

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

Sotiris Blanas[†] Rigas Oikonomou[‡]

Abstract

Using monthly online job postings data at the occupation-US-state level in January–December 2020, we provide novel evidence on how COVID-induced economic uncertainty has impacted the occupational composition of US labour demand. The effects are identified by exploiting monthly variation in country-level uncertainty along with pre-COVID differences in shares of occupation-state pairs in occupational country-wide employment and occupational task content. Some of the effects are consistent with the secular and episodic aspects of routine-biased technological change (RBTC) leading to job polarisation and growing complementarity between cognitive analytical and interactive tasks. Interestingly, however, other effects are seemingly at odds with RBTC-induced job polarisation and, rather, rationalised by idiosyncratic features of the shock (e.g. health emergency) and responses to it (e.g. social distancing, lockdowns). Although additional evidence points to high persistence of most of these effects in 2020, further research in this direction would shed light on whether the latter effects will persist through the post-COVID era or phase out.

Keywords: Occupational demand; Occupational characteristics; Task content; Online job postings; Economic uncertainty; COVID-19; Pandemic

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

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[†]Corresponding author: IMT School for Advanced Studies Lucca, Piazza San Ponziano 6, 55100, Lucca, Italy. Email: sotirios.blanas@imtlucca.it.

[‡]UCLouvain and University of Surrey. Email: rigas.oikonomou@gmail.com.

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. 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](#)) and on shifts of job seekers across growing and shrinking occupations and industries ([Hensvik et al., 2021](#); [Marinescu et al., 2021](#); [Carrillo-Tudela et al., 2022](#)).

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, considering a broad set of occupational characteristics such as routine intensity, service-orientedness, physical contact intensity, and essentiality.¹ To this end, we exploit monthly data from Burning Glass Technologies (BGT) on online job postings of two-digit (SOC) occupations in all fifty US states and the District of Columbia over January 2020 – December 2020 and data on occupational characteristics from various sources. 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 begin the analysis by documenting the evolution of the country-wide number of online job postings to the total US population over the period examined. This ratio declined sharply over the first wave of the pandemic and lockdown (March–April), which accords with evidence provided by pertinent studies for the US and other countries (e.g. [Forsythe et al., 2020](#);

¹Occupational characteristics refer to the task content of occupations, and vice versa. Thus, they are used interchangeably in the text.

²This 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](#)).

Hensvik et al., 2021). It recovered only partially when the lockdown was lifted (May–October), and plummeted again during the second pandemic wave and ensuing lockdown (November–December). Similarly to the country-level variable, the per-capita numbers of online job postings of all occupations covered in our sample declined sharply during the first wave of the pandemic –but in different magnitudes, while in subsequent months they also exhibited different trends. As a consequence, the shares of online job postings of some occupations in the total number of online job postings (e.g. community and social service, healthcare practice, healthcare support, protective service) increased, while those of other occupations (e.g. arts and entertainment, sales, food preparation and service, personal care and service) decreased over the period examined.

Motivated by these trends, we identify the heterogeneous effects of the COVID-19 shock on the relative demand for different occupations by regressing the monthly share of online job postings by occupation-state pair on the interaction between a measure of occupation-state-level economic uncertainty and a measure of occupational task content. We focus on economic uncertainty as it is a key driving force of firms’ hiring decisions. To capture it empirically in the baseline specification, we rely on the monthly index of US news-based Economic Policy Uncertainty (EPU) of Baker et al. (2016). We also consider using alternative measures of economic uncertainty such as the monthly composite index of US EPU (of the same study) or the monthly indices of sales revenue or employment growth uncertainty in the US, as constructed based on micro-level data of the Survey of Business Uncertainty (SBU). As the original measures are country-specific, we apportion these to occupation-state pairs according to their pre-COVID (2019) shares in country-wide employment of the respective occupations. Exploiting, further, variation in occupational task content is key in order to make sense of the documented differences in the relative demand for occupations during the months of 2020. Hence, the interaction term that we create is a shift-share variable, whose estimated coefficient captures the differential effects of economic uncertainty on the relative demand for occupation-state pairs, according to pre-COVID differences in their occupational country-wide employment shares and occupations’ composition of tasks.³

We estimate the specification by OLS with standard errors clustered by occupation-state pair. We also control for unobserved differences across occupation-state pairs (e.g. demo-

³For influential empirical studies implementing the shift-share methodology, see Autor et al. (2013) and Hereshbein & Kahn (2018), among others, and for its theoretical underpinnings, see Adão et al. (2019), Goldsmith-Pinkham et al. (2020), and Borusyak et al. (2022).

graphic composition, levels of income and human capital) by including the relevant dummies, and for time-varying shocks to occupation-state pairs (e.g. country-wide responses of the federal government and the Federal Reserve to the COVID-19 shock) by including month dummies. As the shift-share and outcome variables are unlikely to be simultaneously determined, we interpret the OLS estimates as causal effects.⁴

The first set of results that we obtain reveals that economic uncertainty due to the COVID-19 shock exerted positive differential effects on the relative demand for occupations with relatively high non-routine cognitive interactive or manual task content –especially, when these occupations are also non-essential (e.g. community and social service, life, physical and social science, transportation and material moving), as well as occupations that have both relatively high non-routine cognitive analytical and interactive task content (e.g. architecture and engineering, management). By contrast, economic uncertainty exerted negative differential effects on the relative demand for occupations with relatively high routine cognitive or manual task content (e.g. administrative, production). Importantly, most of these effects persisted over time, as they were observed during the two pandemic waves (February–May and October–December) and the months in-between, and increased in magnitude from the one period to the next.

These findings are in accord with existing evidence showing that the secular phenomenon of routine-biased technological change (henceforth, RBTC) led to job polarisation in the pre-COVID era (e.g. Autor et al., 2003; Spitz-Oener, 2006; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Goos et al., 2014). They are also consistent with the episodic aspect of RBTC, implying the acceleration during economic downturns and their aftermath of the adoption of new technologies undertaking routine tasks (Hershbein & Kahn (2018); Jaimovich & Siu, 2020). The differential effect on the relative demand for occupations with both relatively high non-routine cognitive analytical and interactive task content is also consistent with existing evidence showing that RBTC has contributed to the growing complementarity between analytical and interactive tasks (Borghans et al. (2014); Weinberger (2014); Deming, 2017).

Interestingly, however, we derive an additional set of results that is seemingly at odds with RBTC-induced job polarisation and rather explained by key features of the new setting

⁴Indeed, although the country-level economic uncertainty measure can directly impact the outcome variable, the employment shares and task content measures are treated as exogenous, as they are held fixed in a year preceding the highly unanticipated COVID-19 pandemic outbreak. Also, especially 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 contributed to country-wide economic uncertainty.

that has emerged since the onset of the COVID-19 shock. That is, a major health crisis and the imposition of restrictive measures (e.g. social distancing, lockdown) aiming at restraining the rapid spread of the virus (Ferguson et al., 2020; Gupta et al., 2020). According to our findings, COVID-induced economic uncertainty exerted positive differential effects on the relative demand for essential occupations –especially, those that also have relatively high routine cognitive, routine manual, service-oriented, or contact-intensive task content. Positive differential effects were also exerted on the relative demand for contact-intensive occupations –especially, those that also have relatively high routine cognitive, routine manual, or service-oriented task content. All these effects point to increases in the demand for healthcare practice and support and protective service occupations. Indeed, individuals in these occupations have been all along on the front line in the fight against COVID-19.

Also, the negative differential effects on the relative demand for non-essential occupations with relatively high routine cognitive or manual task content point to some occupational demand trends that are consistent with the job polarisation witnessed in the pre-COVID era, but also to other occupational demand trends that are rationalised by idiosyncratic features of the COVID-19 shock. In particular, these effects point to declines in the relative demand for administrative and some production (e.g. assembly-line) occupations, which experienced employment share losses also in the pre-COVID period –predominantly due to RBTC and offshoring– and contributed to job polarisation. However, the same effects also point to declines in the relative demand for arts and entertainment, personal care and service, and building cleaning and maintenance occupations, among others, which experienced relative employment gains in the pre-COVID period due their being largely shielded from automation and offshoring and the high demand for their services –especially, in densely-populated urban areas. Equally importantly, most of these effects were highly persistent and larger in size from the first pandemic wave through the in-between months and the second pandemic wave.

Related literature The novel empirical evidence of this paper contributes to four streams of literature. Our focus on identifying the differential effects of the COVID-19 shock on the demand for occupations according to their non-routine, routine, customer-oriented, and service-oriented task content emulates the influential literature making the task-based approach in order to study job polarisation and its determinants. In turn, a set of findings that we derive is consistent with key evidence of two streams of this literature. The first shows that RBTC and offshoring have been 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 interactive tasks have become increasingly complementary since the 1980s (Borghans et al., 2014; Weinberger, 2014; Deming, 2017). In fact, machines have started outcompeting human in the execution of some cognitive analytical tasks, while social interaction is, at least up to now, a prerogative of humans (Autor, 2015). The second stream establishes a link between RBTC and job polarisation during recessions. Hershbein & Kahn (2018) show that skill requirements in online job postings increased in US 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.

Moreover, our approach to consider in the analysis additional occupational characteristics, namely, 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 consider a wide range of occupational characteristics allowing for a comprehensive analysis of the heterogeneous effects of the COVID-19 shock on the demand for different occupations. In doing so, it enriches this stream of literature by deriving a set of findings that, as mentioned earlier, is consistent with evidence on job polarisation, but also another set of findings that is at odds with this phenomenon, and can rather be rationalised by features of the pandemic shock (e.g. major health crisis) and individual and collective responses to it (e.g. 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 pre-COVID labour market institutions (e.g. short-time work schemes). 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. In a similar vein, Baylis et al. (2021) find larger employment losses for women in Canada during 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 Montenegro et al. (2020). Further, Mongey et al. (2021) find that while jobs in the US with low tele-work potential and those with high physical proximity requirements were hit disproportionately, those that are also essential did not.⁵

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 late April 2020. A collapse of similar magnitude is also reported for Sweden by Hensvik et al. (2021), who exploit data from the country’s largest online job board. However, the first study also finds 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 evidence provided by Barrero et al. (2020) on realised and predicted job reallocation in the US since the onset of the crisis. Exploiting rich online job postings data 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. Also, Althoff et al. (2022) use data from the US Current Population Survey and provide evidence on disproportionate declines during the COVID-19 shock relative to January 2020 in hours worked by individuals in low-paying service occupations in big cities due to the rising tendency of individuals in high-skill, high-paying occupations –which, by and large, also have high tele-work potential– to move away from these.

A smaller group of studies of this stream of literature look into the labour supply effects of the COVID-19 shock. Hensvik et al. (2021) provide evidence on labour market searches shifting towards occupations that have been hit less severely by the pandemic. Similar shifts have been identified by Marinescu et al. (2021), with the use of data for the US from Glassdoor, and by Bernstein et al. (2020), with the use of data from a job board focused on tech companies (Angel-List Talent). In addition, Carrillo-Tudela et al. (2022) exploit novel and rich information from the job-search module of the UK Household Longitudinal Study (UKHLS) on targeted and realised switches of job seekers across occupations and industries. They find

⁵Large 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).

that although job seekers, by and large, increasingly targeted growing occupations and industries, certain groups of job seekers (i.e., non-employed, low-educated, formerly employed in declining occupations and/or industries), targeted mostly declining occupations and industries. Equally importantly, the authors find that the mismatch between targeted and realised switches of job seekers across occupations is substantial, pointing to a high likelihood of an unemployment mismatch in the UK.

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 test their robustness. 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 for 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).⁶ The data have been subject to robust cleaning processes aiming at the identification and removal of duplicate records of job postings. 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 US states and District of Columbia 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’ State Population Totals and Components of Change, on the 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.⁷

Panel (a) of Figure 1 shows the monthly variation in the ratio of the country-wide number of online job postings to aggregate US population over January 2020 – December 2020. In April, when the disease was spreading fast and lockdown and social distancing measures were

⁶Note that although the COVID-19 crisis continued through 2021, BGT has made publicly available only the data for 2020.

⁷Thus, they are indicative of the subjective perceptions firms have about the short- and longer-run prospects of their own 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. For instance, job vacancy postings tend to cover a disproportionately high number of higher-skilled occupations (e.g. [Hershbein & Kahn, 2018](#)). Also, employers may advertise multiple job vacancies in a single posting. Be that as it may, [Dalton et al. \(2020\)](#) show that 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). We confirm below that this also holds for the online job postings data that we employ in this particular analysis.

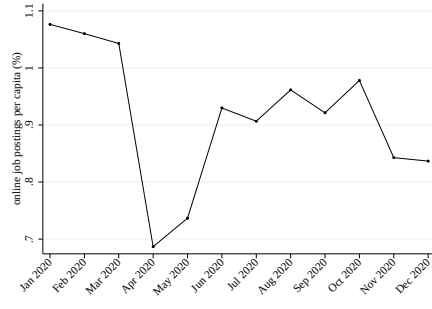
in effect, online job postings per-capita declined steeply, to 0.69% from 1.08% and 1.06% in January and February and roughly 1.04% in March. This translates to a 37% decline in the per-capita number of online job postings between January and April. Similarly, [Forsythe et al. \(2020\)](#) and [Hensvik et al. \(2021\)](#) report declines of around 40% in the number of online job postings in the US and Sweden by late April 2020, based on BGT data and Sweden’s major online job board, respectively. The per-capita number of online job postings 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 is evident from Panel (b) of Figure 1, the trend exhibited by the per-capita number of online job postings bears a very close resemblance to the trend of the total number of monthly job vacancies to population ratio. The latter ratio is calculated using the JOLTS data on monthly job vacancies in the US over 2020 and the Census data on the 2019 US population. In addition to the similar trends, the BGT data at our disposal have a relatively high degree of representativeness, as the (per-capita) number of online job postings accounts for at least half of the official (per-capita) 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 country-specific factors having contributed to the aforementioned trend of US online job postings per-capita, it is noteworthy that we obtain very similar trends for rest of the countries that are available in the BGT dataset, namely, Australia, Canada, New Zealand, Singapore and the UK.⁸ The similarities in the trends are 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).

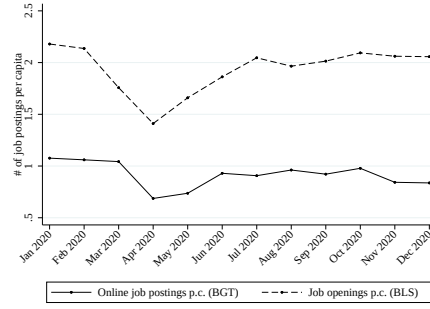
Albeit informative about how US labour demand evolved in the months of 2020, Panels (a) and (b) of Figure 1 mask the possible heterogeneity in the demand for different occupations over that period. Indeed, Panels (a)–(v) of Figure 2 reveal that although there was hardly any two-digit (2010 SOC) occupation that did not experience a precipitous decline in its

⁸Population data for these countries are also available in the BGT dataset and originally collected from national statistical authorities of these countries. Note that we do not include the additional countries in the analysis due to lack of or incomplete data on employment in pairs of occupations and geographic areas, on which we rely for the case of the US in order to make the original country-level economic uncertainty measures occupation-state-specific.

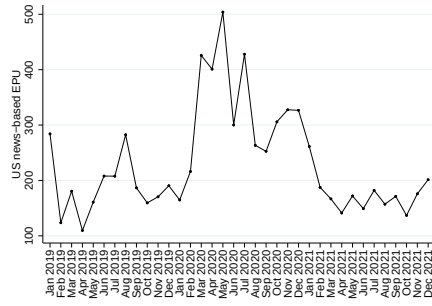
Figure 1: Per-capita number of job postings and economic uncertainty in the US



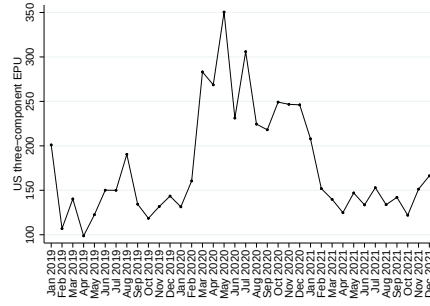
(a) Per-capita # of online job postings



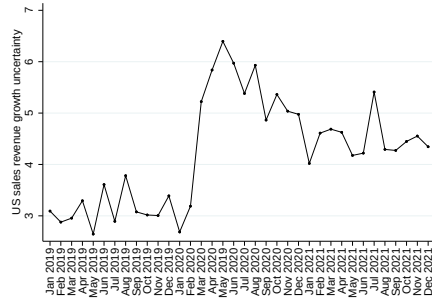
(b) Online (BGT) Vs Total (BLS JOLTS)



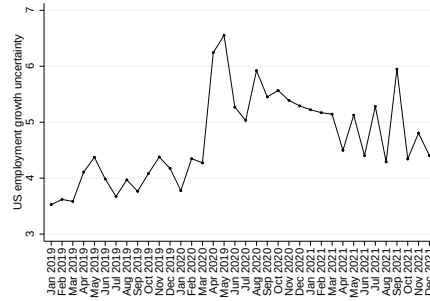
(c) News-based EPU



(d) Composite EPU



(e) Sales revenue growth uncertainty (SBU)

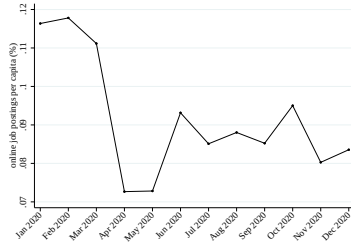


(f) Employment growth uncertainty (SBU)

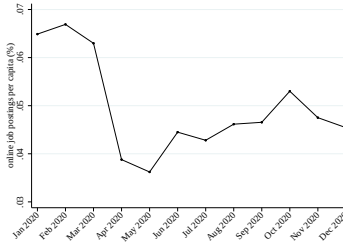
Notes: Panel (a) displays the monthly variation in the per-capita number of online job postings across the US in January 2020 – December 2020. Panel (b) displays the line of Panel (a) along with the monthly variation over the same period in the total number of job vacancies, as reported by the US BLS,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

Source: Per-capita number of online job postings in Panels (a) and (b): Authors' calculations based on monthly online job postings data of Burning Glass Technologies (BGT) for January 2020 – December 2020 and US population data of the US Census' State Population Totals and Components of Change for 2019. Per-capita number of job vacancies in Panel (b): Authors' calculations based on monthly job vacancy data for January 2020 – December 2020 collected from the US Bureau of Labor Statistics (BLS)'s Job Openings and Labor Turnover Survey (JOLTS) and US population data of the US Census' State Population Totals and Components of Change for 2019. 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. \(2020\)](#).

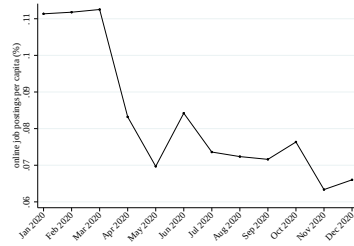
Figure 2: Online job postings per-capita in the US by two-digit (SOC) occupation



