code.
Source: Authors' calculations based on data of Deming (2017).

Table B3: Additional occupational characteristics by (two-digit SOC) occupation

Two-digit (SOC) occupation code & title	Essential		Contact intensity		Work-from-home	
	Main	Alternative	Main	Alternative	O*NET	Manual
11 Management	0	0	47	47	0.66	0.66
13 Business and Financial Operations	0	0	50	49	0.80	0.86
15 Computer and Mathematical	0	0	43	43	1.00	1.00
17 Architecture and Engineering	0	0	50	49	0.44	0.71
19 Life, Physical, and Social Science	0	0	48	48	0.62	0.42
21 Community and Social Service	1	1	58	58	0.50	0.58
23 Legal	0	0	49	49	0.88	0.88
25 Education, Training, and Library	0	0	65	67	0.93	0.76
27 Arts, Design, Entertainment, Sports, and Media	0	0	58	56	0.63	0.33
29 Healthcare Practitioners and Technical	1	1	82	84	0.09	0.06
31 Healthcare Support	1	1	87	90	0.11	0.00
33 Protective Service	1	1	71	70	0.14	0.00
35 Food Preparation and Service	0	0	75	75	0.06	0.00
37 Building and Grounds Cleaning and Maintenance	0	0	54	55	0.00	0.00
39 Personal Care and Service	0	0	74	73	0.25	0.00
41 Sales and Related	1	0	58	55	0.54	0.43
43 Office and Administrative Support	0	0	56	57	0.60	0.52
45 Farming, Fishing, and Forestry	1	1	43	45	0.06	0.00
47 Construction and Extraction	0	0	69	69	0.02	0.00
49 Installation, Maintenance, and Repair	0	0	63	64	0.02	0.00
51 Production	1	1	57	56	0.05	0.00
53 Transportation and Material Moving	1	1	64	62	0.06	0.00

Notes: For the identification of (non-)essential two-digit 2010 SOC occupations in columns (1) and (2), we rely on the data of Mongey et al. (2021). We classify an occupation as (non-)essential if its employment share in essential industries is at least (less than) 60%. For the calculation of the measures of physical contact intensity by two-digit 2010 SOC occupation in columns (3) and (4), we rely on the data of Leibovici et al. (2020). We calculate the simple average of the physical contact intensity measures across four-digit 2010 SOC occupations by the corresponding two-digit SOC code. For the calculation of the scores by two-digit 2010 SOC occupation in columns (5) and (6), we rely on Dingel & Neiman (2020)'s work-from-home measures for 8-digit 2010 SOC and 6-digit 2010 SOC occupations, respectively. Using O*NET information on tele-work, the authors calculate the first measure as the fraction of tasks of occupations that can be performed from distance. Hence, value 0 indicates that zero fraction of tasks of an occupation can be performed from distance, while value 1 indicates that all tasks of an occupation can be performed from distance. Alternatively, the authors assign manually value 0, 0.5 or 1 to each 6-digit 2010 SOC code. We produce the scores of columns (5) and (6) by computing simple averages of these measures across 8-digit and 6-digit SOC codes, respectively, by the corresponding two-digit SOC code.
Source: Authors' assignments of unit or zero values based on the data and methodology of Mongey et al. (2021) in columns (1) and (2). Authors' calculations based on Leibovici et al. (2020) in columns (3) and (4) and on Dingel & Neiman (2020) in columns (5) and (6).

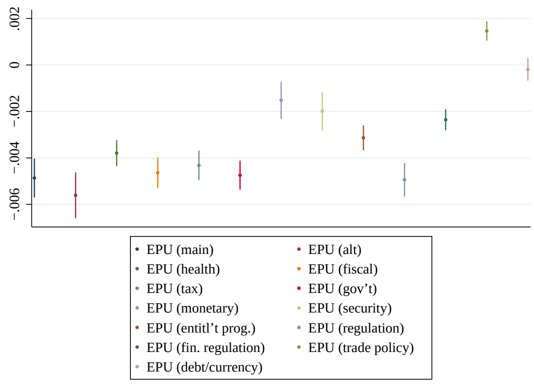
Table B4: Autor & Dorn (2013) task content scores by (two-digit SOC) occupation

