Working from home after COVID-19: Evidence from job postings in 20 countries

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Abstract: We study the adoption of telework during and after the COVID-19 pandemic. We assemble a novel high-frequency database of job postings advertising work from home (telework) covering 20 countries and 55 occupational categories from January 2019 to September 2022, using data from the online job site Indeed. Exploiting changes in pandemic severity across countries and differences in the feasibility of telework across occupations in a triple differences identification strategy, we find that (i) increases in pandemic severity substantially raise advertised telework but (ii) declines have no effect on advertised telework. Even though technologies that enable effective telework – such as rapid broadband internet, file sharing via the cloud and video calls – had been available for many years, the pandemic may have triggered path dependence in its adoption. Public policies will need to adapt to make the most of permanently higher telework in terms of productivity and worker well-being.

JEL classification codes: D23, E24, J23, G18, M50

Keywords: remote working, telework, COVID-19, mobility restrictions, stringency index

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1. INTRODUCTION

The COVID-19 crisis has led to major changes in production and consumer preferences, including a shift to working from home (telework), with potentially important implications for productivity and worker well-being. In this paper, we study whether the increased move to telework during the pandemic signals a structural change or only reflects temporary adjustments by firms to mitigate COVID-induced disruptions.

To analyze the persistence of telework adoption, we assemble a unique dataset of firms' online job postings based on proprietary data from the job site *Indeed*. This dataset, which we make public and will update regularly[1], tracks the share of job postings advertising remote or telework across 55 different occupational categories (henceforth occupations) in 20 OECD countries, at monthly frequency and in near real-time. A key advantage of advertised telework relative to survey data on realized telework is that it is less susceptible to reflect the impact of ad-hoc work-from-home arrangements implemented to keep activity going during the crisis. Job postings represent an explicit commitment by firms to make telework available to the worker in the short to medium term and, as such, provide the best available measure of firms' expectations. By contrast, surveys do not carry any financial or organizational consequences for the surveyed manager. Moreover, another advantage of our data is that they range from January 2019 to September 2022, covering the entire pandemic period and the successive reopening of economies, and as such provide the best current basis for understanding the post-pandemic persistence of telework.

We start with a descriptive analysis of the data and find that the incidence of advertised telework almost quadrupled during the first two years of the pandemic, on average across countries. Importantly, however, there are large differences in the increase in advertised telework, across occupations and countries. To some extent, cross-country differences can be explained by differences in the degree to which governments restricted mobility in response to the pandemic. Differences across occupations are in turn to a great extent explained by differences in the organizational feasibility of telework, which we

[1] The dataset is available here hiringlab.org/remote-work.

measure using the classification of jobs into teleworkable and non-teleworkable of Dingel & Neiman (2020).

We then move on to formally analyze the role of the pandemic as a driver of the increase in advertised telework. To do so, we source two alternative indicators of pandemic severity – the Oxford COVID-19 Government Response Stringency Index and Google mobility data – and trace out the dynamic effects of a change in pandemic severity on the share of advertised telework over a six-month window. For the estimation, we combine the local projections method with a triple differences specification, where the treatment is given by the interaction between the change in the chosen pandemic severity indicator and the variable measuring the organizational feasibility of telework. The former captures country-time-level developments in the pandemic, while the latter serves as an occupation-level exposure variable that determines the intensity of the treatment. Where telework is not technically or organizationally feasible, pandemic severity should have no effect on its uptake.

The advantages of this triple differences (DDD) approach that exploits variation across countries, occupations and over time are three-fold. First, it allows us to control for unobserved country-time-specific shocks that may be correlated with changes in both pandemic severity and advertised telework by including country-by-time fixed effects.[2] Second, it mitigates potential reverse causality concerns. While the adoption of telework at the country-level may have an influence on pandemic severity, it is unlikely that differences in telework adoption across occupations influence country-wide developments in pandemic severity. Third, because our dependent variable measures changes in advertised telework at the country-occupation-level, we can disregard potential cross-country differences in the representativeness of different occupations in online job advertisements, which could lead to biased estimates if the analysis were carried out at the country-level.

Our results are unequivocal: we find that an increase in pandemic severity has large and persistent positive effects on the share of job postings that advertise telework. Depending on the specific indicator

[2] For instance, the seasonal pattern of telework may be correlated with the timing of government restrictions if government restrictions tend to be eased and the share of teleworkable job advertisements is systematically lower during the summer months.

to measure pandemic severity, a one standard deviation increase in pandemic severity leads to a 0.6 to 0.8 percentage point increase in the share of advertised telework in occupations with high feasibility of telework (those above the 67th percentile of the distribution of telework feasibility, for example marketing and software development occupations) relative to those with a low potential (those below the 33rd percentile, such as retail trade and hospitality occupations). By contrast, a decrease in pandemic severity of the same magnitude does not have any effect. Our findings are robust to a range of alternative specifications, the inclusion of control variables, and alternative inference mechanisms. We also present various pieces of evidence in support of the parallel trends assumption, including a placebo test on pre-pandemic data.