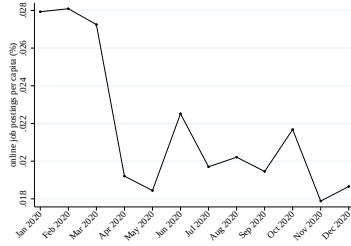
(a) Management



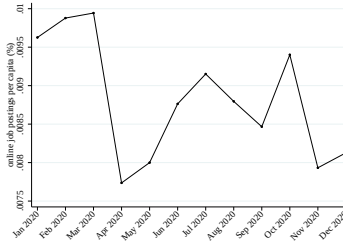
(b) Business & Financial



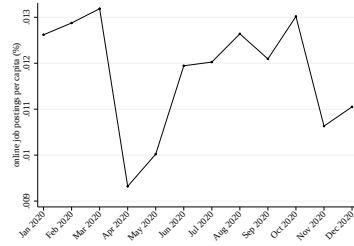
(c) Computer & Mathematical



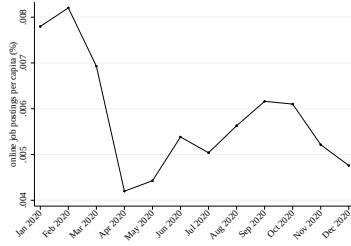
(d) Architecture & Engineering



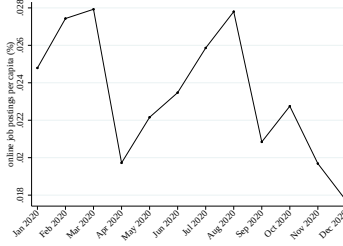
(e) Life, Physical, & Social Science



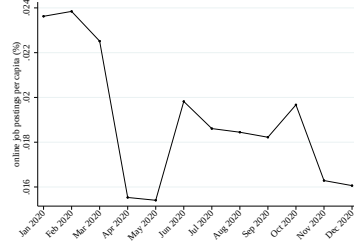
(f) Community & Social Service



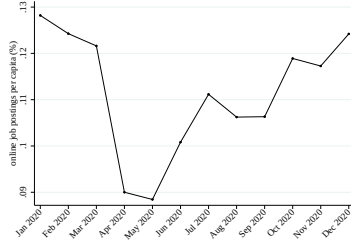
(g) Legal



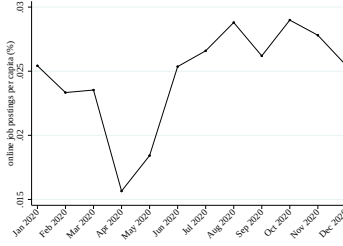
(h) Education, Training, & Library



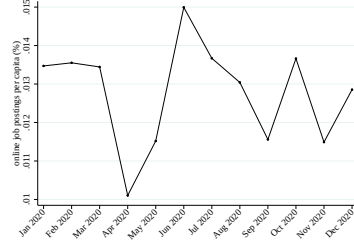
(i) Arts & Entertainment



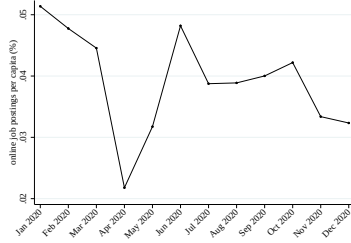
(j) Healthcare Practice



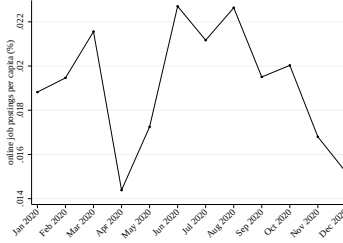
(k) Healthcare Support



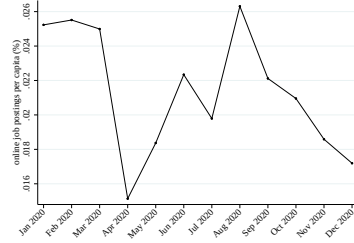
(l) Protective Service



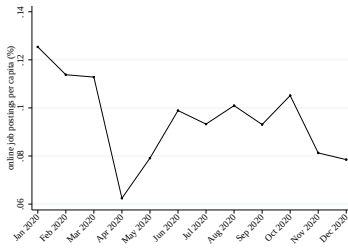
(m) Food Preparation & Service



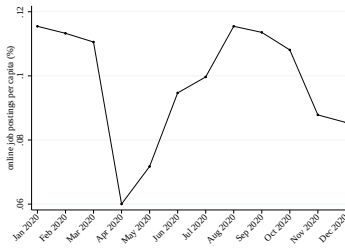
(n) Building Cleaning



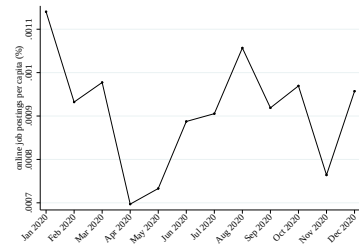
(o) Personal Care & Service



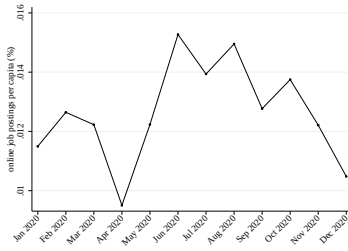
(p) Sales & Related



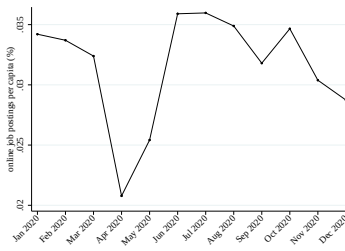
(q) Office & Administrative



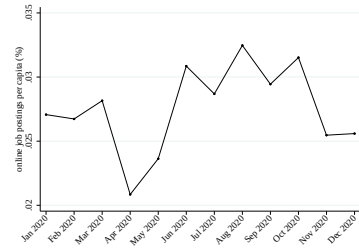
(r) Farming, Fishing, & Forestry



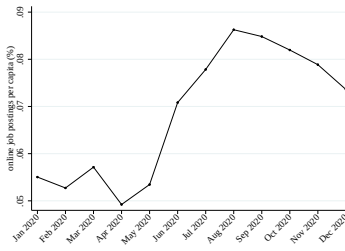
(s) Construction & Extraction



(t) Installation & Repair



(u) Production

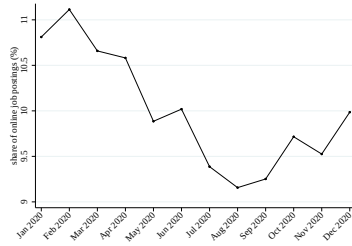


(v) Transportation

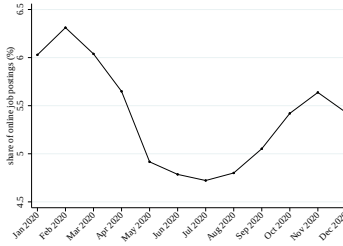
Notes: Monthly variation in the ratio of the number of online job postings of each two-digit (2010 SOC) occupation in the US to the total US population in January 2020 – December 2020.

Source: Authors' calculations based on monthly online job postings data of Burning Glass Technologies (BGT) for January 2020 – December 2020 and US population data of the US Census' State Population Totals and Components of Change for 2019.

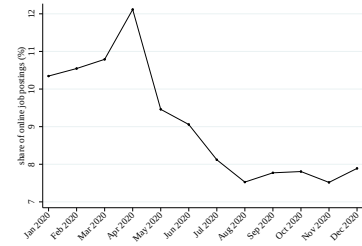
Figure 3: Share of online job postings in the US by two-digit (SOC) occupation



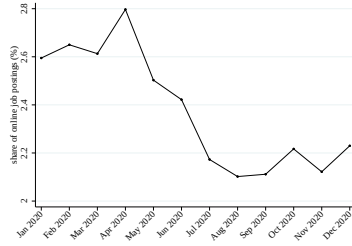
(a) Management



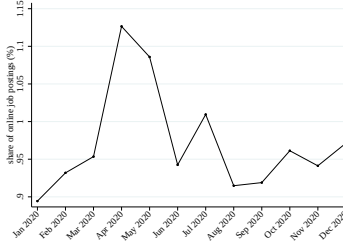
(b) Business & Financial



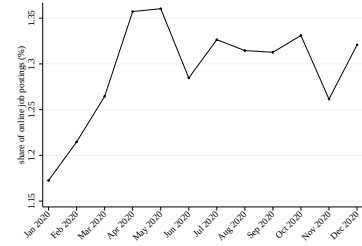
(c) Computer & Mathematical



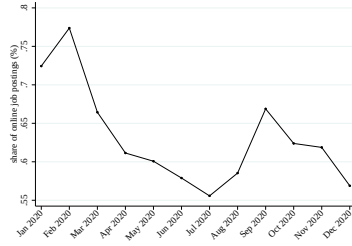
(d) Architecture & Engineering



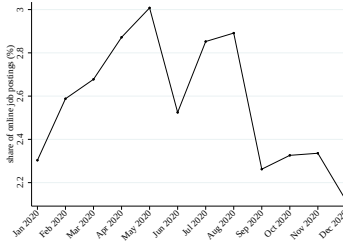
(e) Life, Physical, & Social Science



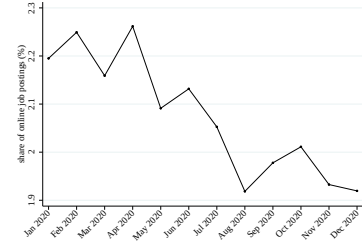
(f) Community & Social Service



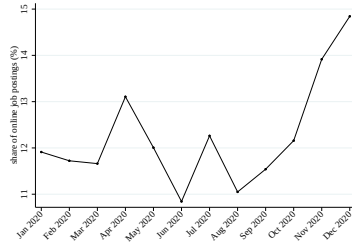
(g) Legal



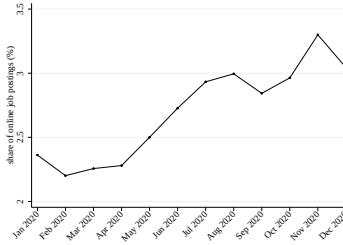
(h) Education, Training, & Library



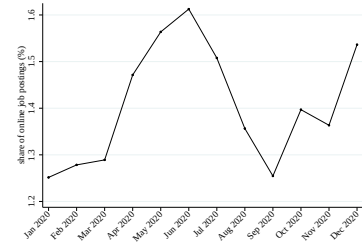
(i) Arts & Entertainment



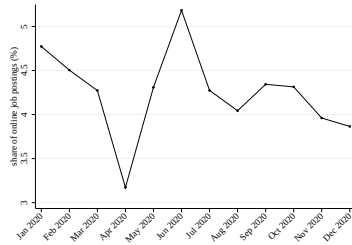
(j) Healthcare Practice



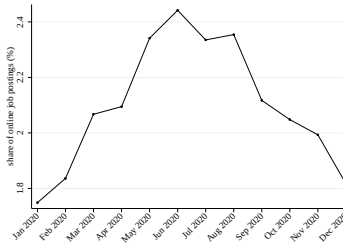
(k) Healthcare Support



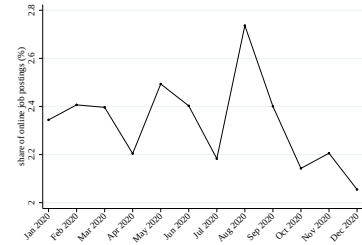
(l) Protective Service



(m) Food Preparation & Service



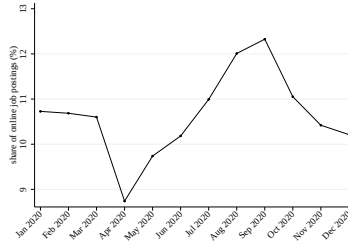
(n) Building Cleaning



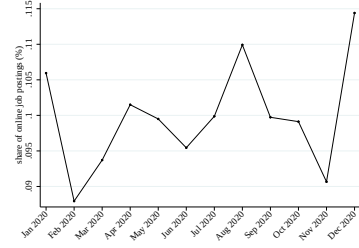
(o) Personal Care & Service



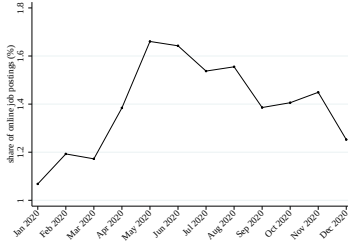
(p) Sales & Related



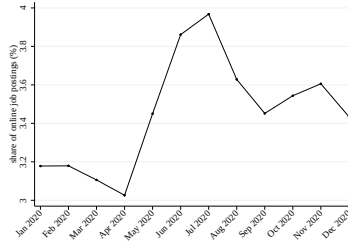
(q) Office & Administrative



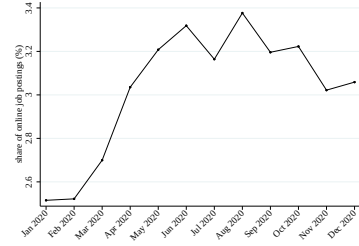
(r) Farming, Fishing, & Forestry



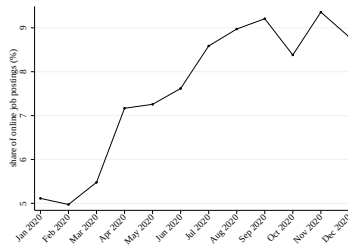
(s) Construction & Extraction



(t) Installation & Repair



(u) Production



(v) Transportation

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 monthly online job postings data of Burning Glass Technologies (BGT).

online job postings per-capita during the first wave of the pandemic, 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.

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 in the country-wide number of online job postings over the months of 2020 in Panels (a)–(v) of Figure 3. With respect to January 2020 (i.e., pre-COVID month), community and social service, healthcare practice and support, protective service, farming, production, transportation, life, physical and social science, and construction occupations gained higher shares in the total number of online job postings, while the rest of the occupations experienced losses.

2.2 Variables for the task content of occupations

As occupations comprise different types of tasks and in different proportions, we adopt the task-based approach in order to be able to make sense of the salient heterogeneity in the evolution of the absolute and relative occupational demand during COVID-19. This is the same conceptual approach as the one followed by the literature rationalising the declines in relative employment of routine-intensive occupations based on their greater susceptibility to technological change and offshoring (Autor et al., 2003; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Goos et al., 2014; Jaimovich & Siu, 2020).

However, in the COVID-19 context, the routine and non-routine intensities of occupations may be insufficient to yield clear insights about the implications of the shock for occupational demand. Consider, for instance, arts and entertainment, food preparation and service, and personal care and service occupations. These occupations, primarily due to being largely shielded from automation and offshoring, experienced employment share gains in the pre-COVID period. This contrasts with the losses in their shares of online job postings since the beginning of the COVID-19 crisis, as documented in the previous section. Arguably, these losses can be better understood by the fact that these occupations are contact-intensive but non-essential and thus, the execution of their tasks was severely restricted or even prohibited over the months of 2020, as priority had to be given to the containment of the rapid spread of the virus. Relatedly, despite being contact-intensive, healthcare practice, healthcare support and protective service occupations increased their shares of online job postings over the months of 2020, and this may be partly due to the fact that individuals in such occupations provided essential care services, among others, amid a major health crisis. Based on this reasoning, we create measures of the task content of occupations considering a broader range of tasks

than simply their routine and non-routine intensities. To save on space, we give here a rather brief account of the construction of variables and associated data sources and relegate their full description to Appendix Section A.1.

For each two-digit 2010 SOC occupation, we construct measures of their: non-routine cognitive analytical, non-routine cognitive interactive, non-routine manual, routine cognitive, and routine manual task content using the data of [Autor et al. \(2003\)](#) for occ1990dd-level occupations; social, coordination, interaction, customer-oriented, and service-oriented task content using the data of [Deming \(2017\)](#) for occ1990dd-level occupations; physical contact intensity using the data of [Leibovici et al. \(2020\)](#) for four-digit (2010 SOC) occupations; and tele-work potential using the data of [Dingel & Neiman \(2020\)](#) for eight- and five-digit (2010 SOC) occupations based on O*NET information and the authors' manual classification, respectively. 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 weighted means (Panel A of Tables B1 and B2). For the measures of [Autor et al. \(2003\)](#) and [Deming \(2017\)](#), we use as weights the country-wide employment shares of occ1990dd-level occupations in 2012. Information on these shares is drawn from [Deming \(2017\)](#). For the measures of [Leibovici et al. \(2020\)](#), we use as weights the 2019 country-wide employment shares of four-digit (2010 SOC) occupations, while for the measures of [Dingel & Neiman \(2020\)](#), we use the same weights but at the six- and five-digit (2010 SOC) level, respectively. Information on these shares is drawn from the Occupation Employment and Wage Statistics of the US Bureau of Labour Statistics (columns (3), (5), and (7) of Table B3). All measures are time-invariant and thus perceived as variables capturing fixed occupational characteristics. Higher values of each of these measures indicate a higher intensity of the relevant type of tasks.

The occupational rankings by occupational characteristic that emerge are intuitive and in accord with existing evidence. Architecture and engineering, computer and mathematical, healthcare practice, and community and social service occupations have the highest non-routine cognitive analytical task content, while management, architecture and engineering, life, physical, and social science, and community and social service occupations are among those with the highest non-routine cognitive interactive task content (columns (1) and (2) of Panel A of Table B1). Management occupations, in particular, also have among the highest content of social, coordination, and interaction tasks (columns (1)–(3) of Panel A of Table B2). Transportation, protective service, building cleaning and maintenance, and healthcare

practice occupations are among those with the highest non-routine manual task content. Healthcare practice and support and production occupations have the highest routine manual task content, while healthcare practice, production, installation, maintenance, and repair, and architecture and engineering occupations are among those with the highest routine cognitive task content (columns (3)–(5) of Panel A of Table B1).

In addition, community and social service, management, business, and legal occupations are among the most customer-oriented, while sales, healthcare practice, personal care and service, community and social service, and protective service occupations are the most service-oriented (columns (4) and (5) of Panel A of Table B2). Healthcare practice and support, personal care and service, food preparation and service, protective service, and community and social service occupations are among the most contact-intensive (column (3) of Table B3). Regarding tele-work potential, this is the highest in computer and mathematical, education and library, legal, and management occupations (columns (5) and (7) of the same table).⁹

Finally, we create a dummy variable indicating whether a two-digit 2010 SOC occupation is essential (value one) or not. To this end, we follow the methodology of [Mongey et al. \(2021\)](#), which is industry-based, rather than task-based. In particular, using relevant data from the authors at the two-digit 2010 SOC occupation level, we classify an occupation as essential if it accounts for at least 75% of total employment in essential industries, and as non-essential otherwise. Under this methodology, the following occupations are labeled as essential: healthcare practice, healthcare support, protective service, and farming, fishing, and forestry (column (1) of Table B3).¹⁰

⁹Importantly, when we aggregate the measures up to the two-digit 2010 SOC level by calculating their unweighted means (Panel B of Tables B1 and B2, and columns (4), (6), and (8) of Table B3) or medians (tables available upon request), the rankings of occupations are very similar to the main ones. Using alternative weights for the measures that originate from those of [Autor et al. \(2003\)](#) and [Deming \(2017\)](#) also yields occupational rankings that are very similar to the main ones (additional tables available upon request). In particular, we use as weights the country-wide employment shares of occ1990dd-level occupations in 1980, 1990, 2000, or 2005, as opposed to 2012. Information on the 1980 shares is drawn from [Deming \(2017\)](#) or [Autor & Dorn \(2009\)](#), while information on the 1990, 2000, and 2005 shares is drawn from the latter study.

¹⁰By setting a threshold of employment share in essential industries at 60%, rather than 75%, three additional occupations are classified as essential: community and social service, production, and transportation and material moving (column (2) of the same table). Considering community and social service occupations (e.g. rehabilitation counselors) as essential is plausible, given that many COVID-19 patients have been in need of entering in short- or long-term recovery programmes. Similarly, the services provided by individuals in some production and transportation occupations could also be deemed as essential. For instance, in order for meat, dairy, and bakery products to reach the final consumer, they have to be transported to the relevant store for sale. This implies that the services of truck drivers, food processing workers, butchers, and bakers, among others, are indispensable parts of the supply chain. Therefore, we construct a second dummy variable for essential occupations based on the alternative classification and use it in robustness checks.

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 variable is the news-based Economic Policy Uncertainty (EPU) index of [Baker et al. \(2016\)](#) for the US. Alongside the baseline measure, we draw information on the composite US EPU measure.¹¹ The base value of the EPU measures is equal to 100, and 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 – December 2021. 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 factors.

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).¹² 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

¹¹One 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.5. For this 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.5 and [Baker et al. \(2016\)](#).

¹²The latter is a reversal of the rise 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”.

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 countries other than the US. 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 December 2021 (Panels (a) and (b) of Figure B3).¹³

In addition, we use alternative measures of economic uncertainty in the US, 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.¹⁴ 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.¹⁵

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

¹³Information on these EPU measures is retrieved from the same source as for the US measures. The individual countries for which we calculate the unweighted mean are: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Korea, Netherlands, Russia, Spain, Singapore, UK, Sweden, and Mexico.

¹⁴For detailed information about the survey and the SBU measures, see Altig et al. (2020) and <https://www.atlantafed.org/research/surveys/business-uncertainty>.

¹⁵Naturally, the measures of sales revenue and employment growth expectations exhibited opposite trends (Panels (a) and (b) of Figure B4). Also, there are strong and significant correlations between the news-based EPU 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).

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 their content of the broad range of tasks under consideration. Our goal in the econometric analysis is to identify the differential effects of COVID-induced economic uncertainty on occupational demand by exploiting the salient heterogeneity along the latter dimension.

3 Econometric model

To identify how COVID-induced economic uncertainty has impacted the relative demand for occupation-state pairs, we estimate the following specification:

$$\begin{aligned} SH_OJP_{ost} = & \alpha_{os} + \alpha_t + \beta_{EPU_{ost}} * EPU_{ost} + \beta_{EPU_{ost}, C_o} * EPU_{ost} * C_o \\ & + \beta_{EPU_t, C_o} * EPU_t * C_o + \epsilon_{ost}, \end{aligned} \quad (1)$$

where SH_OJP_{ost} is the percentage share of online job postings of occupation o in US state s in month t of the year 2020. The specification includes dummies for occupation-state pairs, which can account for time-invariant heterogeneity in terms of the proportions of individuals with different demographic characteristics, health status, and levels of human capital and real disposable income, among other factors. It also includes month fixed effects, which account for time-varying shocks to all occupation-state pairs, namely: the onset of the COVID-19 pandemic outbreak and the timing of the imposition and relaxation of country-wide restrictive measures, the aggregate business cycle over the months of 2020, and the implementation of expansionary fiscal and monetary policies over the same period by the US federal government and the Fed, respectively (e.g. Coronavirus Aid, Relief, and Economic Security (CARES) Act, quantitative easing).

The COVID-19 shock has elevated economic uncertainty, which is a key driver of hiring decisions of firms. For this reason, we include in the specification the US news-based EPU as the baseline country-level measure of COVID-induced economic uncertainty (EPU_t), after apportioning it to each occupation-state pair (EPU_{ost}), and then, interact the newly-constructed

measure with a variable for the content of a certain type of tasks (e.g. non-routine cognitive analytical, routine manual, customer-oriented) of the corresponding occupation (C_o). To allocate the country-wide EPU measure to each occupation-state pair, we weigh 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 and occupation-country-level employment in 2019 is drawn from the US Bureau of Labour Statistics (BLS).¹⁶ Two components of the term of main interest, $EPU_{ost} * C_o$, are not captured by the fixed effects and are thus included in the specification: EPU_{ost} and $EPU_t * C_o$.

Essentially, for the construction of the main term we implement a shift-share methodology, which has become increasingly popular in the literature (e.g. Autor et al., 2013; Hershbein & Kahn, 2018) and has recently been underpinned by solid theoretical frameworks (Adão et al., 2019; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Relying on employment shares in 2019, which is the proximate year before the onset of the COVID-19 shock, is in accord with the logic that lagging the shares by many years may weaken the predictive power of the shift-share variable (Borusyak et al., 2022). Equally importantly, using time-invariant shares is a common practice making clearer the analogy of this methodology to difference-in-differences research designs (Goldsmith-Pinkham et al., 2020).

Holding the shares fixed in a year preceding the highly unpredictable COVID-19 shock also points to their exogeneity. Similarly, the measures of occupational task content are also treated as exogenous, as they represent time-invariant occupational characteristics and have been created using data corresponding to years prior to the COVID-19 shock. As for the time-varying country-level EPU, although it could exert a direct effect on the share of online job postings of a given occupation-state pair, it is highly unlikely, especially due to the size of the US economy, that changes in the share of online job postings of an occupation-state pair can feedback into country-wide economic uncertainty. Hence, in the absence of reverse causality, we estimate Eq. 1 by OLS and interpret the coefficient estimates as causal effects. In particular, we argue that the estimate of β_{EPU_{ost}, C_o} captures the differential effects of COVID-induced economic uncertainty on the relative demand for occupation-state pairs, based on pre-COVID differences in their shares in country-wide employment of the corresponding occupations along with differences in the corresponding occupations' task content.