Two-digit (SOC) occupation code & title	Abstract	Non-routine manual	Routine
11 Management	6.09	0.49	2.54
13 Business and Financial Operations	3.75	0.02	2.05
15 Computer and Mathematical	6.01	0.68	3.57
17 Architecture and Engineering	7.72	1.04	6.13
19 Life, Physical, and Social Science	6.23	0.75	4.57
21 Community and Social Service	5.05	0.09	1.36
23 Legal	3.15	0.08	2.55
25 Education, Training, and Library	4.92	1.34	2.04
27 Arts, Design, Entertainment, Sports, and Media	3.23	2.00	3.87
29 Healthcare Practitioners and Technical	4.44	1.09	5.01
31 Healthcare Support	1.76	1.09	5.26
33 Protective Service	1.41	2.40	1.58
35 Food Preparation and Service	1.04	1.12	2.41
37 Building and Grounds Cleaning and Maintenance	1.32	2.26	3.48
39 Personal Care and Service	1.71	0.91	2.67
41 Sales and Related	3.15	0.56	2.91
43 Office and Administrative Support	1.80	0.22	4.87
45 Farming, Fishing, and Forestry	2.85	2.42	2.64
47 Construction and Extraction	1.60	3.04	6.17
49 Installation, Maintenance, and Repair	2.12	1.61	6.92
51 Production	2.07	0.99	6.67
53 Transportation and Material Moving	1.97	3.80	3.16

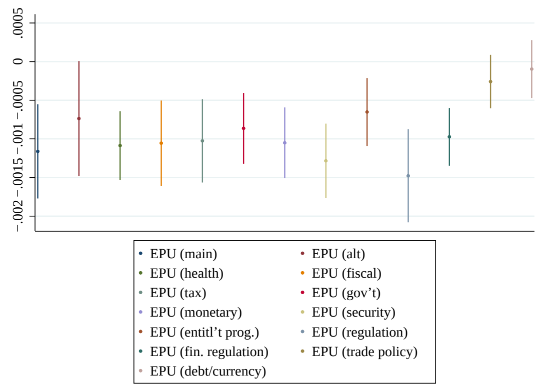
Notes: For the calculation of the scores by two-digit 2010 SOC occupation, we rely on Autor & Dorn (2013)'s 1980 measures of the abstract, non-routine manual, and routine task content of 330 occupations (identified by their occ1990dd codes). The authors calculate the scores of the abstract, non-routine manual, and routine task content of occupations by aggregating the original five task scores of Autor et al. (2003) who rely on the 1997 DOT: non-routine cognitive analytical and non-routine cognitive interactive; non-routine manual; routine manual and routine cognitive. After mapping occ1990dd codes to two-digit 2010 SOC codes according to the US IPUMS CPS (see Appendix Section A.2), we calculate the simple average of the measures across occ1990dd codes by the corresponding two-digit SOC code.
Source: Authors' calculations based on data of Autor & Dorn (2013).

C Additional econometric results

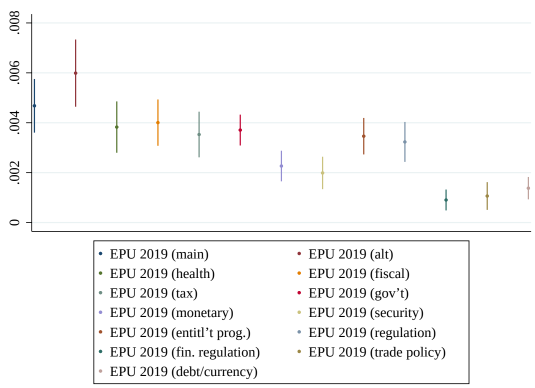
Figure C1: Covid-induced economic uncertainty by area and occupational demand



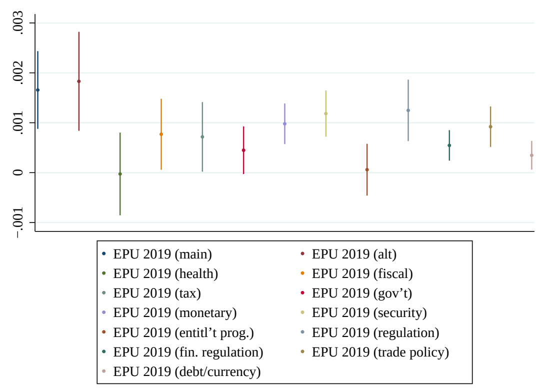
(a) Job postings per capita, EPU in 2020



(b) Share of job postings, EPU in 2020



(c) Job postings per capita, EPU in 2019



(d) Share of job postings, EPU in 2019

Notes: OLS estimations with robust standard errors and two-digit (SOC) occupation-US state and month fixed effects.