A limitation of our econometric approach, which controls for any country-time development, is that we estimate the differential effect of a change in pandemic severity across occupations with different telework potential, rather than its absolute effect. Hence, to get an idea of the overall effect of the pandemic on the level of advertised telework at the country-level, we perform a simple back-of-the-envelope calculation, combining the coefficients that we estimate with country shares of teleworkable jobs, as measured by Dingel & Neiman (2020). Under the assumption that the absolute effect of a change in pandemic severity is zero in occupations with no telework potential, we find that the pandemic might have increased the share of job postings advertising telework by about 6 percentage points in the average country.

Our interpretation of our key result that a decrease in pandemic severity does not reverse the prior increase in advertised telework is that the pandemic has permanently unlocked the potential for telework in occupations where such mode of working is feasible. This may be because the experience of telework has been positive or because firms have invested in IT infrastructure and digital skills (Barrero, Bloom & Davis, 2021). Even though technologies that enable effective telework – such as rapid broadband internet, file sharing via the cloud and video calls – had been available for a number of years, the pandemic was the type of historical accident that can lead to path dependence in the adoption of technologies (David, 1985) or organizational practices (Erickson and Kuruvilla, 1998; Schreyögg, Sydow and Holtmann, 2011). Such path dependence can arise because of learning-by-doing, irreversible investments or forced experimentation (David, 1985; Porter 1991; Larcom, Rauch and Willems, 2017; Arieli et al., 2020).

An alternative interpretation is that the easing of government restrictions and the associated increases in mobility are perceived as temporary, as firms might anticipate a future resurgence of the pandemic. While we cannot fully rule out this possibility, one major advantage of our dataset is that it covers the period after a significant share of the population in most advanced economies had been vaccinated, and any easing of mobility restrictions was likely to be perceived as more persistent than in the earlier stages of the pandemic. Our results show that even after the start of large-scale vaccination campaigns the easing of restrictions had no statistically significant effect on advertised telework, with advertised telework in September 2022 being close to its pandemic peak despite restrictions being at their lowest level since the start of the pandemic. This suggests that our findings are more consistent with the interpretation of path dependence than with the interpretation that the persistence of telework is driven by expectations that the pandemic will persist in the medium term and that restrictions on mobility will tighten again.

Our paper makes two main contributions to the understanding of the lasting economic effects of the pandemic and potential divergences across countries and sectors. First, we construct a unique telework dataset based on proprietary data from the near-universe of online job advertisements in 20 OECD countries collected by and posted on the job site Indeed. Using state-of-the-art text analysis algorithms, we identify postings that mention the possibility of telework in the title, description or location, and we construct a variable measuring the share of job postings advertising telework. We will make this dataset publicly available and aim to provide regular updates, which will allow monitoring the evolution of telework in the near to medium term.

To the best of our knowledge, we are the first to measure the adoption of telework in OECD countries through firms' job postings. Most existing literature relies either on measures of telework feasibility (Dingel and Neiman, 2020; Alipour et al 2020) or intentions (e.g. Aksoy et al. 2022, Barrero et al 2021; Criscuolo et al 2021) rather than actually observed telework, as we do in this paper. Surveys (e.g. Bartik et el, 2020; Adams-Prassl et al, 2020) are able to capture realized telework, but typically are available only for single countries. Even more importantly, survey measures of telework adoption may fluctuate around recurring pandemic waves, reflecting ad-hoc arrangements implemented during the pandemic. Instead, job postings mentioning telework represent an explicit commitment by the firm to make telework available to the worker and as such capture expectations about its adoption at least in the medium term.

Two exceptions in the growing telework literature are the studies by Bamieh and Ziegler (2022) and Hu et al. (2021), who use data from two online job portals in Austria and China, respectively, to study the evolution of telework over time in those countries. Our cross-country and cross-occupation setting allows us to estimate the impact of the pandemic in a credible way. Besides the two studies mentioned above, job vacancy data is also used in others, including Azar et al. (2022) and Hershbein and Kahn (2018), but this earlier literature does not focus on telework.

Our second contribution is to formally analyze the role of the pandemic in the adoption of telework across many advanced economies. We are able to do so thanks to the richness of our vacancy dataset. First, the availability of information on telework at the country-occupation-time-level allows us to exploit differences in the intensity and timing of the pandemic and differences in policy responses, as well as the fact that advertised telework should not respond to country-wide mobility restrictions uniformly across occupations, reflecting heterogeneity in technological and organizational feasibility of telework. Second, since our data is at the monthly frequency and spans the period up to the spring of 2022, our analysis covers the adoption of lockdowns and other mobility restrictions as well as the gradual easing of restrictions and return to mobility as the pandemic receded.