¹⁶Alternatively, we use the share of employment of occupation-state pair os in country-wide employment in 2019: $EPU_{ost} = EPU_t * \frac{E_{os,2019}}{E_{US,2019}}$. Information on country-wide employment for that year is also drawn from the BLS.

Given that changes in the values of the country-level and occupation-state-level EPU and occupation-level task content measures cannot be easily conceptualised, the interpretation of the magnitudes of the coefficient estimates of the specification is not straightforward. To facilitate their interpretation, we standardise the aforementioned variables so that they have mean equal to zero and standard deviation equal to one.¹⁷

Standard errors are clustered by occupation-state pair so that we account for spatial correlations across occupations and occupational correlations across US states, which is in line with studies utilising similar data and estimating similar specifications to ours (e.g. [Hershbein & Kahn, 2018](#)). Also, Eq. 1 is always weighted by the employment levels of occupation-state pairs in 2019. This weighting scheme allows us to account for the volume of online job postings of an occupation-state pair relative to its total employment, or, in other words, for differences in the (per-capita) numbers and shares of online job postings of occupation-state pairs due to differences in their aggregate employment levels. This is also in line with weighting schemes of pertinent empirical studies (e.g. [Hershbein & Kahn, 2018](#); [Borusyak et al., 2022](#)).

Although our identification strategy is unlikely to produce estimates that suffer from a simultaneity bias, unobserved factors that are included in the error term, ϵ_{ost} , may lead to an omitted variable bias. Given the sets of fixed effects that we include in the specification, such a bias may stem from time-varying unobserved differences across US states –especially, differences in the types of anti-COVID measures and other pertinent policies implemented and the timing of their enforcement and abandonment. Importantly, though, we address this concern in a robustness exercise by replacing month dummies with dummies for state-month pairs. Relatedly, time-varying heterogeneity across occupations, such as differential changes in their task composition, demographic composition and pay, could also introduce an omitted variable bias in the specification. However, we argue that such a bias is likely to be negligible, if it exists at all, given that we examine a period of only twelve months. Rather, within-occupation changes happen over longer time spans, as they are predominantly structural and often driven by factors such as technological changes, which take time to occur and their effects to materialise. For instance, [Hershbein & Kahn \(2018\)](#) provide evidence on changes in the skill composition of occupations induced by RBTC by exploiting annual variation across several years (2010–2015) after the year of reference (2007). As a consequence, occupation-month dummies are likely to absorb variation in occupational task content, which will not

¹⁷The standardisation of the measures of occupational task content is also motivated by the fact that they have different scales (see Appendix Sections A.1 and B).

allow for the coefficient estimate of the term of main interest to be precisely identified. For this reason, we abstract from controlling for occupation-month dummies.

4 Econometric results

4.1 COVID-induced economic uncertainty and occupational demand

We kick off the econometric analysis by identifying the effects of COVID-induced economic uncertainty on the absolute and relative demand for occupation-state pairs while disregarding, for the moment, heterogeneity in occupational task content. To this end, we estimate Eq. 1 without the terms $EPU_{ost} * C_o$ and $EPU_t * C_o$ and focus exclusively on the interpretation of the coefficient estimate of EPU_{ost} , which is constructed based on the benchmark country-level measure of economic uncertainty, the news-based EPU. As the dependent variable, we use the log of the number or per-capita number of online job postings, which measure the absolute demand for occupation-state pairs, or the share of online job postings, which measure the relative demand for such pairs. The per-capita number and share of online job postings are in percentages. The results are shown in columns (1)–(3) of Panel A of Table 1. Columns (4)–(6) of the same panel display the results when we use the composite, rather than the news-based, EPU as the country-level measure of economic uncertainty.

In all six columns, the coefficient estimate of the main explanatory variable is negative and statistically significant at 1%. This suggests that COVID-induced economic uncertainty led to disproportionate declines in the absolute and relative demand for occupation-state pairs that accounted for higher shares in country-wide employment of the corresponding occupations in the most recent year prior to the COVID-19 pandemic outbreak (2019). In other words, the elevated uncertainty due to the COVID-19 shock and the ensuing reluctance or incapacity of firms to proceed to new hires across the US hit disproportionately occupations in US states that were over-represented prior to the shock in the respective occupational categories at the country level. The identified effects are also quantitatively significant: an increase of one standard deviation in the occupation-state-level measures of news-based and composite EPU decreased the number of online job postings by 1.026 and 1.031 (columns (1) and (4)), the per-capita number of online job postings by 0.0032 and 0.0038 percentage points (columns (2) and (5)), and the share of online job postings by 0.17 and 0.14 percentage points (columns (3) and (6)), respectively.

Using the news-based EPU by policy area as the country-level measure of economic uncertainty, we find that uncertainty in all areas except for trade policy and debt and currency management resulted in disproportionate declines in the per-capita numbers and shares of online job postings of occupation-state pairs (Panels (a) and (b) of Figure C1).¹⁸ Hence, similarly to aggregate measures such as the news-based and composite EPU, uncertainty about health, security, and purely economic (e.g. fiscal, monetary) issues had adverse effects on the absolute and relative occupational demand. Global economic uncertainty and uncertainty in countries other than the US also exerted disproportionately negative and significant effects on the absolute and relative occupational demand, pointing to the universality of the COVID-19 shock. We obtain these findings by estimating the specification using the Global EPU or Global EPU PPP (columns (1)–(3) and (4)–(6) of Panel B of Table 1), or the mean or median of the news-based EPU across all available countries other than the US (columns (1)–(3) and (4)–(6) of Panel A of Table C1).¹⁹ Disproportionately negative and significant effects on the absolute and relative occupational demand were also exerted by the SBU measures of sales revenue and employment growth uncertainty (columns (1)–(3) and (4)–(6) of Panel C of Table 1), confirming that the main results are insensitive to the utilisation of measures of economic uncertainty in the US whose construction is predicated upon different data and methodologies.²⁰ Quantitatively, it is noteworthy that some of the negative effects that are identified using the alternative economic uncertainty measures are of larger size. In particular, an increase of one standard deviation in occupation-state-level employment growth uncertainty decreased the per-capita number of online job postings by 0.0068 (column (5) of Panel C of Table 1), while a similar increase in occupation-state-level economic uncertainty,

¹⁸By contrast, trade policy uncertainty led to a disproportionate increase in the per-capita number of online job postings, but its effect on the share of online job postings is statistically insignificant. The effects of debt and currency management uncertainty on the per-capita number and share of online job postings are also statistically insignificant.

¹⁹Similarly to replacing US-specific economic uncertainty measures with non-US-specific ones, we use in additional estimations the values of the different EPU measures for the months of 2019, rather than 2020, while maintaining the 2020 values of the outcome variables. 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 variation in economic uncertainty in the months of 2019, then this exercise should yield very similar results qualitatively to those of 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, and are mostly statistically significant at 1% (Panels (c) and (d) of Figure C1 and Panels B and C of Table C1).

²⁰This is also the case when we use the SBU measure of sales revenue or employment growth expectations. Intuitively, we find that both exerted differential positive and significant effects on absolute and relative occupational demand (columns (1)–(3) and (4)–(6) of Panel D of Table C1). In additional exercises, we confirm that the main results are robust to weighing country-level economic uncertainty measures by the 2019 shares of occupation-state pairs in country-wide employment (Table C2), to addressing a possible omitted variable bias by replacing month dummies with occupation-month and state-month dummies (Table C3), and to clustering standard errors either by occupation or state only, or to using non-clustered robust standard errors (results available upon request).

based on the Global EPU or Global EPU PPP, decreased the share of online job postings by 0.23 percentage points (columns (3) and (6) of Panel B of Table 1).

Table 1: COVID-induced economic uncertainty and occupational demand

Panel A: News-based or composite EPU as the key regressor						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
News-based EPU	-0.026*** [0.005]	-0.0032*** [0.0005]	-0.17*** [0.04]			
Composite EPU				-0.031*** [0.009]	-0.0038*** [0.0008]	-0.14*** [0.05]
Constant	8.41*** [0.007]	0.063*** [0.0007]	6.58*** [0.05]	8.42*** [0.01]	0.064*** [0.001]	6.55*** [0.08]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.916	0.942	0.985	0.916	0.941
Panel B: Global EPU or Global EPU PPP as the key regressor						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
Global EPU	-0.042*** [0.01]	-0.0054*** [0.001]	-0.23*** [0.07]			
Global EPU PPP				-0.044*** [0.01]	-0.0057*** [0.001]	-0.23*** [0.08]
Constant	8.44*** [0.02]	0.067*** [0.002]	6.67*** [0.1]	8.44*** [0.02]	0.067*** [0.002]	6.68*** [0.1]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.916	0.941	0.985	0.916	0.941
Panel C: SBU measure of sales revenue or employment growth uncertainty as the key regressor						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
Sales growth uncertainty (SBU)	-0.036*** [0.01]	-0.0040*** [0.001]	-0.11 [0.08]			
Emp. growth uncertainty (SBU)				-0.056*** [0.02]	-0.0068*** [0.002]	-0.18* [0.1]
Constant	8.43*** [0.02]	0.064*** [0.002]	6.50*** [0.1]	8.46*** [0.03]	0.069*** [0.002]	6.60*** [0.2]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.916	0.941	0.985	0.917	0.941

Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns of all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The per-capita number of online job postings (*OJP p.c.*) and share of online job postings (*OJP share*) are in percentages. The economic uncertainty measures are occupation-state-specific. The occupation-state-level measures of economic uncertainty have been standardised. Dummies for occupation-state pairs and for months are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

As stressed earlier, the months of 2020 were marked by two COVID-19 pandemic waves, accompanied by the imposition of strict lockdowns and other restrictive measures (e.g. travel bans), and a few months in-between, when some of the restrictive measures had been relaxed (e.g. international travel) or eliminated (e.g. lockdown). To investigate how the differential effects of the COVID-19 shock on the absolute and relative demand for occupation-state pairs evolved over these three sub-periods, we estimate the specifications of Table 1 after replacing the country-level economic uncertainty measure with dummy variables for the months of the first and second pandemic waves (February–May and October–December) and the in-between period (June–September). Then, the reference group includes January 2020. Because of this

replacement, we also add to the specification the three aforementioned dummies in lieu of the month dummies.

The estimation results suggest that the first and second waves of the pandemic exerted differential negative and significant effects on the log of the number and per-capita number of online job postings, but the effects of the first wave were slightly stronger. The first wave also exerted a differential negative and significant effect on the share of online job postings, while the effect of the second wave is statistically insignificant. Also, there are no statistically significant effects of the in-between period on any of the outcome variables except for the per-capita number of online job postings. The latter differential effect is negative but smaller in size than those of the two pandemic waves (Panels (a), (c), and (e) of Figure C2).²¹

4.2 Accounting for the task content of occupations

In this section, we proceed to the core of the analysis in which we identify differential effects by exploiting heterogeneity in an additional dimension, the occupational task content. To this purpose, we estimate the standard version of the specification, as shown in Eq. 1, by incorporating a measure of the occupations' composition of each of the types of tasks described in Section 2.2. The dependent variable is the share of online job postings of occupation-state pairs, while the country-level measure of economic uncertainty is the news-based EPU.²² The estimation results are displayed in Table 2.

In line with the results of the previous section, the coefficient estimates of EPU_{ost} in columns (1)–(5) of Panel A and columns (1)–(4) of Panel B are negative and significant at 1%. However, the coefficient estimates of the term of main interest, $EPU_{ost} * C_o$, in columns (2) and (3) of Panel A have the opposite sign and are significant at 5%, suggesting that there are differential positive effects on the relative demand for occupations with higher non-routine cognitive interactive and non-routine manual task content, respectively. Equally importantly, the sum of the coefficient estimates of the terms of the specification is statistically significant at 1% in column (2), but statistically insignificant in column (3), according to the p-values of the relevant F-tests at the bottom of the panel. Hence, the share of online job postings drops by 0.121 ($-0.14 + 0.059 - 0.04$) due to increases of one standard deviation in the country-level

²¹Considering May 2020 as part of the in-between period, rather than of the first pandemic wave, and using in the specifications the relevant dummy variables yields very similar results and insights (Panels (b), (d), and (f) of Figure C2). This is also the case in the following exercises in which we use dummies for the two pandemic waves and the in-between period. The results from these robustness checks are available upon request.

²²We use the news-based EPU in all exercises that follow, unless stated otherwise.

EPU, the occupation-state-level EPU, and the non-routine cognitive interactive task content of occupations.²³

In addition, the coefficient estimate of the term of main interest in column (1) of Panel A is positive but statistically insignificant. However, the overall effect in this column is significant at 10%. Hence, although there is not a differential effect on the relative demand for occupations with higher non-routine cognitive analytical task content, the significant overall effect points to a decrease in the share of online job postings by 0.142 percentage points due to increases of one standard deviation in the country- and occupation-state-level EPU and the non-routine cognitive analytical task content of occupations. In columns (4) and (5) of the same panel, the coefficient estimate of the term of main interest is negative and significant at 5% and 1%, respectively, suggesting that there are differential negative effects on the relative demand for occupations with higher routine manual and routine cognitive task content. On top of that, the overall effects are significant at 1%, suggesting that increases of one standard deviation in the country- and occupation-state-level EPU along with an increase of the same magnitude in the routine cognitive or routine manual task content of occupations leads to a decline in the share of online job postings by 0.157 or 0.215 percentage points. The differential effects of Panel A are reminiscent of RBTC-induced job and skill polarisation of the pre-COVID era, that is, the employment losses of routine occupations (e.g. administrative, production) relative to non-routine cognitive and manual ones (e.g. engineering, personal care and service, building cleaning) and the wage bill losses of medium-skilled workers, who are disproportionately employed in routine occupations, relative to the high-skilled and low-skilled (Autor et al., 2003; Acemoglu & Autor, 2011; Autor & Dorn, 2013; Michaels et al., 2014; Blanas, 2022).

Turning to Panel B, the coefficient estimates of the term of main interest in columns (1) and (2) are positive but statistically insignificant, pointing to the absence of differential effects on the relative demand for customer- and service-oriented occupations, respectively. While the overall effect on the relative demand for service-oriented occupations is also statistically insignificant, that on the relative demand for customer-oriented occupations is significant at 1%. Hence, the share of online job postings drops by 0.196 percentage points due to increases of one standard deviation in the country- and occupation-state-level EPU and the customer-oriented task content of occupations. Albeit significant only at 10%, the coefficient estimates

²³Recall that these variables have been standardised so that the magnitudes of the coefficient estimates per column are interpreted based on standard deviation changes in the three aforementioned variables.

of the main term in columns (3) and (4) suggest that there is a positive differential effect on the relative demand for contact-intensive occupations and a negative differential effect on the relative demand for occupations with higher tele-work potential. The overall effect on the relative demand for the first type of occupations is not statistically significant, but that on the relative demand for the second type of occupations is significant at 1%. The latter suggests that the share of online job postings decreases by 0.25 percentage points due to increases of one standard deviation in the country- and occupation-state-level EPU and the tele-work potential of occupations. In column (5) of the same panel, the coefficient estimate of EPU_{ost} is negative and significant at 1%, while that of the term of main interest is positive and significant at 5%. These results suggest that the relative demand for essential occupations was impacted positively by economic uncertainty induced by the COVID-19 shock, while the relative demand for non-essential occupations was impacted negatively. The overall effect, though, on the relative demand for essential occupations is statistically insignificant.

The differential negative effect on the relative demand for occupations with relatively high tele-work potential may seem to be counter-intuitive at first sight, as tele-work played a remarkably important role in facilitating social distancing while ensuring business continuity. Similar evidence, however, has been provided by Forsythe et al. (2020). This effect likely suggests that, due to elevated uncertainty and low expected demand over the months of 2020 (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. The differential positive effect on the relative demand for contact-intensive occupations may also seem to be counter-intuitive. In fact, the relative demand for some of these occupations –most notably, food preparation and service and personal care and service (e.g. waiters, hairdressers)– increased in the pre-COVID era, mostly due to their being shielded from automation and offshoring. In sharp contrast to these pre-COVID trends, the demand for such contact-intensive occupations over the months of 2020 declined precipitously, as shown in Section 2.1, given that the provision of services by individuals in these occupations was severely limited or even prohibited by the enforcement of restrictive measures aiming at the containment of the spread of the virus (e.g. social distancing, lockdown). However, as we will show in subsequent sections, this result points to the increasing demand for services related to different aspects of the pandemic –most notably, healthcare practice and support, public protection and safety, and rehabilitation, which are provided by other highly contact-

intensive occupations. As we advance in the analysis, it will become clearer that the positive effect on the relative demand for essential occupations also points to the rising demand for such services during the months of 2020. In sum, most of the differential effects of Panel B are novel and, unlike the findings of Panel A, may be inconsistent with pre-COVID trends leading to job polarisation. To understand better the underlying mechanisms of the effects in the two panels, we conduct in the next sections exercises based on pairwise combinations of occupational characteristics.

Before doing so, we conduct robustness checks on the results of Table 2. First, we show that these are insensitive to making the country-level news-based EPU occupation-state-specific by weighing it by the shares of occupation-state pairs in country-wide employment (Table C4). Second, we confirm that the results remain largely unchanged after using variables for occupational task content that are constructed slightly differently from the main ones. In particular, we incorporate in the specifications continuous variables for occupational task content that are calculated as unweighted, rather than weighted, averages of the respective original measures (columns (1)–(5) of Panel A and columns (1)–(4) of Panel B of Table C5). As for dummy variable for the essential status of occupations, we incorporate one that identifies an occupation as essential if it accounts for at least 60%, rather than 75%, of total employment in essential industries (column (5) of Panel B of Table C5).²⁴ Also, we obtain very similar results to those of Panel A of Table 2 by using instead [Autor & Dorn \(2013\)](#)’s measures of abstract (i.e., non-routine cognitive), non-routine manual, and routine task content of two-digit (2010 SOC) occupations. These are calculated as weighted or unweighted averages of the original measures constructed by the authors (columns (1)–(3) and columns (4)–(6) of Table C6).²⁵ As a final check and in line with our discussion in Section 3, we account for a possible omitted variable bias in the specifications stemming from time-varying unobserved heterogeneity across US states (e.g. lockdown status, timing of imposition and relaxation or removal of restrictive measures). We do so by replacing month dummies with dummies for state-month pairs (Table C7).²⁶

²⁴Very similar effects to those in column (4) of Panel B of Table 2 are also obtained when we use the tele-work measure based on the manual classification of [Dingel & Neiman \(2020\)](#) and calculate it as the weighted average of the original measure across five-digit 2010 SOC codes (results available upon request).

²⁵For the construction of these measures, see Appendix Section A.1. For the rankings of occupations by task content measure, see Panels A and B of Table B4.

²⁶As already stressed in Section 3, it is highly unlikely that occupations underwent significant differential changes over the short (twelve-month) period that we examine. Hence, adding to the specifications dummies for occupation-month pairs may be simply capturing occupational variation, which would not allow the coefficient estimates of the term of main interest to be precisely identified. In tables that are available upon request, we show that this is actually the case.

Table 2: COVID-induced economic uncertainty, tasks and relative occupational demand

Panel A: Non-routine cognitive, non-routine manual, routine task content					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
News-based EPU	-0.16*** [0.04]	-0.14*** [0.03]	-0.11*** [0.02]	-0.14*** [0.02]	-0.15*** [0.03]
News-based EPU * cogn. analytical	0.022 [0.06]				
Country-level news-based EPU * cogn. analytical	-0.0040 [0.02]				
News-based EPU * cogn. interactive		0.059** [0.03]			
Country-level news-based EPU * cogn. interactive		-0.040*** [0.01]			
News-based EPU * non-routine manual			0.044** [0.02]		
Country-level news-based EPU * non-routine manual			0.11*** [0.02]		
News-based EPU * routine cognitive				-0.12*** [0.03]	
Country-level news-based EPU * routine cognitive				0.037*** [0.01]	
News-based EPU * routine manual					-0.089** [0.04]
Country-level news-based EPU * routine manual					0.024 [0.02]
Constant	6.57*** [0.05]	6.57*** [0.04]	6.52*** [0.03]	6.56*** [0.03]	6.56*** [0.04]
Observations	13464	13464	13464	13464	13464
R^2	0.942	0.942	0.943	0.942	0.942
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost}, C_o} + \beta_{EPU_{t}, C_o} = 0$	0.0713	0.000257	0.268	1.22e-15	1.38e-08
Panel B: Customer-oriented, service-oriented, contact-intensive, tele-work, essential task content					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
News-based EPU	-0.16*** [0.05]	-0.16*** [0.03]	-0.16*** [0.03]	-0.15*** [0.03]	-0.17*** [0.03]
News-based EPU * customer	0.031 [0.03]				
Country-level news-based EPU * customer	-0.067*** [0.01]				
News-based EPU * service		0.079 [0.07]			
Country-level news-based EPU * service		-0.0067 [0.02]			
News-based EPU * contact			0.073* [0.04]		
Country-level news-based EPU * contact			0.016 [0.02]		
News-based EPU * tele-work				-0.068* [0.04]	
Country-level news-based EPU * tele-work				-0.032* [0.02]	
News-based EPU * essential					0.36** [0.2]
Country-level news-based EPU * essential					0.0091 [0.05]
Constant	6.55*** [0.05]	6.57*** [0.05]	6.56*** [0.04]	6.55*** [0.04]	6.55*** [0.05]
Observations	13464	13464	13464	13464	13464
R^2	0.942	0.942	0.942	0.942	0.942
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost}, C_o} + \beta_{EPU_{t}, C_o} = 0$	2.66e-08	0.125	0.115	8.70e-12	0.137

Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns of both panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The share of online job postings (*OJP share*) is in percentages. The economic uncertainty measure is occupation-state-specific, unless stated otherwise. The country-level measure of economic uncertainty, the occupation-state-level measure of economic uncertainty, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs and for months are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

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 occupations with both relatively high non-routine cognitive analytical and interactive task content experienced the largest gains in employment shares over 1980–2010, followed by occupations that have relatively high cognitive interactive and low cognitive analytical task content. These trends are the mirror image of relative employment losses for occupations with relatively high cognitive analytical and low cognitive interactive task content and occupations with both relatively low cognitive analytical and interactive task content. Evidence on the increasing complementarity between cognitive analytical and 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 have also started encroaching cognitive analytical tasks. By contrast, cognitive interactive tasks are largely shielded from automation ([Autor, 2015](#)).