Table C1: Alternative measures of Covid-induced economic uncertainty

Panel A: Mean and median EPU across countries, excl. US						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	log # of OJP	OJP p.c.	OJP share	log # of OJP	OJP p.c.	OJP share
Mean of EPU_{ost}	-0.025**	-0.0088***	-0.0019***			
	[0.010]	[0.0008]	[0.0006]			
Median of EPU_{ost}				-0.034***	-0.0095***	-0.0023***
				[0.009]	[0.0007]	[0.0006]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.987	0.929	0.953	0.987	0.930	0.953
Panel B: US sales revenue and employment growth expectations						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	log # of OJP	OJP p.c.	OJP share	log # of OJP	OJP p.c.	OJP share
SBU_{ost} (sales gr. exp.)	0.0056**	0.0017***	0.00074***			
	[0.002]	[0.0002]	[0.0001]			
SBU_{ost} (emp. gr. exp.)				0.011***	0.0014***	0.00064***
				[0.003]	[0.0002]	[0.0002]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.987	0.929	0.953	0.987	0.929	0.953
Panel C: Global EPU in 2019						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	log # of OJP	OJP p.c.	OJP share	log # of OJP	OJP p.c.	OJP share
Global EPU_{ost} 2019	0.97***	0.10***	0.059***			
	[0.2]	[0.01]	[0.01]			
Global EPU_{ost} PPP 2019				0.86***	0.081***	0.056***
				[0.2]	[0.01]	[0.01]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.987	0.929	0.953	0.987	0.929	0.953
Panel D: Mean and median EPU across countries, excl. US, in 2019						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	log # of OJP	OJP p.c.	OJP share	log # of OJP	OJP p.c.	OJP share
Mean of EPU_{ost} 2019	0.94***	0.10***	0.086***			
	[0.2]	[0.02]	[0.01]			
Median of EPU_{ost} 2019				0.23	0.032**	0.070***
				[0.2]	[0.02]	[0.01]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.987	0.929	0.954	0.987	0.929	0.953

Notes: OLS estimations with robust standard errors in all columns of all panels. Two-digit (SOC) occupation-US state and month fixed effects are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C2: Alternative measures of occupational characteristics

Panel A: Cognitive analytical/interactive, non-routine manual, routine cognitive/manual					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
EPU_{ost}	-0.0022*	-0.0013***	-0.0021***	-0.00083	-0.00020
	[0.001]	[0.0004]	[0.0004]	[0.002]	[0.0005]
EPU_t * cogn. analytical (alt)	-0.00026				
	[0.0004]				
EPU_{ost} * cogn. analytical (alt)	0.0012				
	[0.001]				
EPU_t * cogn. interactive (alt)		0.00024			
		[0.0003]			
EPU_{ost} * cogn. interactive (alt)		0.00032			
		[0.0003]			
EPU_t * non-routine manual (alt)			0.0022***		
			[0.0005]		
EPU_{ost} * non-routine manual (alt)			0.0017**		
			[0.0007]		
EPU_t * routine manual (alt)				0.00041	
				[0.0005]	
EPU_{ost} * routine manual (alt)				-0.00035	
				[0.002]	
EPU_t * routine cognitive (alt)					0.0010***
					[0.0003]
EPU_{ost} * routine cognitive (alt)					-0.0014***
					[0.0004]
Observations	13,464	13,464	13,464	13,464	13,464
R^2	0.953	0.953	0.954	0.953	0.953
Panel B: Customer/Service-orientedness, physical contact intensity, tele-work, essential					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
EPU_{ost}	0.0014	-0.0021**	-0.0056***	0.000054	-0.0021***
	[0.0010]	[0.0010]	[0.002]	[0.0006]	[0.0003]
EPU_t * customer (alt)	-0.0020***				
	[0.0004]				
EPU_{ost} * customer (alt)	-0.0025***				
	[0.0009]				
EPU_t * service (alt)		-0.00064			
		[0.0004]			
EPU_{ost} * service (alt)		0.0011			
		[0.0010]			
EPU_t * contact (alt)			0.00048		
			[0.0006]		
EPU_{ost} * contact (alt)			0.0045***		
			[0.002]		
EPU_t * tele-work (alt)				-0.00036	
				[0.0004]	
EPU_{ost} * tele-work (alt)				-0.0017***	
				[0.0006]	
EPU_t * essential (alt)					0.00013
					[0.0002]
EPU_{ost} * essential (alt)					0.052***
					[0.01]
Observations	13,464	13,464	13,464	13,464	13,464
R^2	0.954	0.953	0.953	0.953	0.954