The remainder of the paper is structured as follows. Section 2 describes the data and methodology and briefly discusses the key stylized facts. Section 3 formally conducts the analysis and Section 4 concludes.

2. DATA AND METHODOLOGY

Our sample covers 20 OECD countries (Australia, Austria, Belgium, Canada, France, Germany, Ireland, Israel, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Poland, Spain, Sweden, Switzerland, United Kingdom and the United States) and spans the period from January 2019 through September 2022. In the rest of this section, we describe the data used in the analysis in more detail, briefly review a couple of key stylized facts regarding the evolution of advertised telework during the COVID-19 pandemic and explain the empirical framework.

2.1. DATA

We construct job postings data using proprietary information contained on the online job site Indeed. Indeed features job advertisements posted directly on its proprietary website as well as thousands of online job boards, career sites and recruiter listings, thus covering the near-universe of online job postings in the countries covered in the analysis. Indeed de-duplicates job offers so that when the same job is collected from multiple sources it is shown only once. However, despite the de-duplication process, online job postings data does not reflect a precise number of available jobs, as an opening may not be advertised online at all or one posting may reflect multiple openings. For instance, Hershbein and Kahn (2018) show that high skilled occupations tend to be overrepresented in online vacancies in the United States. However, the potential overrepresentation of certain occupations in online job postings is likely to have become less relevant in our sample period as the popularity of online job postings has increased over time. Moreover, as it will become clearer further below, representativeness is not an issue in our empirical set-up since we carry out the analysis at the country-occupation-time level, and thus we do not use information on the weights of the different occupation categories in overall postings.

We start by extracting key information from the postings, such as job title, posting date and other keywords, using state-of-the-art text analysis algorithms. This allows us to (i) divide job postings in 55 unique occupation categories, and (ii) check whether the advertisement explicitly mentions the possibility to telework in the title, description or location. Annex Table A.1 lists the 55 occupations, while Annex Table A.2 contains the list of keywords that we use to identify teleworkable jobs. Because advertisements directed to high-skilled workers usually contain more detailed information on the job offered than those directed to lower-skilled workers, we are able to classify them at a relatively finer level of disaggregation. For instance, we divide engineering jobs into chemical, civil, electrical, industrial, and mechanical engineering, while all manufacturing and production jobs are in the same occupation category.

We exclude from the sample several healthcare occupations, which we consider to be an outlier during the pandemic: (i) physicians and surgeons, (ii) medical technicians, (iii) pharmacists as well as (iv) nursing and dental occupations. The results would be virtually unchanged if these occupations were included in the sample (see Section 3.2). We then construct two variables: (1) the total number of postings and (2) the share of postings that explicitly mention the possibility of teleworking in the title, description or location at the country-occupation-month-level.[3]

We complement the dataset by sourcing variables that measure the severity of the pandemic from different points of view. Our main aim is to measure how the pandemic has affected mobility, which in turn we expect to impact the adoption of telework. We source the stringency index from the Oxford COVID-19 Government Response Tracker from Hale et al. (2021) to measure the extent of government-imposed restrictions, which we expect to have a direct effect on mobility.[4] For a robustness check exercise, from the same source we also retrieve the government response index, which tracks both restrictions to mobility and health mandates (such as obligation to get vaccines and wear facial coverings). We also consider mobility outcomes and construct a mobility variable as the average of three Google mobility indicators, measuring the frequency of people's visits to (i) shops, restaurants as well as to cultural and entertainment venues, (ii) the workplace, and (iii) transit and transportation hubs (sourced from Google COVID-19 Community Mobility Reports).[5] We think about this variable as summing up the joint effects of explicit government restrictions and voluntary changes in behavior

[3] The overall number of postings is seasonally adjusted, but the share of job postings advertising telework is not. In constructing the share of job postings advertising telework, neither the numerator (the number of job postings advertising telework) nor the denominator (the overall number of job postings) is seasonally adjusted.

[4] The Oxford COVID-19 stringency index is the weighted mean of different sub-indexes measuring the intensity of (i) school closures, (ii) workplace closures, (iii) restrictions to public events, (iv) restrictions to gatherings, (v) closure of public transport, (vi) stay at home requirements, (vii) restrictions to internal movements, (iix) controls to international travel, and (ix) public information campaigns on a 0-100 scale. When restrictions apply uniformly across the country, the different sub-indexes receive equal weights. If instead some restrictions are different across states/regions, the respective sub-index codes the intensity of the restriction in the most restricted region/state but gets a lower weight in the overall index.