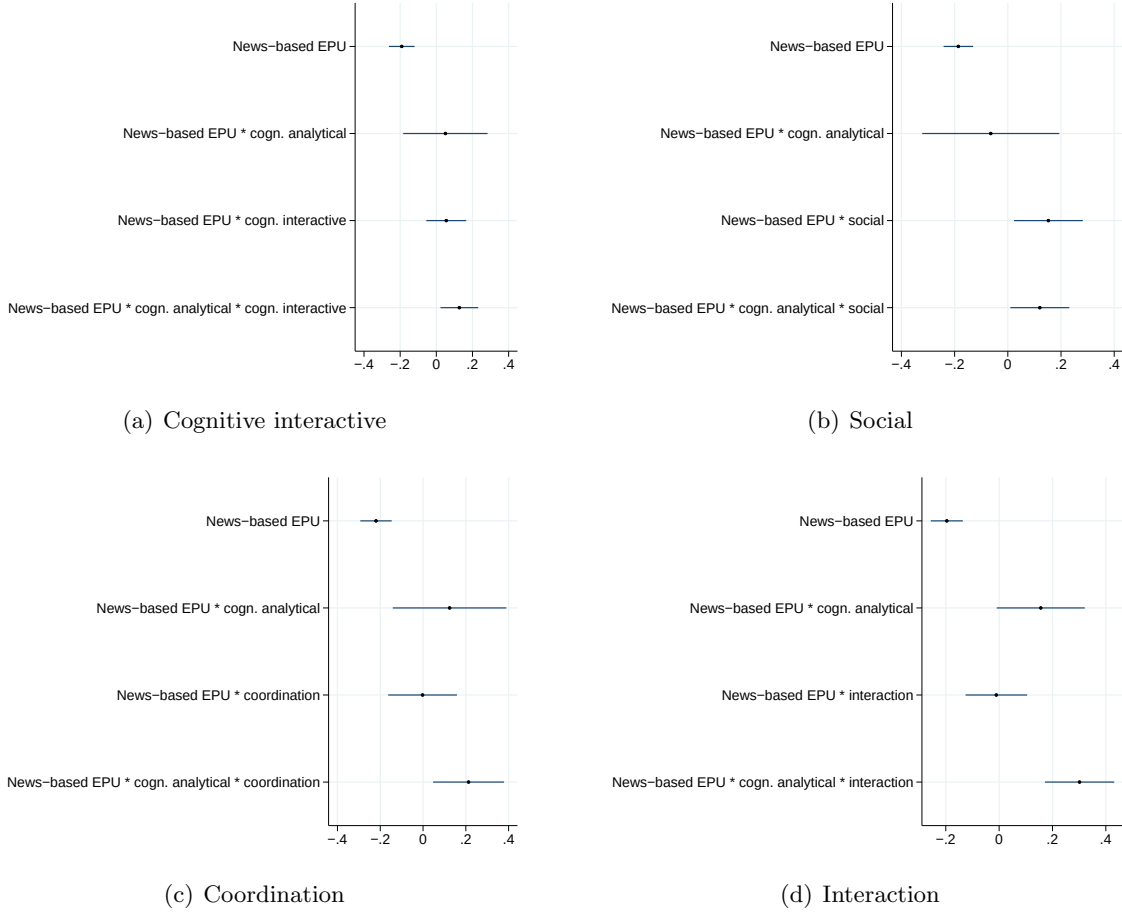
Motivated by this evidence, we re-estimate the specification in column (1) of Table 2 after augmenting it with an interaction term comprising the occupation-state-level EPU and the measures of non-routine cognitive analytical and interactive task content of occupations that we construct based on the original measures of [Autor et al. \(2003\)](#). To uncover the nature of interactive tasks that may be important jointly with analytical tasks, we also estimate this version of the specification after replacing the second task content measure with the measure of the social, coordination, or interaction task content that we construct based on the relevant measures of [Deming \(2017\)](#).

The estimation results are displayed in Figure 4.²⁷ Similarly to the results of the previous section, the coefficient estimate of occupation-state-level EPU is negative and significant. However, as indicated by the positive and significant coefficient estimate of the interaction of the occupation-state-level EPU with the two task content measures in Panel (a), there is a positive differential effect on the relative demand for occupations that have both relatively high cognitive analytical and interactive task content. A positive differential effect is also identified for occupations that have both relatively high analytical and social, coordination, or interaction task content (Panels (b)–(d)). These effects suggest that the interplay of analytical

²⁷In addition to the interactions of the occupation-state-level EPU with the individual task content measures and the combination of these, the specification includes interactions of the country-level EPU with these measures, but their coefficient estimates are not disclosed for the sake of exposition. This is the case in all subsequent graphs showing results obtained from interactions of an occupation-state-specific economic uncertainty measure with combinations of different task content measures.

and interactive tasks shaped the occupational composition of US labour demand during the COVID-19 shock in a very similar way to the 1980–2010 period. According to Panel (b) and again in line with the evidence of [Deming \(2017\)](#), there is also a positive differential effect on the relative demand for occupations with higher social task content, irrespective of their analytical task content.

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



Notes: OLS estimations with standard errors clustered by occupation-state pair in all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The dependent variable is the share of online job postings in percentages. The economic uncertainty measure is occupation-state-specific. The equations also include interactions of the country-level uncertainty measure with pairs of occupational characteristics and individual occupational characteristics, but their coefficient estimates are not disclosed for the sake of exposition. The country-level measure of economic uncertainty, the occupation-state-level measure of economic uncertainty, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs and for months are included in the equations.

Looking into the timing and possible persistence of these effects leads to additional insights. We do so by re-estimating the specifications after replacing the country-level EPU (and month dummies) with dummy variables for the months of the first and second waves of the

pandemic and the period in-between. We find that the first pandemic wave exerted positive and significant differential effects on the relative demand for occupations with both relatively high cognitive analytical and interactive or coordination task content, while the effects of the second pandemic wave and the period in-between are statistically insignificant (Panels (a), (c) and (d) of Figure C3).²⁸ Hence, the positive differential effects shown in Figure 4 may be driven only by the months of the first pandemic wave.

4.2.2 The joint role of essential and other tasks

As already stressed, individuals in essential occupations have had an active role in tackling various aspects of the COVID-19 shock. To identify how the essential status of occupations interacts with other occupational characteristics and economic uncertainty in shaping relative occupational demand, we re-estimate the specifications in columns (1)–(5) of Panel A and columns (1)–(3) of Panel B of Table 2 after adding to these the interaction of the occupation-state-level EPU with the corresponding task content measure and the dummy variable for the essential status of occupations. We abstract from using jointly a measure of tele-work potential and the dummy for essential occupations as essentiality implies very low tele-work potential.²⁹

COVID-induced economic uncertainty exerted positive and significant differential effects on the relative demand for non-essential occupations with higher non-routine cognitive interactive or non-routine manual task content, and for essential occupations with higher non-routine cognitive analytical, routine cognitive, or routine manual task content (Panels (b), (c), (a), (d), and (e), respectively). Albeit significant only at 10%, there are also positive differential effects on the relative demand for essential occupations with relatively high cognitive interactive, customer-oriented, service-oriented, or contact-intensive task content (Panels (b), (f), (g), and (h), respectively). By contrast, there exist negative and significant differential effects on the relative demand for non-essential occupations with relatively high routine cognitive or routine manual task content (Panels (d) and (e)).

²⁸The effect of the first pandemic wave, as well as of the second, are insignificant when we estimate the specification using the social task content measure. This is also the only specification that yields a negative and significant differential effect of the in-between period (Panel (b) of the same figure).

²⁹In fact, the measures of tele-work potential for essential occupations, as defined in column (1) of Table B3, ranges between 0 and 0.08 (columns (5) and (7) of the same table). This range remains unchanged for all essential occupations but one, according to their definition in column (2). The corresponding values for community and social service occupations are indeed larger (0.35 or 0.50), but still lower than the group of occupations with relatively high tele-work potential. The results are shown in Figure 5.

The first positive effect of Panel (b) likely explains the increases that we document in Figure 3 in the relative demand for community and social service and life, physical and social science occupations, which are both non-essential, according to the main classification, and have relatively high cognitive interactive task content (column (1) of Table B3 and column (2) of Table B1). This result is in line with the relative employment gains of these and other occupations with such characteristics (e.g. architecture and engineering, management, computer and mathematical) in the pre-COVID era, which were partly attributed to RBTC and contributed to job polarisation. Another result consistent with RBTC-induced job polarisation is the positive effect in Panel (c), which likely explains the increases in the relative demand for transportation and material moving and installation, maintenance and repair occupations (Figure 3). Indeed, these occupations are non-essential and their relatively high non-routine manual task content implies that they are less amenable to automation (column (1) of Table B3 and column (3) of Table B1).

In addition, the negative effect of Panel (d) likely explains the decreases that we document in this paper in the relative demand for arts and entertainment, sales, office and administrative support, production, and building cleaning and maintenance occupations, as these occupations are both non-essential and have relatively high routine cognitive task content (column (1) of Table B3 and column (4) of Table B1). Similarly, the negative effect of Panel (e) likely explains the documented decreases in the relative demand for the first four occupations of the previous list and personal care and service occupations, which are non-essential and, at the same time, have relatively high routine manual task content (column (1) of Table B3 and column (5) of Table B1). The declines in the relative demand for administrative and some of the production occupations (e.g. secretaries, assembly-line workers) are in line with what was observed in the pre-COVID period. This not the case, though, for the rest of aforementioned occupations. In fact, arts and entertainment, sales, building cleaning and maintenance, and personal care and service occupations experienced relative employment gains in the per-COVID period, as they also have relative high non-routine manual task content and are largely location-specific, which has rendered them relatively shielded from automation and offshoring. On top of that, there was strong demand for their services until before the pandemic hit –especially, in densely-populated urban areas. Due to the imposition of restrictive measures for the containment of the spread of the virus, demand for the vast majority of services provided by individuals in these occupations fell dramatically. Hence, the negative effects in Panels (d) and (e) are

mostly at odds with RBTC-induced job polarisation and, rather, better explained by the setting that was generated by the pandemic outbreak.

The rest of the identified effects are also at odds with job polarisation and better rationalised by the peculiarity of the COVID-19 shock. In particular, the positive effects in Panels (d) and (e) likely explain the increases that we documented earlier in the relative demand for healthcare practice and support and farming occupations, as these are essential and also have relatively high routine cognitive or manual task content (column (1) of Table B3 and columns (4) and (5) of Table B1). Likewise, the positive effects in Panels (a) and (b) likely explain the documented increases in the relative demand for healthcare practice occupations, which also have relatively high cognitive analytical and interactive task content (columns (1) and (2) of Table B1), while the positive effects in Panels (f), (g) and (h) likely explain the increases in healthcare practice and support and protective service occupations, as they are all essential and, at the same time, customer-oriented, service-oriented, and contact-intensive (column (1) of Table B3, columns (4) and (5) of Table B2 and column (3) of Table B3).

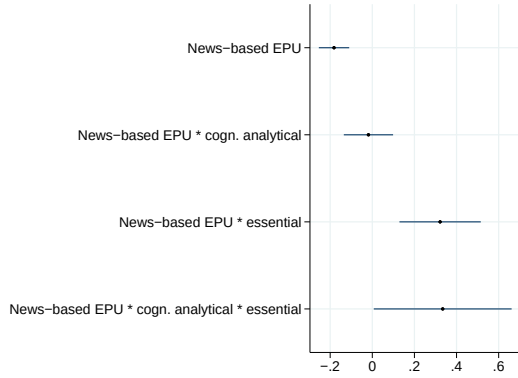
Given that most of the effects identified in this section run counter to job polarisation, studying their timing and possible persistence becomes even more relevant. To this purpose, we re-estimate the specifications of Figure 5 with dummies indicating the months of the two pandemic waves and those in-between. The results yield valuable insights. In addition to the effects being very much in line with those identified using the news-based EPU, most of these were exerted by the two pandemic waves and the in-between months, with their magnitudes becoming stronger from one sub-period to the next (Figure C4).³⁰ In other words, the identified effects, whether they are consistent with RBTC-induced job polarisation or with idiosyncratic features of the COVID-19 shock, were highly persistent and increasing in size over the months of 2020.

Unlike the results obtained using the news-based EPU, this exercise also reveals that the in-between period exerted a negative and significant differential effect on the relative demand for non-essential customer-oriented occupations (Panel (f) of the same figure). This effect points to declines in the relative demand for personal care and service, sales, and administrative occupations, among others with such characteristics. These effects suggest that firms might

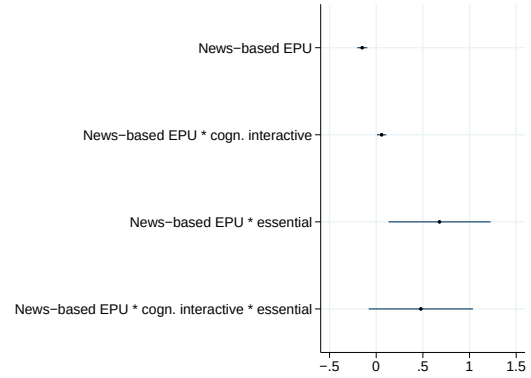
³⁰The only differences with respect to the results obtained using the news-based EPU are the insignificant effects of the two pandemic waves and the period in-between on the relative demand for essential occupations that have relatively high routine cognitive or manual task content (Panels (d) and (e) of the same figure) and of the in-between period on the relative demand for non-essential occupations with relatively high cognitive interactive task content (Panel (b) of the same figure).

have anticipated already in the summer months of 2020 that a new pandemic wave would arrive in Fall, which would be followed by the re-imposition of restrictive measures, and were thus hesitant to proceed to new hires of individuals in such occupations. The intuition for the negative and significant differential effect of the in-between period on the relative demand for non-essential contact-intensive occupations is very similar (Panel (h) of the same figure).

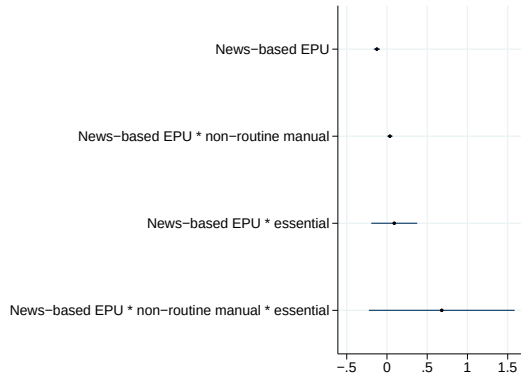
Figure 5: The joint role of essential and other tasks



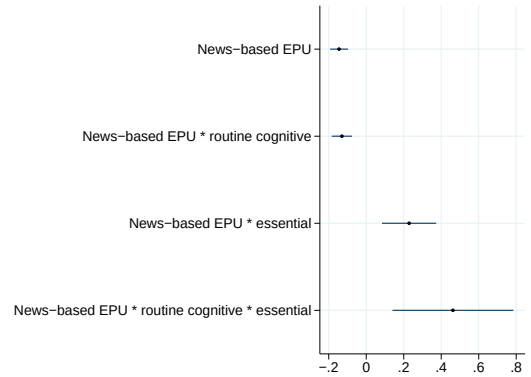
(a) Cognitive analytical



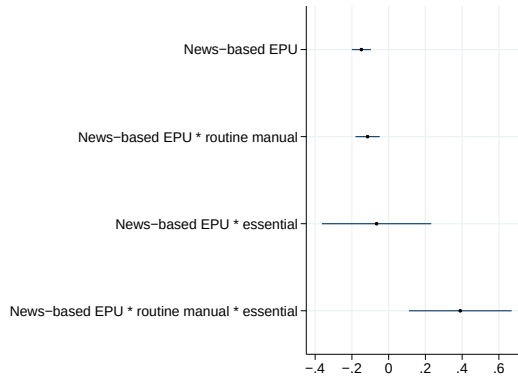
(b) Cognitive interactive



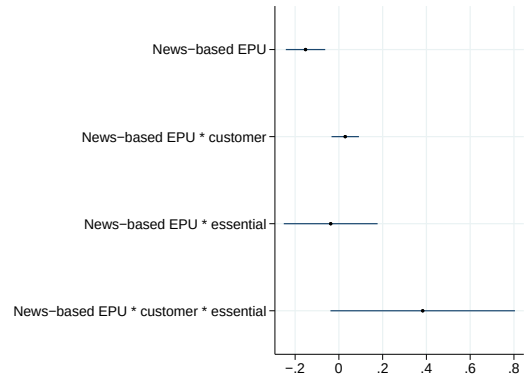
(c) Non-routine manual



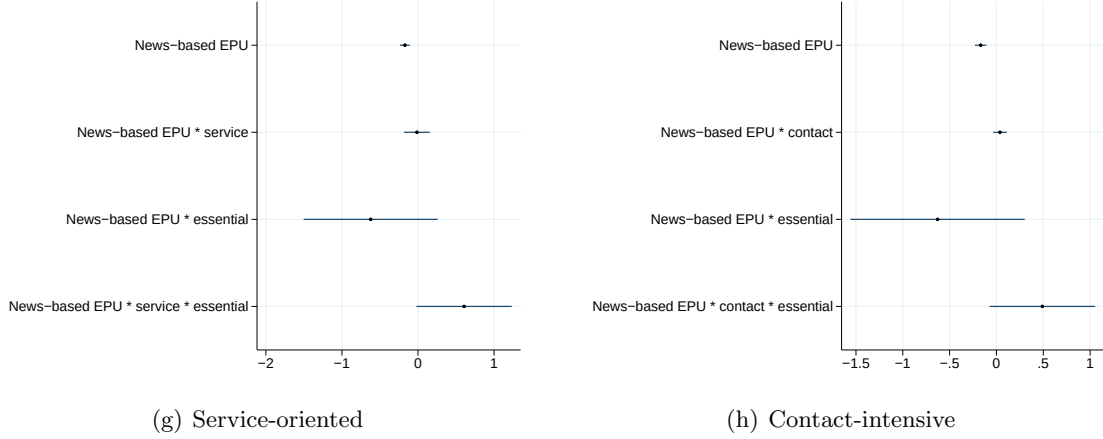
(d) Routine cognitive



(e) Routine manual



(f) Customer-oriented



Notes: OLS estimations with standard errors clustered by occupation-state pair in all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The dependent variable is the share of online job postings in percentages. The economic uncertainty measure is occupation-state-specific. The equations also include interactions of the country-level uncertainty measure with pairs of occupational characteristics and individual occupational characteristics, but their coefficient estimates are not disclosed for the sake of exposition. The country-level measure of economic uncertainty, the occupation-state-level measure of economic uncertainty, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs and for months are included in the equations.

4.2.3 The joint role of contact-intensive and other tasks

Since the onset of the COVID-19 pandemic outbreak, social distancing practices have limited or even prohibited individuals in various occupations to work in physical contact or close proximity to others. Hence, in a similar spirit to that of the previous section, we now examine how contact intensity along with other occupational characteristics and economic uncertainty have shaped the occupational composition of labour demand. To do so, we re-estimate the specifications in columns (1)–(5) of Panel A and columns (1), (2) and (4) of Panel B of Table 2 adding to these the interaction of occupation-state-level EPU with the measure of physical contact intensity and other task content measures.³¹

The estimation results, displayed in Figure 6, point to insignificant differential effects of COVID-induced economic uncertainty on the relative demand for contact-intensive occupations with relatively high cognitive analytical, cognitive interactive, non-routine manual, customer-oriented, or tele-work task content (Panels (a), (b), (c), (f), and (h), respectively). By contrast, there exist positive and significant differential effects on the relative demand for contact-intensive occupations with relatively high routine cognitive, routine manual, or service-oriented task content (Panels (d), (e), and (g), respectively). The latter effects likely

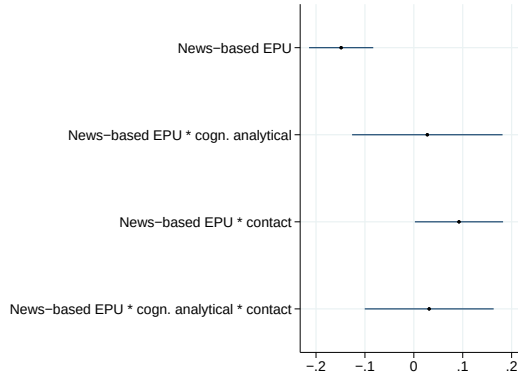
³¹The joint role of physical contact intensity and essentiality has been omitted as it has already been studied in Section 4.2.2.

explain the increases that we documented earlier in the relative demand for healthcare practice and support occupations, which have relatively high content of all the aforementioned tasks, but also for protective service occupations, which are both contact-intensive and service-oriented (column (3) of Table B3, columns (4) and (5) of Table B1, and column (5) of Table B2). Hence, similarly to Section 4.2.2, we make sense of these effects based on the new setting that has emerged since the COVID-19 pandemic outbreak, which has been largely marked by increasing demand for health and public safety services.

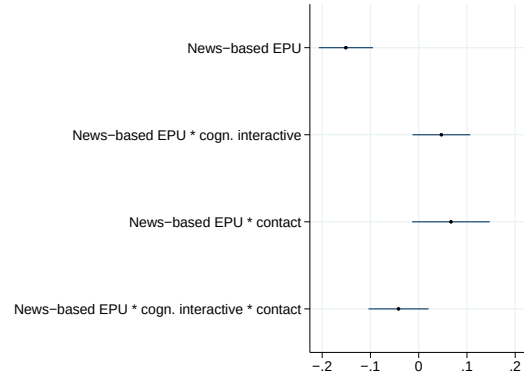
By re-estimating the specifications using dummies for the months of the two pandemic waves and those in-between, we obtain results suggesting that the effects identified using the news-based EPU might have been driven by all three sub-periods (Panels (d), (e) and (g) of Figure C5). In terms of size, the two strongest differential effects on the relative demand for contact-intensive occupations with relatively high routine cognitive or manual task content were exerted by the second pandemic wave and the in-between months, while the strongest differential effect on the relative demand for contact-intensive service-oriented occupations was exerted by the in-between period and was followed by that of the second pandemic wave.