Notes: OLS estimations with robust standard errors in all columns of both panels. Two-digit (SOC) occupation-US state and month fixed effects are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C3: Accounting for Autor & Dorn (2013)'s abstract, manual, routine task content

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share	OJP share
EPU_{ost}	-0.0023***	-0.0022***	-0.00079	-0.0018***	-0.0020***	-0.00017
	[0.0006]	[0.0004]	[0.0007]	[0.0006]	[0.0004]	[0.0006]
EPU_t * abstract	-0.00013					
	[0.0003]					
EPU_{ost} * abstract	0.0014**					
	[0.0005]					
EPU_t * non-routine		0.0021***				
		[0.0004]				
EPU_{ost} * non-routine		0.0019**				
		[0.0008]				
EPU_t * routine			0.00084***			
			[0.0003]			
EPU_{ost} * routine			-0.00042			
			[0.0007]			
EPU_t * abstract (alt)				-0.000022		
				[0.0003]		
EPU_{ost} * abstract (alt)				0.00079		
				[0.0005]		
EPU_t * non-routine (alt)					0.0022***	
					[0.0005]	
EPU_{ost} * non-routine (alt)					0.0016**	
					[0.0008]	
EPU_t * routine (alt)						0.0010***
						[0.0003]
EPU_{ost} * routine (alt)						-0.0012**
						[0.0006]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.953	0.954	0.953	0.953	0.954	0.953

Notes: OLS estimations with robust standard errors in all columns. Two-digit (SOC) occupation-US state and month fixed effects are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C4: Controlling for US state-month fixed effects

Panel A: Cognitive analytical/interactive, non-routine manual, routine cognitive/manual					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
EPU_{ost}	-0.0032***	-0.0029***	-0.0029***	-0.0018	-0.0016***
	[0.001]	[0.0005]	[0.0004]	[0.002]	[0.0005]
EPU_t * cogn. analytical	-0.00032				
	[0.0004]				
EPU_{ost} * cogn. analytical	0.0012				
	[0.001]				
EPU_t * cogn. interactive		-0.00016			
		[0.0003]			
EPU_{ost} * cogn. interactive		0.00098***			
		[0.0004]			
EPU_t * non-routine manual			0.0021***		
			[0.0004]		
EPU_{ost} * non-routine manual			0.0017**		
			[0.0008]		
EPU_t * routine manual				0.00030	
				[0.0006]	
EPU_{ost} * routine manual				-0.00037	
				[0.002]	
EPU_t * routine cognitive					0.00097***
					[0.0003]
EPU_{ost} * routine cognitive					-0.00073*
					[0.0004]
N	13,464	13,464	13,464	13,464	13,464
R^2	0.953	0.953	0.954	0.953	0.953
Panel B: Customer/Service-orientedness, physical contact intensity, tele-work, essential					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
EPU_{ost}	0.000031	-0.0024**	-0.0058***	-0.00073	-0.0030***
	[0.001]	[0.001]	[0.002]	[0.0008]	[0.0004]
EPU_t * customer	-0.0021***				
	[0.0004]				
EPU_{ost} * customer	-0.0018*				
	[0.001]				
EPU_t * service		-0.00034			
		[0.0004]			
EPU_{ost} * service		0.00026			
		[0.001]			
EPU_t * contact			0.00071		
			[0.0006]		
EPU_{ost} * contact			0.0037**		
			[0.002]		
EPU_t * WFH				-0.00039	
				[0.0004]	
EPU_{ost} * WFH				-0.0017**	
				[0.0007]	
EPU_t * essential					-0.00024
					[0.0004]
EPU_{ost} * essential					0.0018***
					[0.0005]
N	13,464	13,464	13,464	13,464	13,464
R^2	0.954	0.953	0.953	0.953	0.954

Notes: OLS estimations with robust standard errors in all columns of both panels. Two-digit (SOC) occupation-US state and US state-month fixed effects are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

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