[5] Different from the Oxford COVID-19 stringency index, Google mobility data take into account all the different trends at the subnational level by averaging across different metropolitan areas within a country. They are available at the daily frequency and measure percent changes in mobility relative to a baseline consisting of the median value, for the corresponding day of the week, during the 5-week period 3 Jan-6 Feb 2020.

on mobility. Finally, to control for the severity of the pandemic in terms of health outcomes, we opt for the incidence of COVID-19 mortality (official COVID-19 fatalities per 100,000 people, sourced from Hale et al., 2021). All these variables are available at the country-month level.

The dataset is completed with a country- and time-invariant variable measuring the organizational feasibility of telework (telework potential) in each occupation, which we use as a treatment intensity variable to identify the effect of the pandemic on advertised telework across the different occupations. We construct this variable borrowing the classification of jobs into teleworkable and non-teleworkable ones developed by Dingel & Neiman (2020).[6] These authors classify each U.S. O*NET occupation into teleworkable or non-teleworkable based on whether they can be carried out entirely at home. To derive an occupation-level measure of teleworkability, we first aggregate O*NET occupations at the U.S. Standard Occupational Classification (SOC)-level. We then match each SOC occupation to one of the 55 Indeed job categories. Next, we assign each of the 55 job categories to a teleworkability score by aggregating the teleworkability scores of SOC occupations using employment shares of each SOC occupation within the given job category as weights. This exercise uncovers great heterogeneity in the organizational feasibility of telework in the different occupations. For instance, in the insurance and legal occupations over 90% of jobs can be done from home, whereas in the therapy and customer service occupations the same share ranged between 20% and 40%. Exact values for the organizational feasibility of telework of each occupation are given in Annex Table A.1.

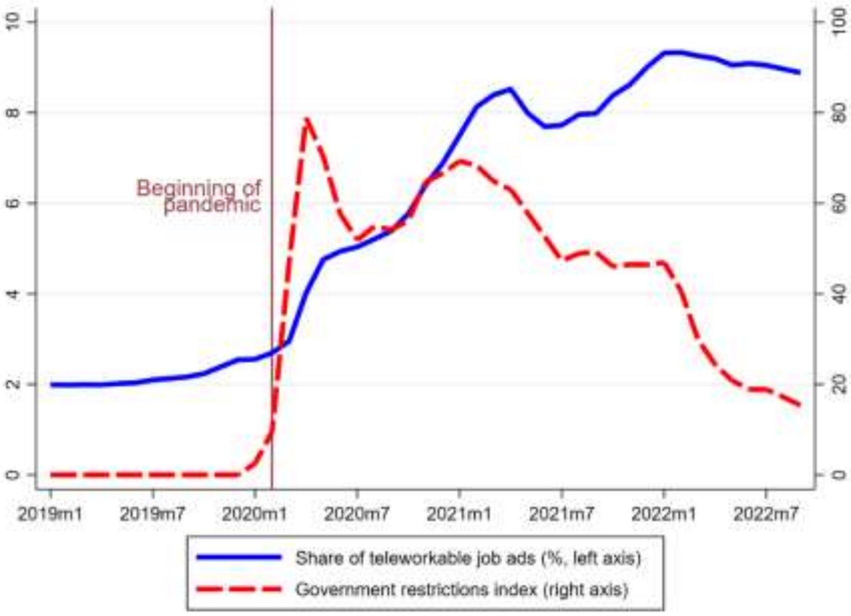
2.2. STYLIZED FACTS

Here we take a first look at the data, starting with the share of job ads advertising telework in the average country covered by the analysis. This increased by almost four times in the two years since the onset of the pandemic, to about 9½ percent in February 2022 (Figure 1). Pandemic severity, measured in terms of government restrictions and proxied by the Oxford COVID-19 stringency index (also shown in Figure 1), seems to have been a catalyst of the increase in the share of job ads mentioning telework in

[6] See Chen (2020) for a similar approach.

the first period of the pandemic, but advertised telework continued to grow almost uninterruptedly, including after periods of easing pandemic severity.

Figure 1. Share of job postings advertising telework and government restrictions, average country