Also, in contrast to the insignificant effects obtained using the news-based EPU, we identify positive and significant differential effects of the in-between period and the second pandemic wave on the relative demand for contact-intensive occupations with relatively high non-routine cognitive analytical task content, with the former effect being larger in size (Panel (a) of the same figure). We also find that the first pandemic wave exerted a positive and significant differential effect on the relative demand for contact-intensive occupations with relatively high non-routine manual task content (Panel (c) of the same figure). The first set of effects points to increases in the relative demand for healthcare practice occupations, while the second set of effects points to the rising relative demand for healthcare support and protective service occupations in addition to healthcare practice occupations.

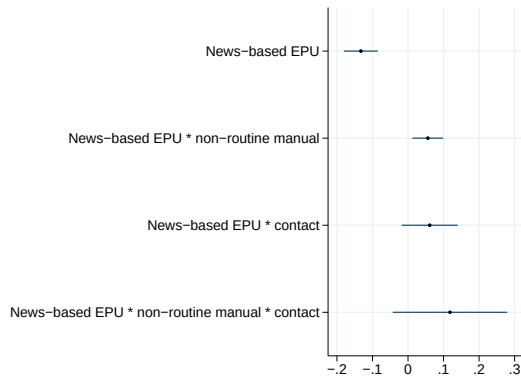
Figure 6: The joint role of contact-intensive and other tasks



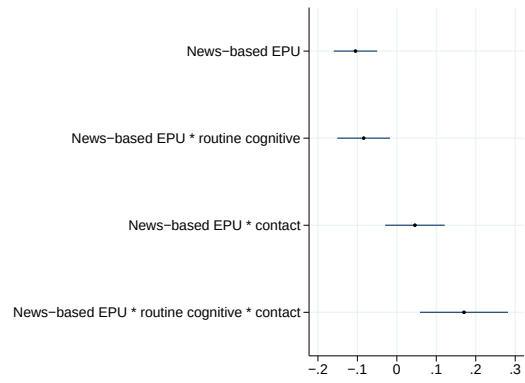
(a) Cognitive analytical



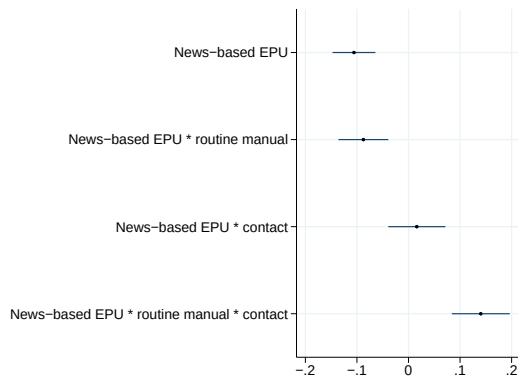
(b) Cognitive interactive



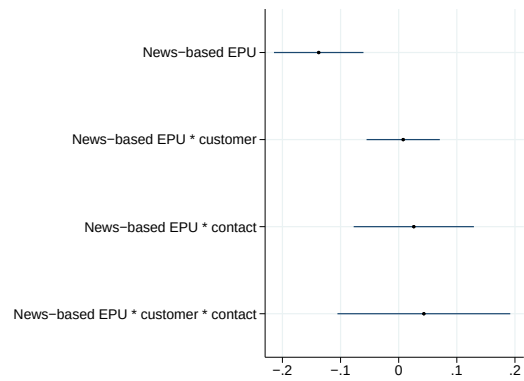
(c) Non-routine manual



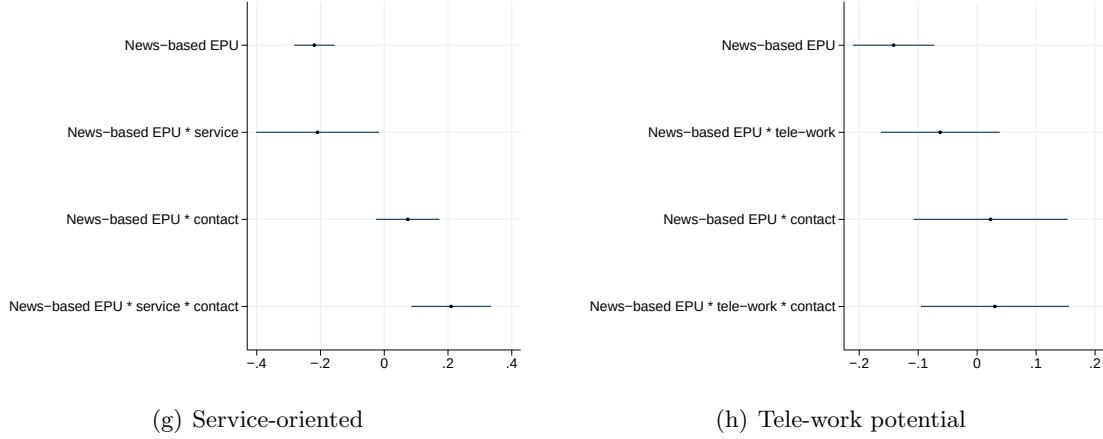
(d) Routine cognitive



(e) Routine manual



(f) Customer-oriented



Notes: OLS estimations with standard errors clustered by occupation-state pair in all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The dependent variable is the share of online job postings in percentages. The economic uncertainty measure is occupation-state-specific. The equations also include interactions of the country-level uncertainty measure with pairs of occupational characteristics and individual occupational characteristics, but their coefficient estimates are not disclosed for the sake of exposition. The country-level measure of economic uncertainty, the occupation-state-level measure of economic uncertainty, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs and for months are included in the equations.

5 Conclusion

The COVID-19 shock has caused large-scale upheaval in 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 industries. This paper is the first to conduct a comprehensive analysis on how the COVID-19 shock, through the economic uncertainty that it has brought about, impacted the relative demand for occupations that differ in their task content. The period that we examine covers all months of 2020, which were marked by the onset of the COVID-19 pandemic outbreak, the rapid spread of the virus, 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 country-level measures of economic uncertainty. We apportion the latter measures to occupation-state pairs according to their pre-COVID (2019) shares in country-wide employment of the corresponding occupations.

The analysis yields effects that are in accord with the secular phenomenon of RBTC leading to job polarisation (e.g. [Autor et al., 2003](#); [Autor & Dorn, 2013](#)) and stronger com-

plementarity between analytical and interactive tasks (Borghans et al. (2014); Weinberger (2014); Deming, 2017), but also with its episodic aspect implying its acceleration during recessions and their aftermath (Hershbein & Kahn (2018); Jaimovich & Siu, 2020). Importantly, though, additional effects are inconsistent with RBTC-induced job polarisation and, rather, rationalised by idiosyncratic features of the COVID-19 shock (e.g. health emergency) and responses to it (e.g. lockdown, social distancing).

Although our evidence suggests that most of the effects were highly persistent in 2020, whether the latter effects will also persist into the post-COVID era, leading to structural shifts in the occupational composition of US labour demand, remains an open question and will depend on various factors. First, in addition to the major health crisis that the COVID-19 pandemic outbreak has brought about and the changes that it has prompted in long-standing modes of healthcare practice and support, there is growing scientific evidence of detrimental long-term effects of the disease (Christakis, 2021). For this reason, the demand for healthcare and rehabilitation services and relevant occupations (e.g. healthcare practice and support and community and social service) will likely remain high in the post-COVID period.

Another factor to consider is tele-presence, which has become common since the onset of the pandemic –initially, as a an effective solution for business continuity, and later, as a conventional human resource practice (Barrero et al., 2021).³² 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. Robotic and Artificial Intelligence systems). As a consequence, the increasingly automation-intensive future may arrive sooner than previously anticipated, implying further task encroachment and changes in the occupational composition of labour demand in the US and other countries (Autor & Reynolds, 2020; Susskind, 2020).

Relatedly, the increasing use of tele-presence software and equipment and other digital technologies may usher in a new era of globalisation that would be marked by relatively high-skilled workers in the service sectors of the US and other advanced countries facing intensified competition from the so-called “tele-migrants”, that is, workers, based in lower-income countries, who can provide services at a lower cost (Baldwin, 2019, 2022). In addition

³²This is also evident by the rising patent applications in the US between January 2020 and September 2020 for digital technologies, such as tele-presence software and equipment, that prop-up tele-work (Bloom et al., 2021).

to that, the disruptions in global supply chains during the pandemic outbreak may eventually lead to their restructuring, as firms and countries have started re-considering the trade-off between efficiency and resilience, and modern technologies (e.g. 3-D printing) may play a major role in this (Antràs, 2020; Baldwin & Freeman, 2022).³³ Shedding light on these factors and their implications for the composition of occupational demand in the US and other advanced countries is intriguing and merits in-depth investigation in future work.

Yet another factor is the de-densification of cities that started with the pandemic and was facilitated by the widespread adoption of tele-work practices (Ramani & Bloom, 2021).³⁴ Until before the onset of the pandemic, 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 (Glaeser et al., 2001; Moretti, 2012; Althoff et al., 2022). 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 pandemic shock reversed this trend, as our evidence also suggests, and if this reversal becomes permanent in the post-COVID era, it can have profound implications for the occupational composition of labour demand in the medium- to long-run. This is definitely another important angle which is worth shedding light upon.

As happened after the end of past pandemics, there is every likelihood that the effects of the pandemic outbreak will endure and re-shape our economies and societies (Christakis, 2021). It is thus crucial that we anticipate the challenges that lie ahead and act accordingly. With regards to labour markets in the US and other countries, insights such as those derived from this paper could be particularly useful to policy makers and guide them to design and implement ambitious medium- to long-term plans that would prepare the workforce for the new state that will emerge in the aftermath of this crisis.

³³Political and geopolitical factors also seem to have been playing an essential role through their influence on trade policy and international relations more broadly (Antràs, 2021).

³⁴Despite large cities' relatively high tele-work potential, realised tele-work was rather limited prior to the COVID-19 pandemic outbreak and had thus negligible effects on their local economies (Mateyka et al., 2010; Dingel & Neiman, 2020; Althoff et al., 2022).

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Appendix

A Data and variables

A.1 Variables for the task content of occupations

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 1980.³⁵ 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 weighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Panel A of Table B1). As weights, we use the country-wide employment shares of occ1990dd occupations in 2012, as provided by Deming (2017). For robustness, we use the country-wide employment shares of occ1990dd occupations in 1980, 1990, 2000, or 2005. The data on employment shares for 1980 are drawn from Deming (2017) or Autor & Dorn (2009), while those for the other three years are drawn from Autor & Dorn (2009). Alternatively, we calculate the unweighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Panel B of Table B1), or their unweighted median (available upon request). Higher values of each of these measures indicate a higher content of the relevant type of tasks.

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 1980.³⁶ 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 weighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Panel A of Table B4). As weights, we use the country-wide employment shares of occ1990dd occupations in 2012, as provided by Deming (2017). For robustness, we use the country-wide employment shares of occ1990dd occupations in 1980, 1990, 2000, or 2005. The data on employment shares for 1980 are drawn from Deming (2017) or Autor & Dorn (2009), while those for the other three years are drawn from Autor & Dorn (2009). Alternatively, we calculate the unweighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Panel B of Table B4), or their unweighted median (available upon request). Higher values of each of these measures indicate a higher content of the relevant type of tasks.

Occupational task content measures of Deming (2017) The author creates task content

³⁵For the definitions of these types of tasks, see Appendix Section A.3.

³⁶For 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, and routine manual and routine cognitive. For the definitions of these categories, see Appendix Section A.3.

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).³⁷ 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. Then, we calculate the weighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Panel A of Table B2). As weights, we use the country-wide employment shares of occ1990dd occupations in 2012, as provided by [Deming \(2017\)](#). For robustness, we use the country-wide employment shares of occ1990dd occupations in 1980, 1990, 2000, or 2005. The data on employment shares for 1980 are drawn from [Deming \(2017\)](#) or [Autor & Dorn \(2009\)](#), while those for the other three years are drawn from [Autor & Dorn \(2009\)](#). Alternatively, we calculate the unweighted mean of the measures across occ1990dd codes by the corresponding two-digit SOC code (Panel B of Table B2), or their unweighted median (available upon request).

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.³⁸ Using the contact intensity scores for four-digit 2010 SOC occupations, we then calculate the weighted mean across these by two-digit 2010 SOC occupation (column (3) of Table B3). As weights, we use the country-wide employment shares of four-digit 2010 SOC occupations in 2019, whose data are drawn from the Occupational Employment and Wage Statistics (OEWS) of the US Bureau of Labour Statistics (BLS). Alternatively, we calculate their unweighted mean (column (4) of Table B3) or unweighted median (available upon request).

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 eight-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

³⁷For the precise O*NET definitions of these types of tasks, see Appendix Section A.4.

³⁸The 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). Hence, higher scores of the index indicate higher contact intensity.

that all tasks can be performed from distance. Alternatively, the authors assign manually 0, 0.5 or 1 to each five-digit 2010 SOC code. Calculating the weighted means of these measures across eight-digit and five-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 (7) of Table B3. As weights, we use the country-wide employment shares of six-digit and five-digit 2010 SOC occupations, respectively, in 2019, whose data are drawn from the Occupational Employment and Wage Statistics (OEWS) of the US Bureau of Labour Statistics (BLS).³⁹ Alternatively, we calculate their unweighted means (columns (6) and (8) of Table B3).

Essential occupations following the methodology 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). Then, they label an occupation as essential if its employment share in essential industries is at least equal to 75%. Following this methodology, we identify as essential the following occupations: healthcare practice, healthcare support, protective service, farming, fishing, and forestry. Alternatively, we set the threshold equal to 60%. Based on this more flexible definition, three occupations are added to the previous list, namely: community and social service; production, transportation and material moving (see columns (1) and (2) 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 (64–68), Life, Physical, and Social Science (69–83, 166, 173), Healthcare Practice (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).

³⁹Note that six-digit is the most disaggregated level for which data are available in OEWS.

A.3 Definitions of different types of tasks in [Autor et al. \(2003\)](#)

Non-routine cognitive analytical Tasks requiring general educational development, use of mathematics, reasoning, etc.

Non-routine cognitive interactive Tasks requiring adaptability to accepting responsibility for the direction, control, or planning of an activity.

Non-routine manual Tasks requiring the move of hands and feet coordinately with each other in accordance with visual stimuli.

Routine manual Tasks requiring finger dexterity for the manipulation of small objects rapidly or accurately.

Routine cognitive Tasks requiring precise attainment of set limits, tolerances, or standards.

For these definitions and associated examples, see also Table 1 and Appendix Table 1 of [Autor et al. \(2003\)](#).

A.4 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.5 Economic policy uncertainty

A.5.1 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 programmes).

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 list of keywords by policy area can be found at: https://www.policyuncertainty.com/categorical_terms.html.

A.5.2 Composite index

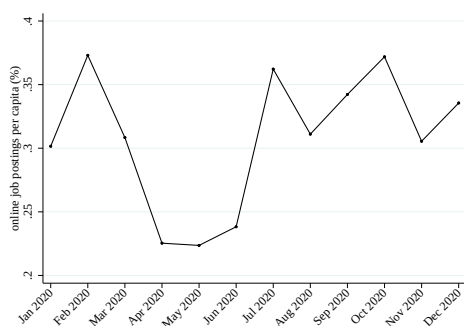
The composite Economic Policy Uncertainty (EPU) index consists of three components. The first component is the news-based EPU. The second relies on tax code expiration data retrieved from reports of the Congressional Budget Office (CBO) that compile lists of temporary federal tax code provisions. Temporary 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

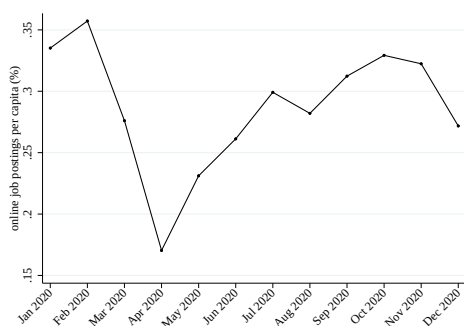
prior to January 2012. Then, they calculate the weighted mean of the three components using weights of $1/2$ on the first component (i.e., news-based EPU), $1/6$ on the second component (i.e., based on temporary tax measures), and $1/6$ on the two sub-components of the third component (i.e., based on disagreement about the CPI forecast and disagreement about the federal/state/local purchases forecast).

B Additional stylised facts

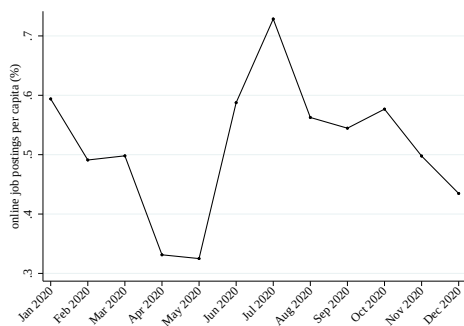
Figure B1: Per-capita number of online job postings in other countries



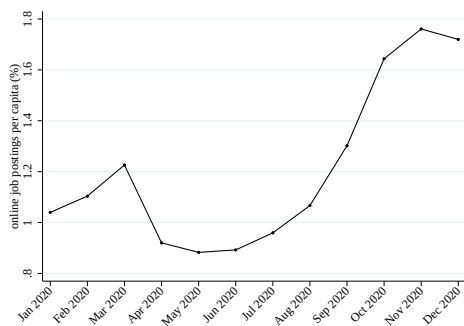
(a) Australia



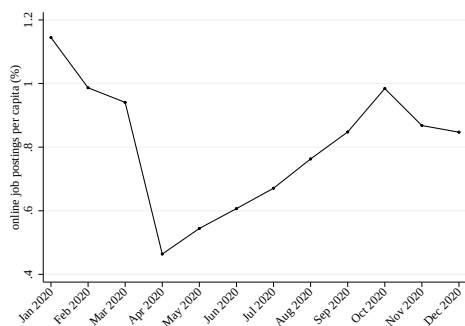
(b) Canada



(c) New Zealand



(d) Singapore

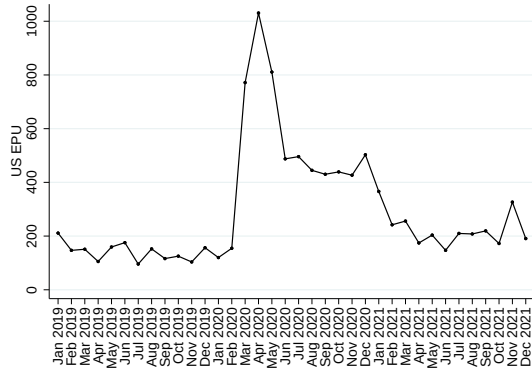


(e) United Kingdom

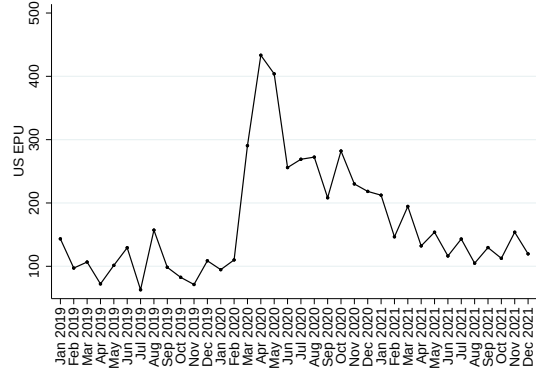
Notes: Monthly variation in the per-capita number of online job postings in Australia, Canada, New Zealand, Singapore, and the United Kingdom in January 2020 – December 2020.

Source: Authors' calculations based on online job postings and population data of Burning Glass Technologies (BGT). Population data correspond to the Australian Bureau of Statistics' 2018 estimates, Statistics Canada's 2019 estimates, Statistics New Zealand's 2019 population summary, Singapore Department of Statistics' 2019 population summary, and UK's Office for National Statistics' mid-2018 estimates.