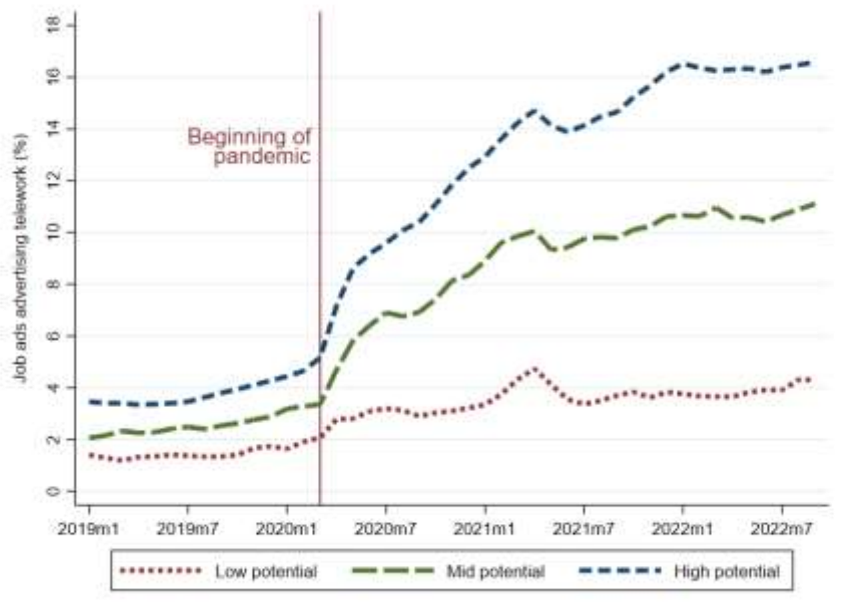


Note: The figure plots the average values of country shares of job postings advertising telework and of the Oxford COVID-19 Government Response Stringency Index across countries. Country shares of job postings advertising telework are obtained by aggregating over the different occupations using their shares in a country's overall job postings as weights. The vertical solid line denotes the beginning of the pandemic (February 2020).
Source: Own calculations based on Hale et al. (2021) and Indeed data.

We also explore the relationship between pandemic severity and the increase in advertised telework across countries. As expected, we find a positive, albeit not very tight, correlation between the two, with cross-country differences in government restrictions explaining about a fourth of the cross-country pattern in the increase of advertised telework during the early pandemic stages and about a sixth during the full pandemic sample (Annex Figure A.1).

Next, in Figure 2, we plot the share of job postings advertising telework distinguishing among occupations with a low, medium, and high potential to telework (respectively those in the lowest, mid, and upper terciles of the distribution of the variable measuring the organizational feasibility of telework). This leads us to our key stylized fact: COVID-19 opened up large differences in the share of advertised telework across occupations with different telework potential. While differences in advertised telework across occupations were limited to a few percentage points before the pandemic, these differences had increased up to over 12 percentage points between occupations with low and high telework potential by mid-2022. Moreover, after growing across most occupations up to April 2021, advertised telework then started to decline and stabilized at low levels in occupations with low telework potential while it maintained its upward trend in mid and particularly high-potential occupations. These different trends suggest that the increase in telework in occupations where feasibility is low may have been a transitory response to the pandemic, while the increase in occupations where telework is more feasible may represent a more structural change. Finally, we note that the share of advertised telework did not decline in any of the occupation categories during 2022. This is different from the country-level development depicted in Figure 1, where we observe a slight decrease, suggesting that the composition of job postings increasingly shifted to occupations with low potential to telework.

Figure 2. Share of job postings advertising telework in occupations with different telework potential



Note: The figure plots developments in the share of job postings advertising telework in occupations in the lower, mid, and upper terciles of the variable measuring telework potential. Statistics refer to the average occupation in each tercile and the average country in the sample. The vertical solid line denotes the beginning of the pandemic (February 2020).
Source: Own calculations based on Dingel & Neiman (2020) and Indeed data.

The current level of advertised telework suggests a large gap with the share of jobs that can be done (and were done) from home at the peak of the pandemic, both estimated at around 40-50% in high-income countries (see Bloom, 2020 and Dingel & Neiman, 2020 respectively). What can explain this gap? One reason may be that some employers are reluctant to advertise a job as teleworkable because this could be seen as a medium-term commitment to telework, lasting beyond the pandemic. In this sense, changes in advertised telework may signal a structural re-organization of work, rather than short-term shifts in and out of telework in response to lockdowns. Another possible reason is that the optimal level of telework might not fully exploit its technological feasibility, but rather settle at an intermediate state between workers being physically present at the workplace and working from home (Criscuolo et. al, 2021).

2.3. EMPIRICAL FRAMEWORK

Our empirical framework combines the local projections method and a triple difference (DDD) regression specification to trace out the causal effects of the pandemic shock on the share of job postings advertising telework over a 6-month window.

We start by describing the local projections method, which was pioneered by Jordà (2005) and has been widely used as a flexible alternative to autoregressive distributed lag specifications (Auerbach & Gorodnichenko 2012; Romer & Romer, 2017; Ramey & Zubairy, 2018). It consists of directly obtaining the response of the dependent variable at horizon $t+k$ to the treatment at time t by estimating a different regression specification for each horizon considered. Impulse response functions (IRFs) are then constructed by plotting the estimated coefficients as point estimates and their standard errors as confidence bands.

To recover the causal effect of the pandemic on advertised telework, we use telework potential as an exposure variable that determines the intensity of the pandemic treatment across different occupations. To do so, we interact changes in the chosen pandemic severity indicator, which varies across countries and over time but not across occupations, with the organizational feasibility of telework, which is predetermined and only varies at the occupation-level. The rationale underpinning this identification is that we expect the pandemic to have larger effects on advertised telework in occupations in which telework is more feasible.

Our main aim is to assess whether telework will revert to its-pandemic trend once the pandemic is under control. For this reason, we separately analyze the effects of a tightening and an easing of pandemic severity on the share of job postings advertising telework. Specifically, we estimate the following regression model:

$$y_{i,j,t+k} - y_{i,j,t-1} = \mu_{i,j} + \beta^{p,k} x_{i,t}^{p} * p_j + \beta^{n,k} x_{i,t}^{n} * p_j + \qquad (1)$$

$$+ \sum_{f=1}^{k} \left(\varphi^{p,f} x_{i,t+f}^{p} * p_j + \varphi^{n,f} x_{i,t+f}^{n} * p_j\right) + \sum_{l=1}^{2} (\sigma^{p,l} x_{i,t-l}^{p} * p_j + \sigma^{n,l} x_{i,t-l}^{n} * p_j) + \tau_{i,t} + \varepsilon_{i,j,t}$$

where the subscripts *i*, *j* and *t* indicate country, occupation and time respectively, $y_{i,j,t}$ is the share of job ads advertising telework in occupation *j* of country *i* at time *t*, $\mu_{i,j}$ are country-occupation fixed effects, $x_{i,t}^{p}$ and $x_{i,t}^{n}$ respectively denote positive and negative changes in pandemic severity (measured either through the government stringency index of Oxford COVID-19 Government Response Tracker or Google mobility data), p_j is the variable measuring potential to telework (the share of jobs in occupation *j* that can be done from home), $\tau_{i,t}$ are country-by-time effects and $\varepsilon_{i,j,t}$ is an error term.

The regression model is made dynamically complete by including forward and backward shocks. Forward shock variables, $\sum_{f=1}^{k}(\varphi^{p,f} x_{i,t+f}^{p} * p_j + \varphi^{n,f} x_{i,t+f}^{n} * p_j)$, control for changes in pandemic severity that take place in between *t* and *t*+*k* and the omission of which could bias the estimates of a shock at *t* itself if changes in the policy shock are autocorrelated (Teulings & Zubanov, 2014). For the same reason, we also add two lags of the shock variables, $\sum_{l=1}^{2}(\sigma^{p,l} x_{i,t-l}^{p} * p_j + \sigma^{n,l} x_{i,t-l}^{n} * p_j)$.

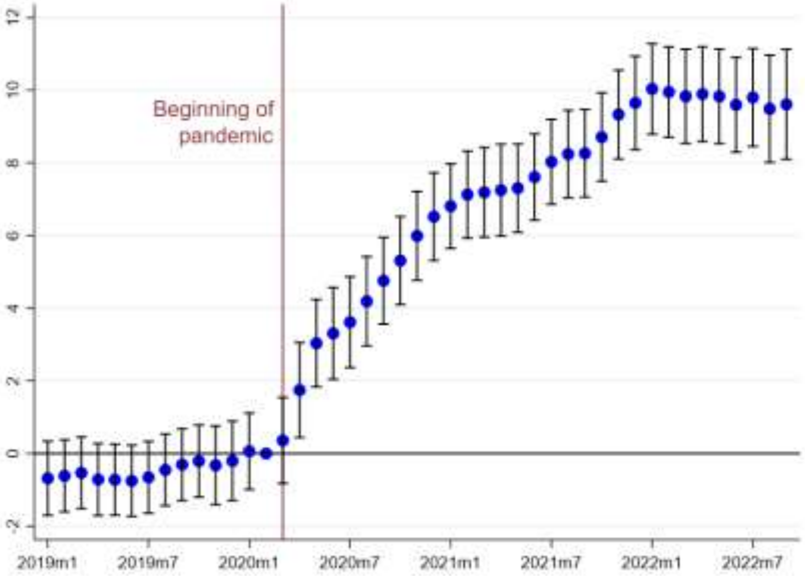
Coefficients are estimated through OLS with Driscoll-Kraay standard errors, which are robust to general forms of spatial and temporal dependence.[7]

In practice, our regression set-up uses occupations with low telework potential as reference group to assess what the evolution of advertised telework in high telework potential occupations would have been in absence of the pandemic. Since country-occupation fixed effects in our difference model control for linear time trends in each occupation, our identifying assumption only requires that telework in high vs. low potential occupations would have followed stable (linear) counterfactual trends in the absence of the pandemic. Visual inspection of the data (Figure 2) suggests that, not only this stable trend assumption holds for the pre-pandemic period, but also that these pre-trends were very similar across high and low telework potential occupations. This would satisfy the parallel trend assumption, which is an even stronger assumption than what we need for identification. We formally verify that the pre-trends were parallel in Figure 3, where we plot estimates of the differences in the level of advertised telework in occupations with high versus low telework potential over time.[8]

[7] The results are robust to using different lag structures and to not include forward shock variables. The statistical significance of the results does not change if two-way (country and time) clustered standard errors instead of Driscoll-Kraay (see Section 3.2).