Figure B2: Economic uncertainty in the US by policy area



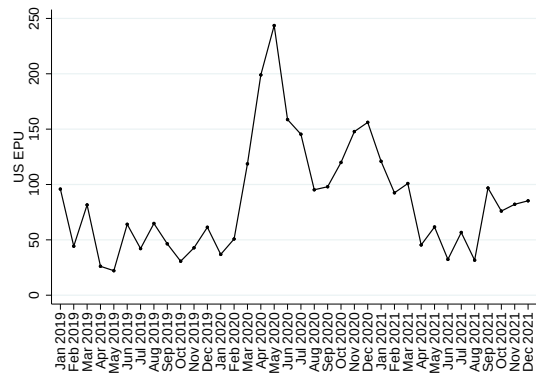
(a) Health policy



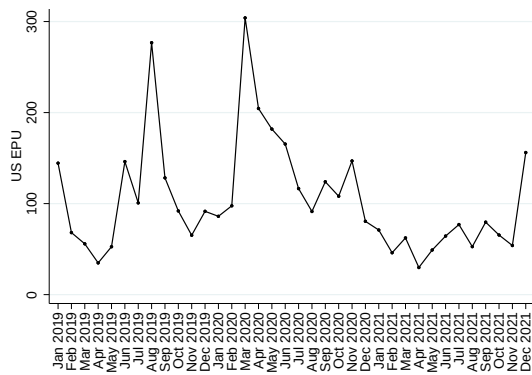
(b) Fiscal policy



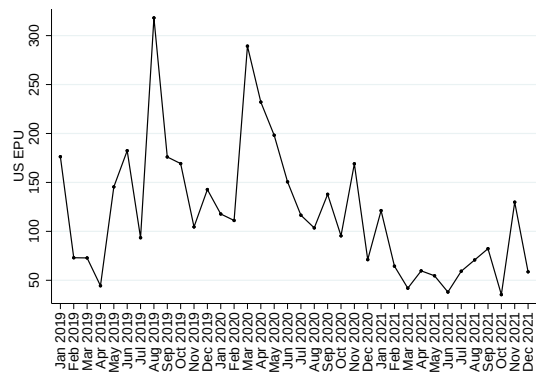
(c) Tax policy



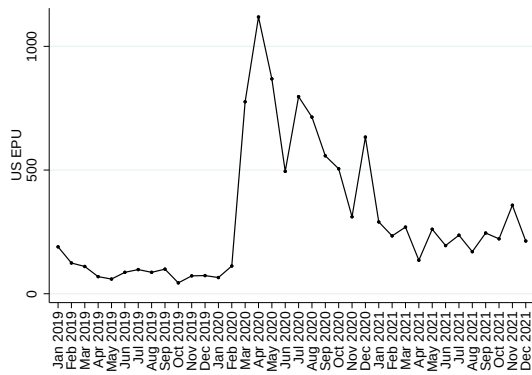
(d) Government policy



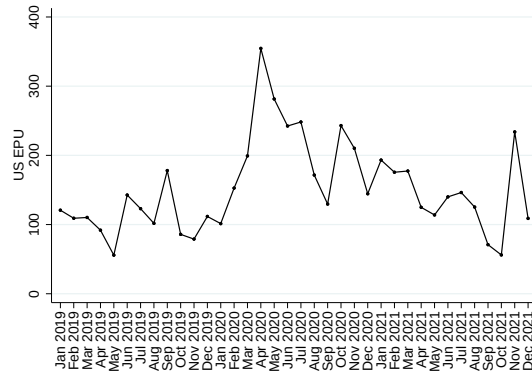
(e) Monetary policy



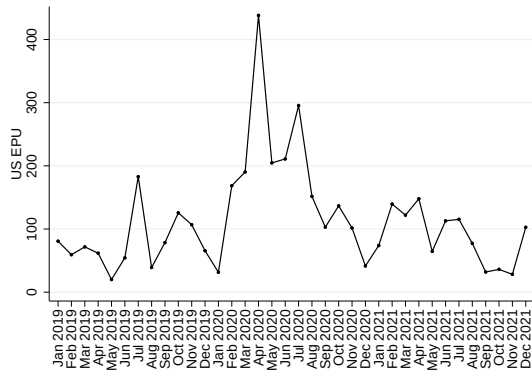
(f) Security policy



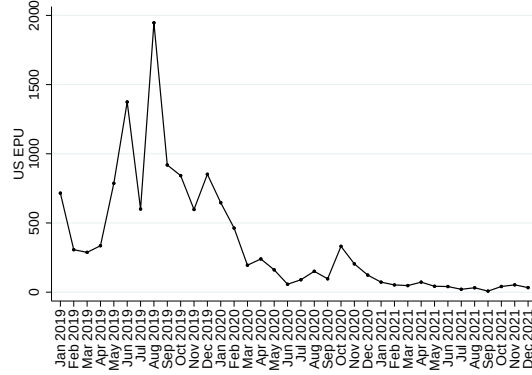
(g) Entitlement programmes



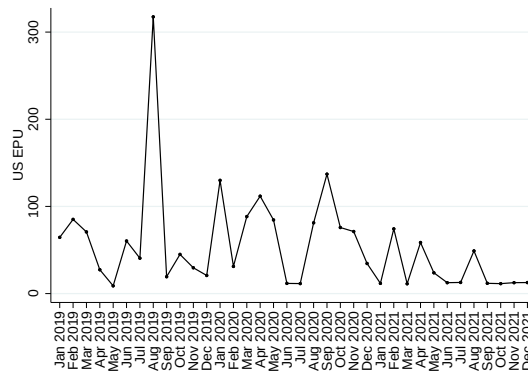
(h) Regulation



(i) Financial regulation



(j) Trade policy

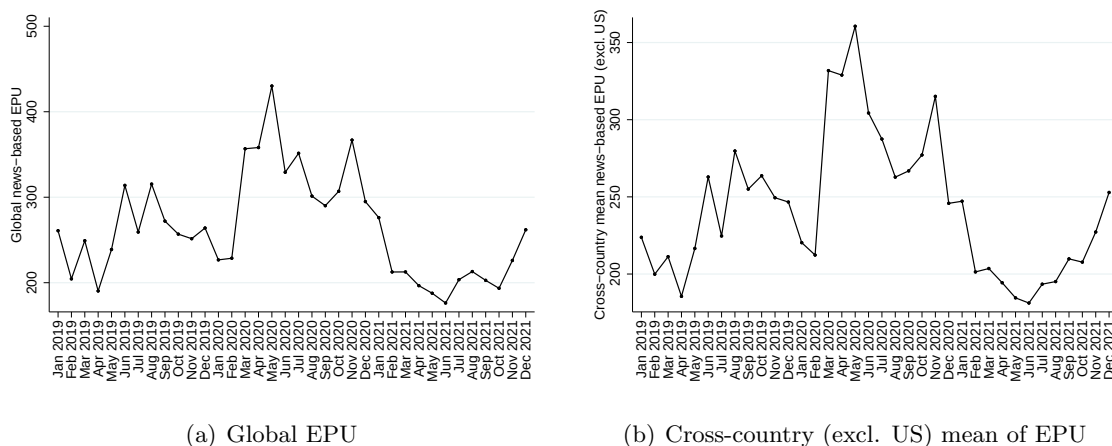


(k) Debt and currency crisis

Notes: Monthly variation in the US news-based EPU by policy area in January 2020 – December 2020.

Source: <https://www.policyuncertainty.com/>; see particularly Baker et al. (2016).

Figure B3: Economic uncertainty globally and in countries other than the US



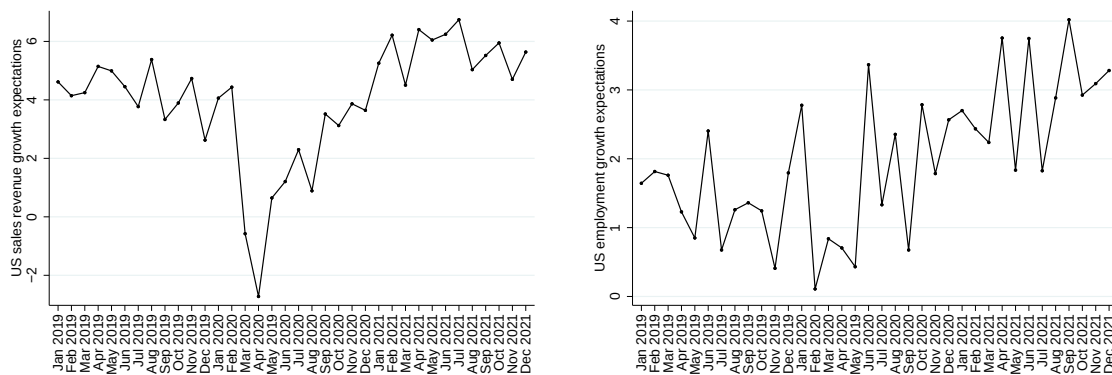
(a) Global EPU

(b) Cross-country (excl. US) mean of EPU

Notes: Monthly variation in the measure of Global news-based EPU and the unweighted mean of the news-based EPU of all countries available except for the US in January 2019 – December 2021. The countries are: 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: Sales revenue and employment growth expectations in the US



(a) Sales revenue growth expectations (SBU)

(b) Employment growth expectations (SBU)

Notes: Monthly variation in the SBU measures of sales revenue and employment growth expectations 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. \(2003\)](#)'s task content scores by two-digit SOC occupation

Panel A: Weighted means across occ1990dd codes by two-digit 2010 SOC codes					
Two-digit (SOC) occupation code & title	Non-routine			Routine	
	cognitive analytical	cognitive interactive	manual	cognitive	manual
11 Management	5.71	7.68	0.32	2.07	2.73
13 Business and Financial Operations	4.64	2.23	0.02	1.02	3.18
15 Computer and Mathematical	7.98	2.82	1.34	3.30	2.51
17 Architecture and Engineering	8.34	6.12	1.20	7.77	4.70
19 Life, Physical, and Social Science	7.97	5.43	0.51	6.16	3.67
21 Community and Social Service	5.54	5.20	0.09	0.21	2.53
23 Legal	4.92	3.77	0.05	2.56	2.41
25 Education, Training, and Library	4.96	4.21	1.56	0.32	3.02
27 Arts, Design, Entertainment, Sports, and Media	4.24	3.73	1.09	2.67	4.76
29 Healthcare Practitioners and Technical	5.88	2.23	1.77	6.28	5.62
31 Healthcare Support	3.42	0.70	1.46	2.98	4.53
33 Protective Service	1.63	1.02	2.46	0.36	2.58
35 Food Preparation and Serving Related	2.00	0.47	1.13	2.31	2.77
37 Building and Grounds Cleaning and Maintenance	1.65	0.63	2.33	4.61	2.99
39 Personal Care and Service	2.84	1.15	0.47	0.68	4.32
41 Sales and Related	4.46	4.35	0.34	2.65	3.62
43 Office and Administrative Support	3.51	0.93	0.14	6.27	4.47
45 Farming, Fishing, and Forestry	2.55	2.89	2.09	3.16	3.20
47 Construction and Extraction	3.22	0.60	3.00	8.36	4.46
49 Installation, Maintenance, and Repair	3.90	0.53	1.97	8.96	4.82
51 Production	3.85	3.05	0.87	7.47	4.37
53 Transportation and Material Moving	1.84	0.60	4.15	1.35	2.71
Panel B: Unweighted means across occ1990dd codes by two-digit 2010 SOC codes					
Two-digit (SOC) occupation code & title	Non-routine			Routine	
	cognitive analytical	cognitive interactive	manual	cognitive	manual
11 Management	5.40	6.71	0.49	2.24	2.78
13 Business and Financial Operations	4.76	2.73	0.02	1.05	3.06
15 Computer and Mathematical	7.90	4.72	0.71	4.90	2.58
17 Architecture and Engineering	8.49	6.75	1.02	7.76	4.68
19 Life, Physical, and Social Science	7.94	4.80	0.71	5.29	3.88
21 Community and Social Service	5.61	4.30	0.16	0.23	2.54
23 Legal	4.47	3.18	0.06	3.65	2.89
25 Education, Training, and Library	4.78	5.28	1.33	0.56	3.49
27 Arts, Design, Entertainment, Sports, and Media	3.83	2.82	1.92	3.28	4.43
29 Healthcare Practitioners and Technical	5.92	2.97	1.09	4.37	5.60
31 Healthcare Support	3.69	0.38	0.79	6.26	4.77
33 Protective Service	1.66	1.24	2.30	0.87	2.48
35 Food Preparation and Serving Related	1.73	0.37	1.10	1.51	2.84
37 Building and Grounds Cleaning and Maintenance	1.81	1.27	2.21	4.22	2.97
39 Personal Care and Service	2.20	1.34	0.93	1.65	3.72
41 Sales and Related	3.91	2.18	0.67	2.18	3.74
43 Office and Administrative Support	2.87	0.79	0.20	5.82	4.07
45 Farming, Fishing, and Forestry	2.44	2.98	2.44	2.88	3.17
47 Construction and Extraction	2.64	0.36	3.15	8.41	4.29
49 Installation, Maintenance, and Repair	3.78	0.43	1.63	8.82	4.91
51 Production	3.53	0.79	0.99	8.76	4.54
53 Transportation and Material Moving	1.62	1.47	3.70	3.10	2.82

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, which are 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 calculate the weighted means of the measures across occ1990dd codes by the corresponding two-digit SOC code using the country-wide employment shares of occ1990dd occupations in 2012 as weights (Panel A), or the unweighted means of these measures (Panel B).

Source: Authors' calculations based on data on occ1990dd's task scores of [Autor et al. \(2003\)](#) and data on country-wide employment shares of occ1990dd occupations of [Deming \(2017\)](#).

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

Panel A: Weighted means across occ1990dd codes by two-digit 2010 SOC codes					
Two-digit (SOC) occupation code & title	Social	Coordination	Interaction	Customer-oriented	Service-oriented
11 Management	6.64	6.36	7.74	6.30	3.85
13 Business and Financial Operations	6.20	2.44	6.34	6.73	3.80
15 Computer and Mathematical	4.94	2.75	6.04	3.40	4.02
17 Architecture and Engineering	5.44	6.47	8.09	3.94	2.58
19 Life, Physical, and Social Science	4.76	2.90	6.98	3.49	3.10
21 Community and Social Service	6.77	4.13	7.42	7.25	8.52
23 Legal	6.02	2.77	7.15	5.69	3.46
25 Education, Training, and Library	5.56	4.84	7.07	4.30	6.67
27 Arts, Design, Entertainment, Sports, and Media	4.22	2.73	4.98	4.11	2.17
29 Healthcare Practice	4.88	4.08	6.69	7.71	7.70
31 Healthcare Support	3.51	1.49	4.62	5.94	6.92
33 Protective Service	4.89	2.41	5.61	6.44	5.47
35 Food Preparation and Service	1.65	1.37	3.75	6.76	4.57
37 Building and Grounds Cleaning and Maintenance	2.01	1.25	2.63	3.64	2.57
39 Personal Care and Service	2.51	1.49	4.05	7.53	5.49
41 Sales and Related	4.47	3.34	5.72	7.98	3.88
43 Office and Administrative Support	2.68	1.77	4.70	5.66	3.47
45 Farming, Fishing, and Forestry	2.34	2.24	3.49	3.02	1.56
47 Construction and Extraction	1.78	1.53	2.15	2.01	1.60
49 Installation, Maintenance, and Repair	1.63	1.29	2.69	2.85	1.78
51 Production	2.55	2.46	3.05	1.97	1.66
53 Transportation and Material Moving	2.58	1.31	3.91	6.00	2.70
Panel B: Unweighted means across occ1990dd codes by two-digit 2010 SOC codes					
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 Practice	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.4. 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 the weighted means of the measures across occ1990dd codes by the corresponding two-digit SOC code using the country-wide employment shares of occ1990dd occupations in 2012 as weights (Panel A), or the unweighted means of these measures (Panel B).

Source: Authors’ calculations based on data on occ1990dd’s task scores and country-wide employment shares of Deming (2017).

Table B3: Additional task content scores by (two-digit SOC) occupation

Two-digit (SOC) occupation code & title	Essential		Contact-intensive		Tele-work (O*NET)		Tele-work (manual)	
	Main	Alt.	Weighted mean	Unweighted mean	Weighted mean	Unweighted mean	Weighted mean	Unweighted mean
11 Management	0	0	48.50	47.06	0.78	0.66	0.84	0.66
13 Business and Financial Operations	0	0	49.32	49.56	0.83	0.80	0.92	0.86
15 Computer and Mathematical	0	0	38.83	43.20	1.00	1.00	1.00	1.00
17 Architecture and Engineering	0	0	49.52	49.53	0.57	0.44	0.87	0.71
19 Life, Physical, and Social Science	0	0	48.97	48.39	0.70	0.62	0.37	0.42
21 Community and Social Service	0	1	63.37	57.67	0.35	0.50	0.50	0.58
23 Legal	0	0	48.87	49.10	0.97	0.88	0.84	0.88
25 Education, Training, and Library	0	0	72.85	64.88	0.99	0.93	0.84	0.76
27 Arts, Design, Entertainment, Sports, and Media	0	0	56.57	57.72	0.67	0.63	0.58	0.33
29 Healthcare Practice	1	1	85.71	81.95	0.01	0.09	0.05	0.06
31 Healthcare Support	1	1	81.31	86.98	0.08	0.11	0	0
33 Protective Service	1	1	69.75	70.80	0.03	0.14	0	0
35 Food Preparation and Service	0	0	72.91	74.96	0	0.06	0	0
37 Building and Grounds Cleaning and Maintenance	0	0	48.63	53.95	0	0	0	0
39 Personal Care and Service	0	0	77.65	74.44	0.52	0.25	0	0
41 Sales and Related	0	0	63.25	57.84	0.29	0.54	0.21	0.43
43 Office and Administrative Support	0	0	55.23	56.14	0.66	0.60	0.55	0.52
45 Farming, Fishing, and Forestry	1	1	48.43	43.28	0.03	0.06	0	0
47 Construction and Extraction	0	0	68.87	69.45	0	0.02	0	0
49 Installation, Maintenance, and Repair	0	0	62.81	63.30	0	0.02	0	0
51 Production	0	1	58.03	57.29	0.01	0.05	0	0
53 Transportation and Material Moving	0	1	58.57	63.68	0	0.06	0	0

Notes: For the identification of (non-)essential two-digit 2010 SOC occupations in columns (1) and (2), we rely on the methodology of [Mongey et al. \(2021\)](#). In column (1), an occupation is classified as (non-)essential, indicated by unit (zero) value, if its employment share in essential industries is at least (below) 75%. In column (2), this threshold is set equal to 60%. In columns (3) and (4), we calculate the weighted and unweighted mean, respectively, of the physical contact intensity measure of [Leibovici et al. \(2020\)](#) across four-digit 2010 SOC occupations by the corresponding two-digit SOC code using the 2019 country-wide employment shares of four-digit 2010 SOC occupations as weights. For the construction of tele-work measures by two-digit 2010 SOC occupation, we rely on [Dingel & Neiman \(2020\)](#)'s tele-work measures using O*NET information (columns (5) and (6)) or their manual classification (columns (7) and (8)). Under the first methodology, the authors create a measure of tele-work of eight-digit 2010 SOC occupations as the fraction of their tasks that can be performed from distance. In this way, a fraction equal to zero indicates that no tasks of an occupation can be performed from distance, while a fraction equal to one indicates that all of its tasks can be performed from distance. Under the second methodology, the authors assign manually value 0, 0.5 or 1 to each five-digit 2010 SOC code. In columns (5) and (6), we calculate the weighted and unweighted mean, respectively, of the first tele-work measure across eight-digit 2010 SOC occupations by the corresponding two-digit 2010 SOC occupation using the 2019 country-wide employment shares of six-digit 2010 SOC occupations as weights. Similarly, in columns (7) and (8), we calculate the weighted and unweighted mean, respectively, of the second tele-work measure across five-digit 2010 SOC occupations by the corresponding two-digit 2010 SOC occupation using the 2019 country-wide employment shares of five-digit 2010 SOC occupations as weights.

Source: Authors' assignments of unit or zero values to dummy variables indicating the essential status of occupations 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). Authors' calculations based on [Dingel & Neiman \(2020\)](#)'s tele-work measures using O*NET information (columns (5) and (6)) or their manual classification (columns (7) and (8)). Calculations in columns (3), (5), and (7) are also based respectively on data on four-, six-, and five-digit 2010 SOC occupations' country-wide employment shares in 2019 of BLS's Occupational Employment and Wage Statistics.

Table B4: [Autor & Dorn \(2013\)](#)'s task content scores by two-digit SOC occupation

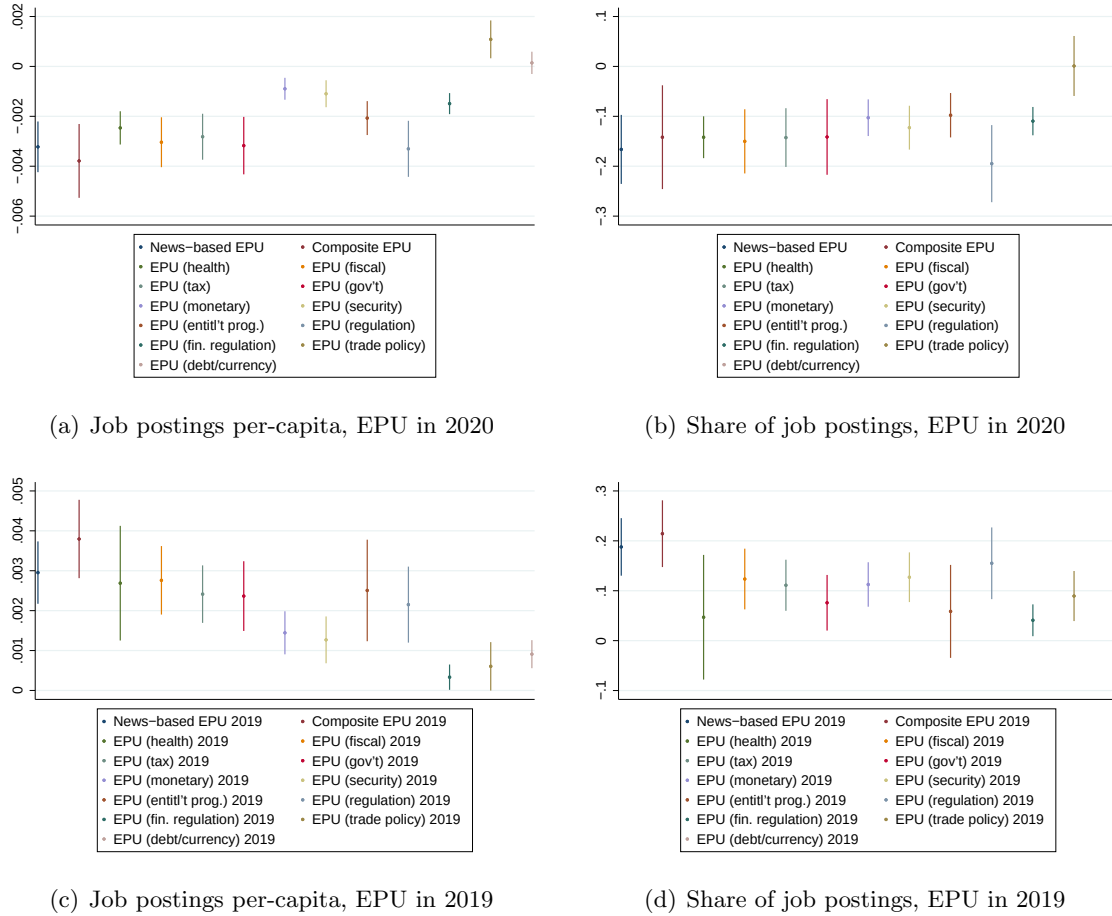
Panel A: Weighted means across occ1990dd codes by two-digit 2010 SOC codes			
Two-digit (SOC) occupation code & title	Abstract	Non-routine manual	Routine
11 Management	6.78	0.37	2.48
13 Business and Financial Operations	3.44	0.03	2.10
15 Computer and Mathematical	5.37	1.34	2.89
17 Architecture and Engineering	7.46	1.29	6.10
19 Life, Physical, and Social Science	6.64	0.53	4.90
21 Community and Social Service	5.52	0.09	1.38
23 Legal	3.21	0.06	2.18
25 Education, Training, and Library	4.43	1.56	1.68
27 Arts, Design, Entertainment, Sports, and Media	3.88	1.18	3.74
29 Healthcare Practice	3.98	1.78	6.11
31 Healthcare Support	1.55	2.02	3.29
33 Protective Service	1.27	2.56	1.40
35 Food Preparation and Service	1.25	1.08	3.02
37 Building and Grounds Cleaning and Maintenance	1.12	2.33	3.75
39 Personal Care and Service	2.06	0.52	2.50
41 Sales and Related	4.40	0.33	3.14
43 Office and Administrative Support	2.25	0.13	5.23
45 Farming, Fishing, and Forestry	2.91	2.38	3.02
47 Construction and Extraction	2.25	2.82	6.12
49 Installation, Maintenance, and Repair	2.29	1.97	7.10
51 Production	3.37	0.78	5.98
53 Transportation and Material Moving	1.22	4.43	2.38
Panel B: Unweighted means across occ1990dd codes by two-digit 2010 SOC codes			
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 Practice	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, and 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 weighted means of the measures across occ1990dd codes by the corresponding two-digit SOC code using the country-wide employment shares of occ1990dd occupations in 2012 as weights (Panel A), or the unweighted means of these measures (Panel B).