[8] The specific test that we run is the following. First, we take the sample of occupations with a high and a low telework potential and estimate the following equation: $y_{i,j,t} = \alpha + t_t + t_t * d_j + \mu_i + \mu_j + \varepsilon_{i,j,t}$ where $y_{i,j,t}$ denotes the share of advertised telework in country *i* and occupation *j* at time *t*; t are time fixed effects, d_j is a dummy variable that takes value 1 for occupations with a high potential to telework and 0 for those with a low potential and μ_i and μ_j are respectively country and occupation fixed effects. Figure 3 reports the estimated t coefficients, with February 2020 set as reference point (hence t is 0 for that month). The t coefficients are all statistically indistinguishable from 0 in the pre-pandemic period, pointing to the absence of statistically significant differences in trends of advertised telework among occupations with low and high telework potential. This is formally confirmed through an F-test (p=0.84).

Figure 3. Difference in advertised telework between high and low telework potential occupations



Note: The figure plots estimated developments in the difference in share of job postings advertising telework between occupations with a high and a low telework potential, defined as those in the upper and lower tercile of the variable measuring telework potential. Estimates are obtained estimating the following regression: $y_{i,j,t} = \alpha + \gamma^t \tau_t + \delta^t \tau_t * d_j + \mu_i + \mu_j + \varepsilon_{i,j,t}$, where $y_{i,j,t}$ denotes the share of advertised telework in country *i* and occupation *j* at time *t*; τ_t are time fixed effects, d_j is a dummy variable that takes value 1 for occupations with a high potential to telework and 0 for those with a low potential and μ_i and μ_j are respectively country and occupation fixed effects. Difference as of February 2020 is taken as the reference point. Whiskers are 90% confidence intervals.
Source: Own calculations based on Dingel & Neiman (2020) and Indeed data.

A key advantage of our triple differences approach is that it lets us include country-by-time fixed effects that control for any unobservable country-specific development that may affect the level of advertised telework uniformly across occupations (and which may correlate with the change in pandemic severity). But there are also two other important advantages. First, reverse causality concerns are greatly mitigated, since reverse causality in our set-up would imply that developments in advertised telework in certain occupations influenced country-level developments during the pandemic. Second, carrying out the analysis at the country-occupation-time-level allows disregarding potential issues with cross-country variation of the representativeness of certain occupations in online job postings. The flipside of our approach is that the inclusion of country-time fixed effects absorbs the average effect of changes in pandemic severity so that our coefficients of interest, $\beta^{\boldsymbol{p,k}}$ and $\beta^{\boldsymbol{n,k}}$, measure the differential effects of such changes across occupations.

To ease interpretation, we standardize the $\beta^{\boldsymbol{p,k}}$ and $\beta^{\boldsymbol{n,k}}$ coefficients to report the differential effect of a one standard deviation change in pandemic severity between occupations with high and low telework potential (measured as the average occupation in the upper and lower terciles of the variable capturing telework potential, p_j). We derive IRFs plotting the $\beta^{\boldsymbol{p},\boldsymbol{k}}$ and $\beta^{\boldsymbol{n},\boldsymbol{k}}$ coefficients for the point estimate (blue solid lines) and 1.6 standard errors for 90% confidence bands (red dashed lines).