Source: Authors' calculations based on data on occ1990dd's task scores of [Autor & Dorn \(2013\)](#) and data on country-wide employment shares of occ1990dd occupations of [Deming \(2017\)](#).

C Robustness checks

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



Notes: OLS estimations with standard errors clustered by occupation-state pair in all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The dependent variable is the per-capita number of online job postings in percentages (Panels (a) and (c)) or the share of online job postings in percentages (Panels (b) and (d)). The occupation-state-level measures of economic uncertainty have been standardised. Dummies for occupation-state pairs and for months are included in the equations.

Table C1: Additional measures of COVID-induced economic uncertainty

Panel A: Mean or median of EPU across countries, excluding the US, as the key regressor						
Dep. var.:	(1)	(2)	(3)	(4)	(5)	(6)
	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
Cross-country mean of EPU	-0.043*** [0.009]	-0.0056*** [0.001]	-0.28*** [0.07]			
Cross-country median of EPU				-0.049*** [0.01]	-0.0063*** [0.001]	-0.30*** [0.08]
Constant	8.44*** [0.01]	0.067*** [0.001]	6.76*** [0.1]	8.45*** [0.01]	0.068*** [0.002]	6.78*** [0.1]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.916	0.941	0.985	0.917	0.942
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES	YES
Panel B: Global EPU in 2019 or Global EPU PPP in 2019 as the key regressor						
Dep. var.:	(1)	(2)	(3)	(4)	(5)	(6)
	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
Global EPU 2019	0.027* [0.01]	0.0040*** [0.0010]	0.41*** [0.09]			
Global EPU PPP 2019				0.021 [0.02]	0.0031*** [0.001]	0.39*** [0.09]
Constant	8.34*** [0.02]	0.053*** [0.001]	5.74*** [0.1]	8.35*** [0.02]	0.054*** [0.002]	5.77*** [0.1]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.915	0.942	0.985	0.915	0.942
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES	YES
Panel C: Mean or median of EPU across countries, excluding the US, in 2019 as the key regressor						
Dep. var.:	(1)	(2)	(3)	(4)	(5)	(6)
	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
Cross-country mean of EPU 2019	0.022 [0.02]	0.0034** [0.002]	0.51*** [0.1]			
Cross-country median of EPU 2019				0.0095 [0.01]	0.00078 [0.0010]	0.29*** [0.09]
Constant	8.35*** [0.03]	0.054*** [0.002]	5.60*** [0.2]	8.36*** [0.02]	0.058*** [0.001]	5.92*** [0.1]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.915	0.942	0.985	0.915	0.942
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES	YES
Panel D: SBU measure of sales revenue or employment growth expectations as the key regressor						
Dep. var.:	(1)	(2)	(3)	(4)	(5)	(6)
	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
Sales growth expectations (SBU)	0.0095*** [0.002]	0.0011*** [0.0002]	0.082*** [0.01]			
Emp. growth expectations (SBU)				0.0026 [0.003]	0.00047** [0.0002]	0.042** [0.02]
Constant	8.37*** [0.002]	0.058*** [0.0001]	6.26*** [0.01]	8.37*** [0.003]	0.058*** [0.0003]	6.29*** [0.02]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.916	0.942	0.985	0.915	0.941
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES	YES

Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns of all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The per-capita number of online job postings (*OJP p.c.*) and share of online job postings (*OJP share*) are in percentages. The economic uncertainty measures are occupation-state-specific. The occupation-state-level measures of economic uncertainty have been standardised. Dummies for occupation-state pairs and for months are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C2: Alternative construction of occupation-state-level measures of economic uncertainty

Panel A: News-based or composite EPU as the key regressor						
Dep. var.:	(1) Log of # of OJP	(2) OJP p.c.	(3) OJP share	(4) Log of # of OJP	(5) OJP p.c.	(6) OJP share
News-based EPU	-0.025*** [0.005]	-0.0031*** [0.0005]	-0.16*** [0.03]			
Composite EPU				-0.029*** [0.009]	-0.0036*** [0.0007]	-0.13*** [0.05]
Constant	8.41*** [0.007]	0.063*** [0.0007]	6.58*** [0.05]	8.42*** [0.01]	0.064*** [0.001]	6.54*** [0.08]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.916	0.942	0.985	0.916	0.941
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES	YES
Panel B: SBU measure of sales revenue or employment growth uncertainty as the key regressor						
Dep. var.:	(1) Log of # of OJP	(2) OJP p.c.	(3) OJP share	(4) Log of # of OJP	(5) OJP p.c.	(6) OJP share
Sales growth uncertainty (SBU)	-0.034*** [0.01]	-0.0038*** [0.001]	-0.098 [0.07]			
Emp. growth uncertainty (SBU)				-0.053*** [0.02]	-0.0063*** [0.001]	-0.16 [0.1]
Constant	8.43*** [0.02]	0.064*** [0.002]	6.49*** [0.1]	8.46*** [0.03]	0.068*** [0.002]	6.59*** [0.2]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.985	0.916	0.941	0.985	0.917	0.941
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES	YES

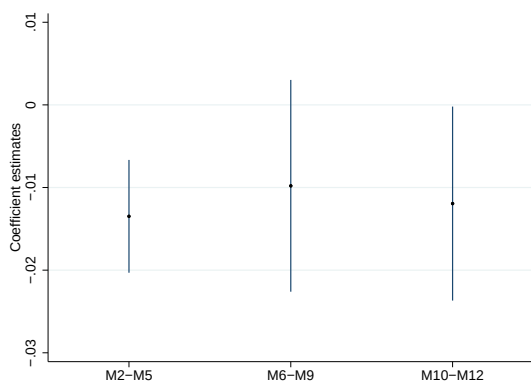
Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns of all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The per-capita number of online job postings (*OJP p.c.*) and share of online job postings (*OJP share*) are in percentages. The economic uncertainty measures are occupation-state-specific. Each of these measure has been constructed as the product between the corresponding country-level measure and the employment share of each occupation-state pair in country-wide employment. The occupation-state-level measures of economic uncertainty have been standardised. Dummies for occupation-state pairs and for months are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C3: Controlling for occupation-month and state-month fixed effects

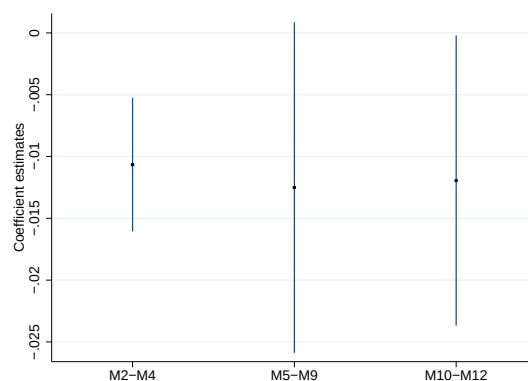
Panel A: News-based or composite EPU as the key regressor						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
News-based EPU	-0.014*** [0.005]	-0.0017*** [0.0005]	-0.13*** [0.03]			
Composite EPU				-0.017** [0.007]	-0.0023*** [0.0007]	-0.14*** [0.04]
Constant	8.40*** [0.007]	0.061*** [0.0007]	6.53*** [0.05]	8.40*** [0.010]	0.062*** [0.0010]	6.55*** [0.06]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.995	0.967	0.973	0.995	0.967	0.973
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Occupation-month FEs	YES	YES	YES	YES	YES	YES
US state-month FEs	YES	YES	YES	YES	YES	YES
Panel B: Global EPU or Global EPU PPP as the key regressor						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
Global EPU	-0.024*** [0.008]	-0.0030*** [0.0009]	-0.20*** [0.06]			
Global EPU PPP				-0.025*** [0.008]	-0.0032*** [0.001]	-0.21*** [0.06]
Constant	8.41*** [0.01]	0.063*** [0.001]	6.64*** [0.09]	8.41*** [0.01]	0.063*** [0.001]	6.65*** [0.09]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.995	0.967	0.973	0.995	0.967	0.973
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Occupation-month FEs	YES	YES	YES	YES	YES	YES
US state-month FEs	YES	YES	YES	YES	YES	YES
Panel D: SBU measure of sales revenue or employment growth uncertainty as the key regressor						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Log of # of OJP	OJP p.c.	OJP share	Log of # of OJP	OJP p.c.	OJP share
Sales growth uncertainty (SBU)	-0.020** [0.009]	-0.0027*** [0.0010]	-0.13** [0.06]			
Emp. growth uncertainty (SBU)				-0.027** [0.01]	-0.0042*** [0.001]	-0.17** [0.08]
Constant	8.41*** [0.01]	0.063*** [0.001]	6.54*** [0.09]	8.42*** [0.02]	0.065*** [0.002]	6.59*** [0.1]
Observations	13,464	13,464	13,464	13,464	13,464	13,464
R^2	0.995	0.967	0.973	0.995	0.967	0.973
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Occupation-month FEs	YES	YES	YES	YES	YES	YES
US state-month FEs	YES	YES	YES	YES	YES	YES

Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns of all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The per-capita number of online job postings (*OJP p.c.*) and share of online job postings (*OJP share*) are in percentages. The economic uncertainty measures are occupation-state-specific. The occupation-state-level measures of economic uncertainty have been standardised. Dummies for occupation-state pairs, occupation-month pairs, and state-month pairs are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

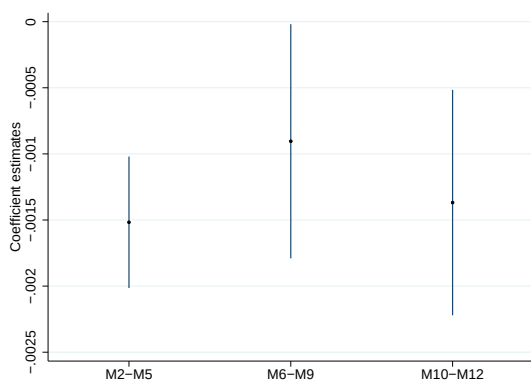
Figure C2: Effects of pandemic waves and in-between period on occupational demand



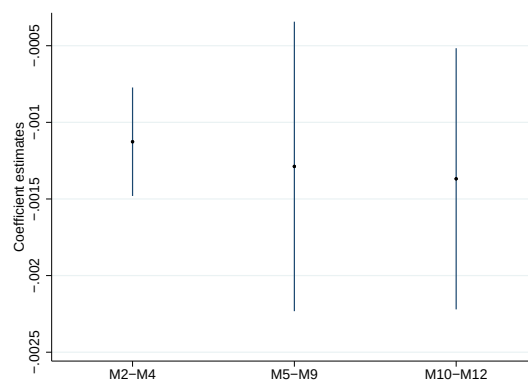
(a) Log of # of online job postings



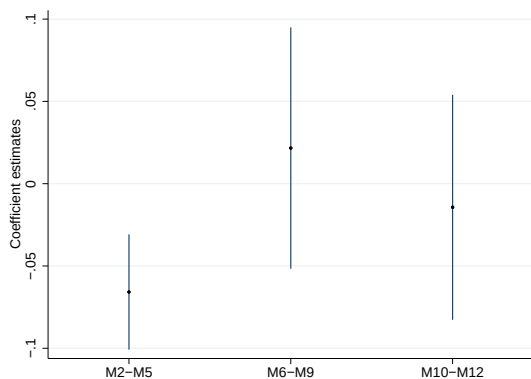
(b) Log of # of online job postings



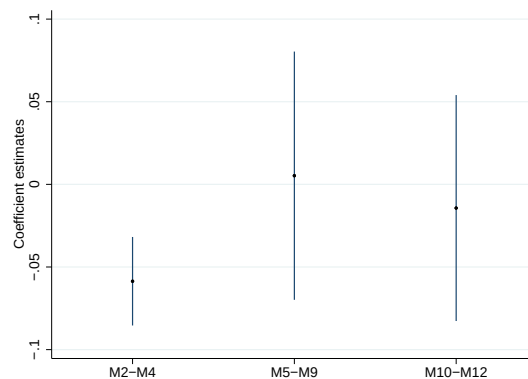
(c) Per-capita # of online job postings



(d) Per-capita # of online job postings



(e) Share of online job postings



(f) Share of online job postings

Notes: OLS estimations with standard errors clustered by occupation-state pair in all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The dependent variable is the share of online job postings in percentages. The dummy variables for the months of the first and second pandemic waves (M2-M5 or M2-M4, M10-M12) and those between the two waves (M6-M9 or M5-M9), whose coefficient estimates are displayed in the panels, are occupation-state-specific. The equations also include the original dummy variables and their interactions with pairs of occupational characteristics and individual occupational characteristics, but their coefficient estimates are not disclosed for the sake of exposition. The original and occupation-state-specific dummy variables, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs are also included in the equations.

Table C4: Alternative construction of occupation-state-level measures of economic uncertainty

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
News-based EPU	-0.15*** [0.04]	-0.13*** [0.03]	-0.11*** [0.02]	-0.14*** [0.02]	-0.14*** [0.03]
News-based EPU * cogn. analytical	0.021 [0.06]				
Country-level news-based EPU * cogn. analytical	-0.0047 [0.02]				
News-based EPU * cogn. interactive		0.062** [0.03]			
Country-level news-based EPU * cogn. interactive		-0.043*** [0.01]			
News-based EPU * non-routine manual			0.043** [0.02]		
Country-level news-based EPU * non-routine manual			0.11*** [0.02]		
News-based EPU * routine cognitive				-0.11*** [0.03]	
Country-level news-based EPU * routine cognitive				0.038*** [0.01]	
News-based EPU * routine manual					-0.087** [0.04]
Country-level news-based EPU * routine manual					0.026 [0.02]
Constant	6.57*** [0.05]	6.57*** [0.04]	6.52*** [0.03]	6.55*** [0.04]	6.56*** [0.04]
Observations	13464	13464	13464	13464	13464
R^2	0.942	0.942	0.943	0.942	0.942
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost,C_o}} + \beta_{EPU_{t,C_o}} = 0$	0.0888	0.00198	0.213	4.79e-15	2.36e-08
Occupation-US state FEs	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES
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
News-based EPU	-0.16*** [0.04]	-0.15*** [0.03]	-0.16*** [0.03]	-0.15*** [0.03]	-0.16*** [0.03]
News-based EPU * customer	0.030 [0.03]				
Country-level news-based EPU * customer	-0.067*** [0.01]				
News-based EPU * service		0.075 [0.06]			
Country-level news-based EPU * service		-0.0066 [0.02]			
News-based EPU * contact			0.073* [0.04]		
Country-level news-based EPU * contact			0.016 [0.02]		
News-based EPU * tele-work				-0.067* [0.04]	
Country-level news-based EPU * tele-work				-0.032* [0.02]	
News-based EPU * essential					0.34** [0.2]
Country-level news-based EPU * essential					0.0098 [0.05]
Constant	6.55*** [0.05]	6.57*** [0.05]	6.56*** [0.04]	6.56*** [0.04]	6.55*** [0.05]
Observations	13464	13464	13464	13464	13464
R^2	0.942	0.942	0.942	0.942	0.942
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost,C_o}} + \beta_{EPU_{t,C_o}} = 0$	2.64e-08	0.123	0.129	8.52e-12	0.133
Occupation-US state FEs	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES

Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns of both panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The share of online job postings (*OJP share*) is in percentages. The economic uncertainty measure is occupation-state-specific, unless stated otherwise. This measure has been constructed as the product between the country-level measure and the employment share of each occupation-state pair in country-wide employment. The country-level measure of economic uncertainty, the occupation-state-level measure of economic uncertainty, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs and for months are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C5: Alternative construction of 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
News-based EPU	-0.13*** [0.04]	-0.11*** [0.03]	-0.12*** [0.02]	-0.16*** [0.03]	-0.16*** [0.03]
News-based EPU * cogn. analytical	0.067 [0.06]				
Country-level news-based EPU * cogn. analytical	-0.0033 [0.02]				
News-based EPU * cogn. interactive		0.097*** [0.02]			
Country-level news-based EPU * cogn. interactive		-0.011 [0.01]			
News-based EPU * non-routine manual			0.058*** [0.02]		
Country-level news-based EPU * non-routine manual			0.091*** [0.02]		
News-based EPU * routine cognitive				-0.089*** [0.03]	
Country-level news-based EPU * routine cognitive				0.049*** [0.01]	
News-based EPU * routine manual					-0.072 [0.05]
Country-level news-based EPU * routine manual					0.038* [0.02]
Constant	6.56*** [0.05]	6.56*** [0.04]	6.53*** [0.03]	6.57*** [0.04]	6.57*** [0.04]
Observations	13464	13464	13464	13464	13464
R^2	0.942	0.942	0.943	0.942	0.942
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost},C_o} + \beta_{EPU_{t},C_o} = 0$	0.421	0.633	0.299	5.84e-09	0.000244
Occupation-US state FEs	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES
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
News-based EPU	-0.14*** [0.05]	-0.17*** [0.03]	-0.16*** [0.03]	-0.14*** [0.03]	-0.19*** [0.02]
News-based EPU * customer	-0.0051 [0.04]				
Country-level news-based EPU * customer	-0.079*** [0.01]				
News-based EPU * service		0.033 [0.07]			
Country-level news-based EPU * service		-0.014 [0.02]			
News-based EPU * contact			0.066 [0.04]		
Country-level news-based EPU * contact			0.027 [0.02]		
News-based EPU * tele-work				-0.070 [0.04]	
Country-level news-based EPU * tele-work				-0.034* [0.02]	
News-based EPU * essential					0.28*** [0.06]
Country-level news-based EPU * essential					0.11*** [0.03]
Constant	6.55*** [0.06]	6.58*** [0.05]	6.56*** [0.05]	6.55*** [0.04]	6.52*** [0.03]
Observations	13464	13464	13464	13464	13464
R^2	0.942	0.942	0.942	0.942	0.943
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost},C_o} + \beta_{EPU_{t},C_o} = 0$	6.82e-10	0.0135	0.142	4.58e-11	0.0000187
Occupation-US state FEs	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES

Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns of both panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The share of online job postings (*OJP share*) is in percentages. The economic uncertainty measure is occupation-state-specific, unless stated otherwise. The continuous variables for occupational task content are created as unweighted means across disaggregated occupations by the corresponding two-digit 2010 SOC occupation (Panel B of Tables B1 and B2 and columns (4) and (6) of Table B3). The dummy for the essential status of occupations is created based on the alternative classification (column (1) of Table B3). The country-level measure of economic uncertainty, the occupation-state-level measure of economic uncertainty, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs and for months are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C6: Autor & Dorn (2013)'s measures of 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
News-based EPU	-0.15*** [0.03]	-0.11*** [0.02]	-0.14*** [0.02]	-0.10*** [0.03]	-0.12*** [0.02]	-0.16*** [0.03]
News-based EPU * non-routine cognitive	0.045 [0.04]					
Country-level news-based EPU * non-routine cognitive	-0.027* [0.02]					
News-based EPU * non-routine manual		0.043** [0.02]				
Country-level news-based EPU * non-routine manual		0.11*** [0.02]				
News-based EPU * routine			-0.12*** [0.03]			
Country-level news-based EPU * routine			0.040*** [0.01]			
News-based EPU * non-routine cognitive				0.11*** [0.03]		
Country-level news-based EPU * non-routine cognitive				-0.0080 [0.01]		
News-based EPU * non-routine manual					0.055*** [0.02]	
Country-level news-based EPU * non-routine manual					0.092*** [0.02]	
News-based EPU * routine						-0.089*** [0.03]
Country-level news-based EPU * routine						0.052*** [0.01]
Constant	6.58*** [0.05]	6.52*** [0.03]	6.56*** [0.03]	6.55*** [0.04]	6.52*** [0.03]	6.57*** [0.04]
Observations	13464	13464	13464	13464	13464	13464
R^2	0.942	0.943	0.942	0.942	0.943	0.942
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost}, C_o} + \beta_{EPU_{it}, C_o} = 0$	0.00258	0.327	3.79e-12	0.979	0.324	0.000000209
Occupation-US state FEs	YES	YES	YES	YES	YES	YES
Month FEs	YES	YES	YES	YES	YES	YES
Task content measures	Weighted means across occ1990dd codes			Unweighted means across occ1990dd codes		

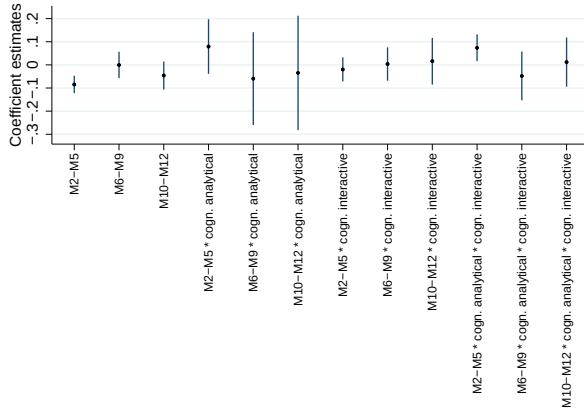
Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns. The equations are weighted by the employment level of each occupation-state pair in 2019. The share of online job postings (*OJP share*) is in percentages. The economic uncertainty measure is occupation-state-specific, unless stated otherwise. The variables for occupational task content in columns (1)–(3) and (4)–(6) are created as weighted and unweighted means, respectively, across disaggregated occupations by the corresponding two-digit 2010 SOC occupation (see task content scores in Panels A and B of Table B4). The country-level measure of economic uncertainty, the occupation-state-level measure of economic uncertainty, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs and for months are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

Table C7: Controlling for US state-month fixed effects

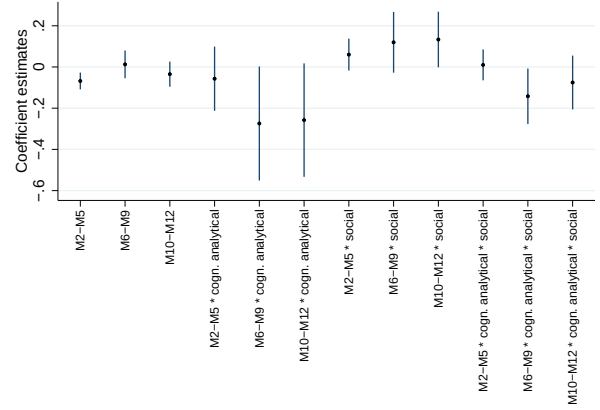
Panel A: Cognitive analytical/interactive, non-routine manual, routine cognitive/manual					
	(1)	(2)	(3)	(4)	(5)
Dep. var.:	OJP share	OJP share	OJP share	OJP share	OJP share
News-based EPU	-0.34*** [0.04]	-0.32*** [0.03]	-0.25*** [0.03]	-0.31*** [0.04]	-0.30*** [0.04]
News-based EPU * cogn. analytical	0.0024 [0.05]				
Country-level news-based EPU * cogn. analytical	-0.014 [0.02]				
News-based EPU * cogn. interactive		0.048** [0.02]			
Country-level news-based EPU * cogn. interactive		-0.045*** [0.01]			
News-based EPU * non-routine manual			0.020 [0.01]		
Country-level news-based EPU * non-routine manual			0.11*** [0.01]		
News-based EPU * routine manual				-0.065* [0.03]	
Country-level news-based EPU * routine manual				0.016 [0.02]	
News-based EPU * routine cognitive					-0.089*** [0.03]
Country-level news-based EPU * routine cognitive					0.027** [0.01]
Constant	6.83*** [0.05]	6.82*** [0.05]	6.70*** [0.04]	6.79*** [0.05]	6.78*** [0.05]
Observations	13464	13464	13464	13464	13463
R^2	0.943	0.943	0.944	0.943	0.943
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost},C_o} + \beta_{EPU_{t},C_o} = 0$	0.00000103	5.04e-14	0.00108	1.04e-30	2.64e-31
Occupation-US state FEs	YES	YES	YES	YES	YES
US state-month FEs	YES	YES	YES	YES	YES
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
News-based EPU	-0.34*** [0.05]	-0.33*** [0.03]	-0.33*** [0.03]	-0.32*** [0.04]	-0.30*** [0.03]
News-based EPU * customer	0.052* [0.03]				
Country-level news-based EPU * customer	-0.059*** [0.01]				
News-based EPU * service		0.036 [0.06]			
Country-level news-based EPU * service		0.0051 [0.02]			
News-based EPU * contact			0.023 [0.03]		
Country-level news-based EPU * contact			0.037** [0.02]		
News-based EPU * tele-work				-0.032 [0.03]	
Country-level news-based EPU * tele-work				-0.048*** [0.02]	
News-based EPU * essential					0.21*** [0.05]
Country-level news-based EPU * essential					0.14*** [0.03]
Constant	6.79*** [0.06]	6.81*** [0.04]	6.80*** [0.05]	6.79*** [0.05]	6.71*** [0.04]
Observations	13464	13464	13464	13464	13464
R^2	0.943	0.943	0.943	0.943	0.943
F-test (p-value): $\beta_{EPU_{ost}} + \beta_{EPU_{ost},C_o} + \beta_{EPU_{t},C_o} = 0$	7.59e-22	0.000000192	6.68e-09	6.15e-32	0.482
Occupation-US state FEs	YES	YES	YES	YES	YES
US state-month FEs	YES	YES	YES	YES	YES

Notes: OLS estimations with standard errors clustered by occupation-state pair in all columns of both panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The share of online job postings (*OJP share*) is in percentages. The economic uncertainty measure is occupation-state-specific, unless stated otherwise. The country-level measure of economic uncertainty, the occupation-state-level measure of economic uncertainty, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs and state-month pairs are included in the equations. Asterisks denote significance at 1% (***), 5% (**), and 10% (*).

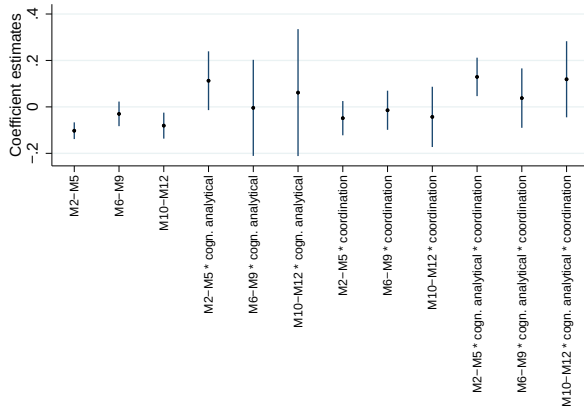
Figure C3: The joint role of non-routine cognitive analytical and interactive tasks



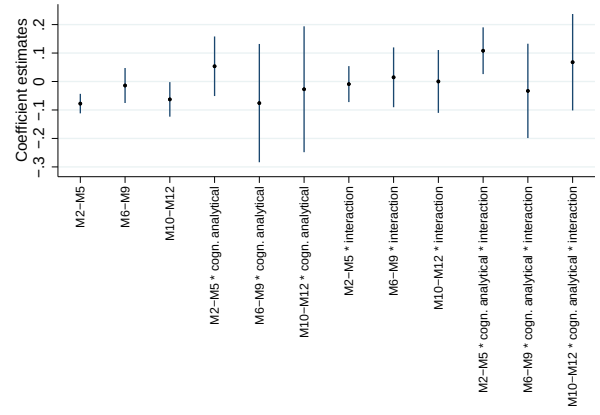
(a) Cognitive interactive



(b) Social



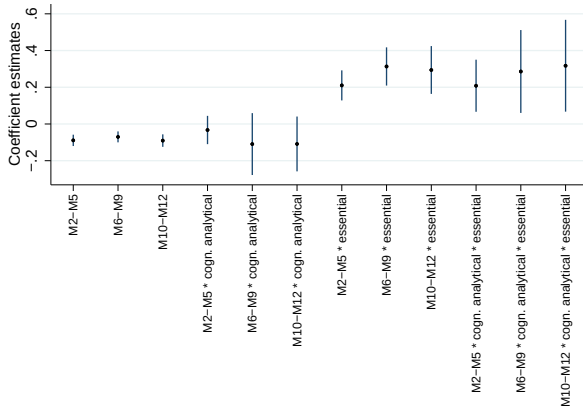
(c) Coordination



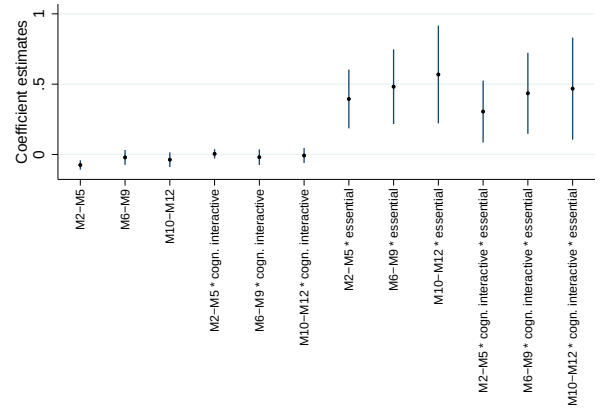
(d) Interaction

Notes: OLS estimations with standard errors clustered by occupation-state pair in all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The dependent variable is the share of online job postings in percentages. The dummy variables for the months of the first and second pandemic waves (M2–M5, M10–M12) and those between the two waves (M6–M9), whose coefficient estimates are displayed in the panels, are occupation-state-specific. The equations also include the original dummy variables and their interactions with pairs of occupational characteristics and individual occupational characteristics, but their coefficient estimates are not disclosed for the sake of exposition. The original and occupation-state-specific dummy variables, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs are also included in the equations.

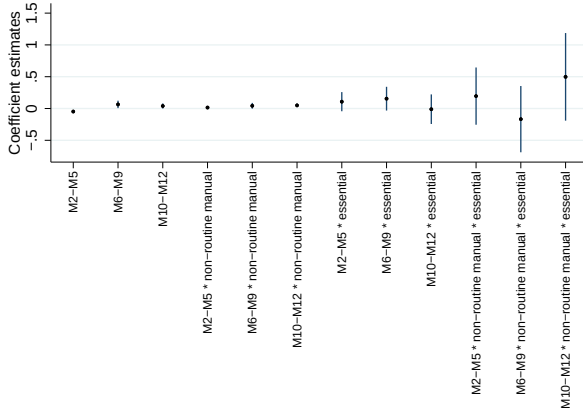
Figure C4: The joint role of essential and other tasks



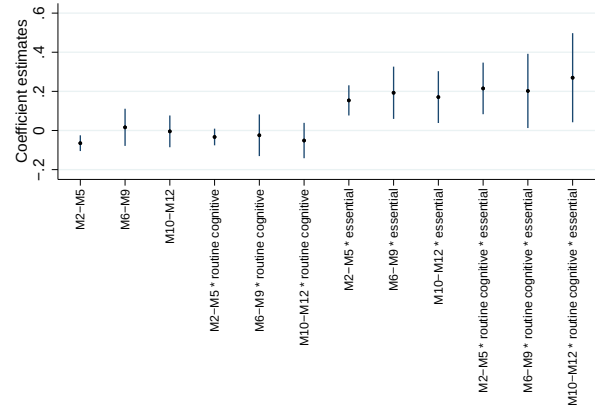
(a) Cognitive analytical



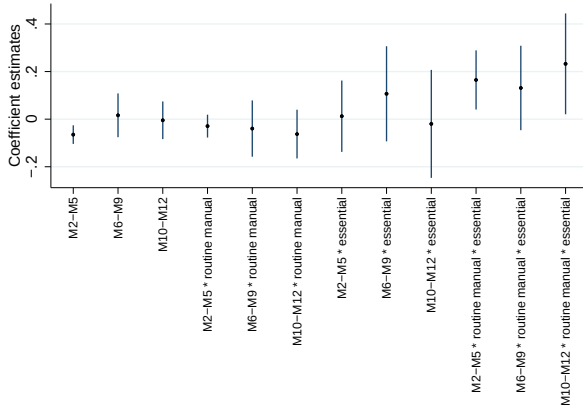
(b) Cognitive interactive



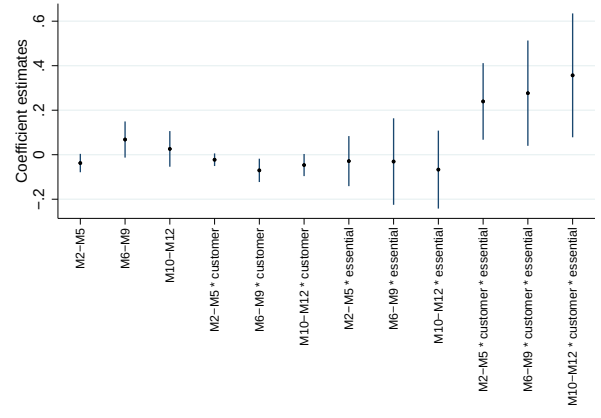
(c) Non-routine manual



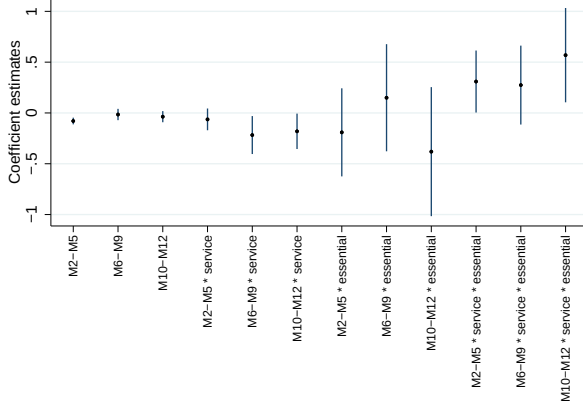
(d) Routine cognitive



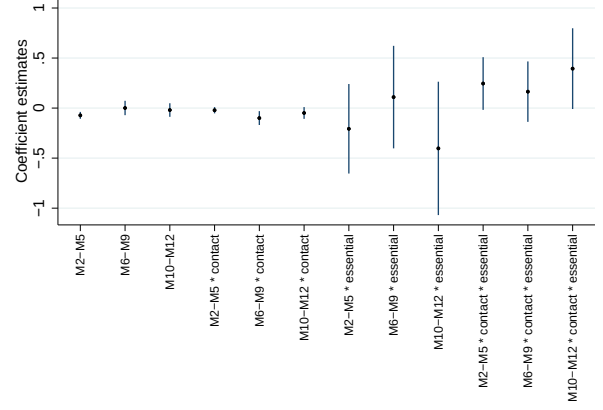
(e) Routine manual



(f) Customer-oriented



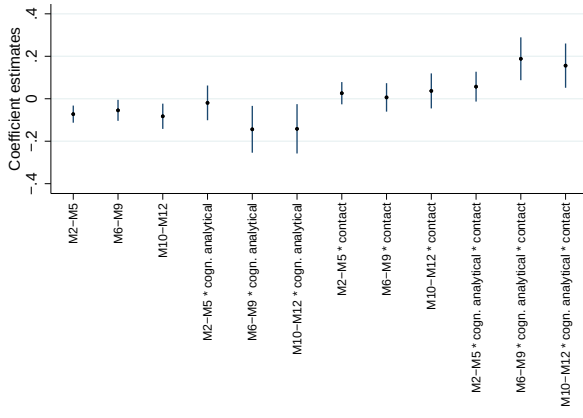
(g) Service-oriented



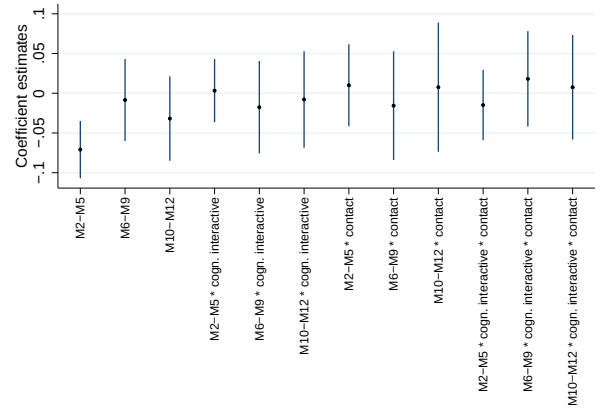
(h) Contact-intensive

Notes: OLS estimations with standard errors clustered by occupation-state pair in all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The dependent variable is the share of online job postings in percentages. The dummy variables for the months of the first and second pandemic waves (M2–M5, M10–M12) and those between the two waves (M6–M9), whose coefficient estimates are displayed in the panels, are occupation-state-specific. The equations also include the original dummy variables and their interactions with pairs of occupational characteristics and individual occupational characteristics, but their coefficient estimates are not disclosed for the sake of exposition. The original and occupation-state-specific dummy variables, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs are also included in the equations.

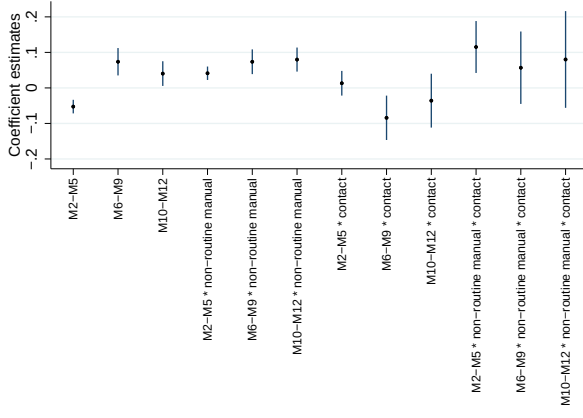
Figure C5: The joint role of contact-intensive and other tasks



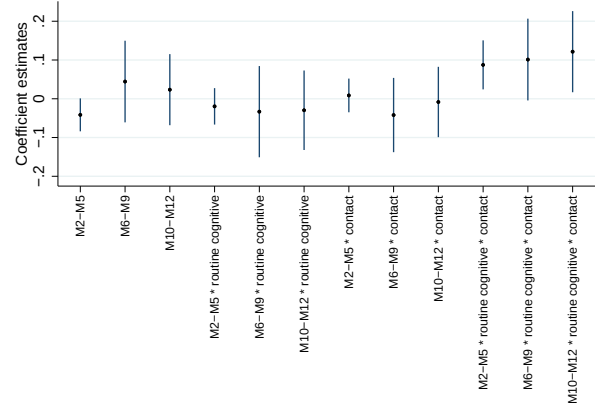
(a) Cognitive analytical



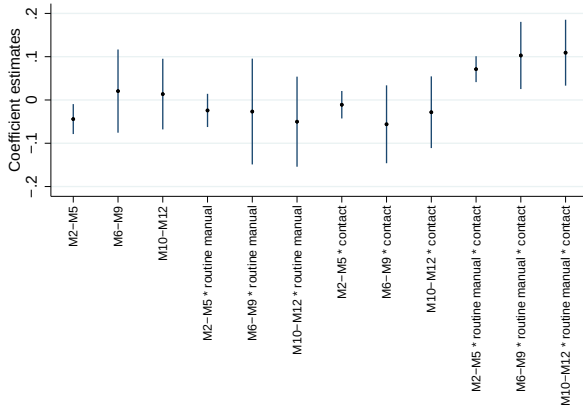
(b) Cognitive interactive



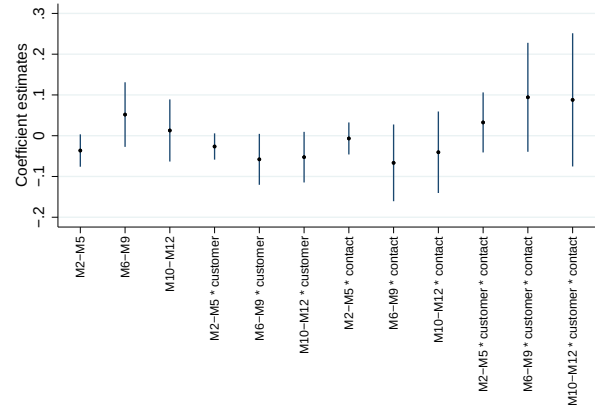
(c) Non-routine manual



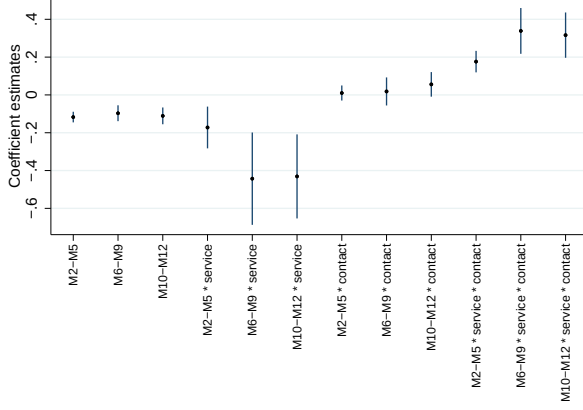
(d) Routine cognitive



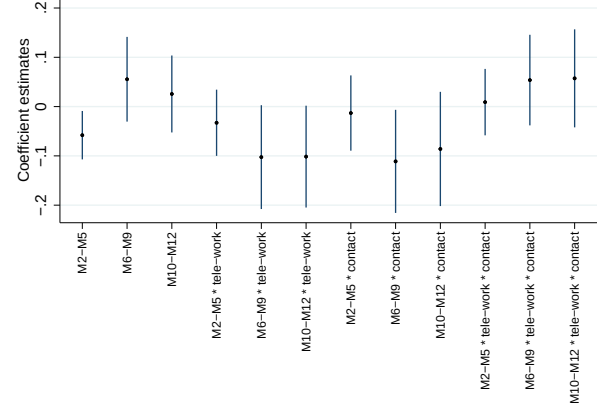
(e) Routine manual



(f) Customer-oriented



(g) Service-oriented



(h) Tele-work potential

Notes: OLS estimations with standard errors clustered by occupation-state pair in all panels. The equations are weighted by the employment level of each occupation-state pair in 2019. The dependent variable is the share of online job postings in percentages. The dummy variables for the months of the first and second pandemic waves (M2-M5, M10-M12) and those between the two waves (M6-M9), whose coefficient estimates are displayed in the panels, are occupation-state-specific. The equations also include the original dummy variables and their interactions with pairs of occupational characteristics and individual occupational characteristics, but their coefficient estimates are not disclosed for the sake of exposition. The original and occupation-state-specific dummy variables, and the variables for occupational characteristics have been standardised. Dummies for occupation-state pairs are also included in the equations.