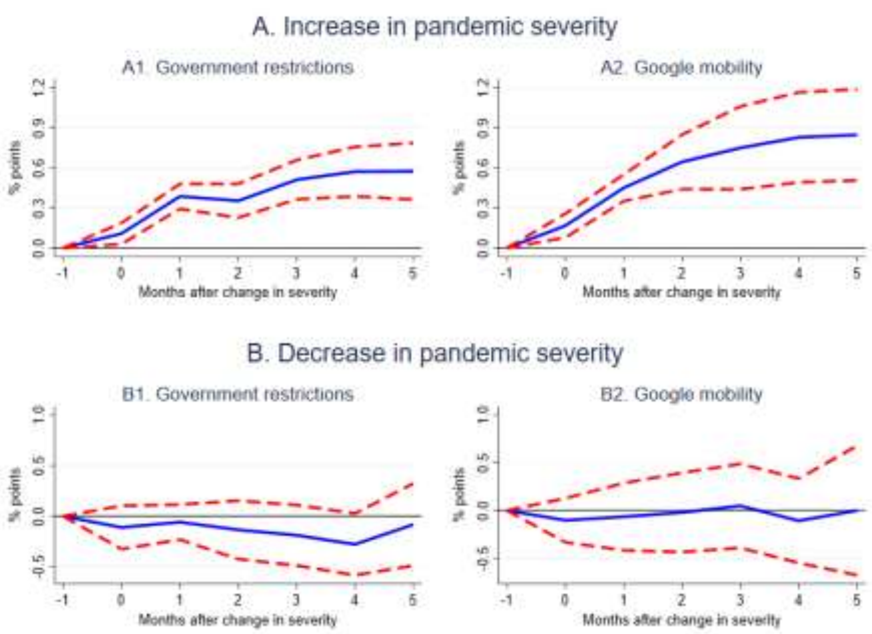
3. RESULTS

3.1. MAIN RESULTS

Figure 4 shows the results. The two top panels report the effects of an increase in pandemic severity on the share of job postings advertising telework over a six-month window (the month of the change in pandemic severity and the 5 following ones), estimated using the different indicators of pandemic severity – the government restrictions index of the Oxford COVID-19 Government Response Tracker (Panel A1) and Google mobility (Panel A2). Similarly, the two lower panels (Panels B1-B2) report the effects of a decrease in pandemic severity estimated using the two different indicators.

Regardless of the measure, we find that an increase in pandemic severity has important positive effects on the share of job postings advertising telework. These effects are large and statistically significant already at impact, increase over the horizon considered and stabilize around 4 to 5 months after the shock. Quantitatively, we estimate that a one standard deviation worsening in pandemic severity raises the share of job postings advertising telework in the average occupation with high telework potential by about 0.6 to 0.8 percentage points relative to the average occupation with low potential over the medium-term, depending on whether we use the government restrictions index (0.6) or Google Mobility (0.8) as pandemic severity indicator. By contrast, we estimate flat responses to an easing in pandemic severity, both when we use government restrictions and when we rely on mobility to measure severity, implying that an easing in pandemic severity does not have any differential effect on advertised telework across occupations.

Figure 4. Differential effects of changes in pandemic severity on advertised telework between high and low telework potential occupations



Note: The figure reports impulse response functions showing the cumulative differential effects of a one standard deviation change in pandemic severity on the share of job postings advertising telework in the average occupation with a high telework potential relative to the average occupation with low telework potential (respectively defined as occupations in the upper and lower terciles of the telework potential distribution), over a 6-month window. Panels A1 and A2 report the effect of a positive change (increase in severity), estimated using the Oxford COVID-19 Stringency Index and Google mobility data to measure pandemic severity. Panels B1 and B2 similarly report the effect of a negative change (decrease in severity). Y-axes report the magnitude of the estimated effects, while x-axes report the horizon of the response. Blue solid lines denote point estimates, while red dashed lines are 90% confidence bands. Estimates are obtained estimating Equation 1.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data.

Taken together, our estimates suggest that changes in advertised telework are highly persistent, in the sense that advertised telework has been catalysed by the pandemic but does not revert to its previous level even when pandemic severity eases. In other words, the pandemic appears to have unlocked the potential to telework in occupations where telework is actually feasible. This could reflect irreversible investments in digital infrastructure, changes in management and learning on the part of businesses and/or permanently higher demand for telework on the part of workers. Even though technologies that enable effective telework – such as rapid broadband internet, file sharing via the cloud and video calls – had been available for a number of years, the pandemic was the type of historical accident that can lead to path dependence in the presence of irreversible investments or learning-by-doing (David, 1985), which could have led to a more productive use of telework than expected at the beginning of the pandemic (OECD, 2020). Other possible mechanisms behind path dependence are forced experimentation triggered by the pandemic lockdowns. This is similar to the London underground closure examined by Larcom, Rauch and Willems (2017), which caused some workers and firms to update their priors on the costs and benefits of working from home, even if those costs and benefits did not change over time. Finally, since the benefits of the use and adoption of many innovations partly depend on how many others are using the technology, the coordinated and massive use of telework during the government-mandated lockdowns could have changed the network externalities from the use of telework and shifted the collective organization of work to a new equilibrium (see Arieli et al., 2020 for a theoretical model of such innovation diffusion in networks), explaining the persistence of telework.

3.2. ROBUSTNESS CHECKS AND ALTERNATIVE SPECIFICATIONS

In this section, we run some sensitivity analyses to assess the robustness of our results. We start by verifying that the different effects that we estimate for a worsening and an improvement in pandemic severity (strong positive response to a worsening and flat response to an improvement) are statistically different from each other at standard confidence levels. Annex Table A.3 reports the point estimates and confidence levels for the effects that we estimate, together with the results of a Wald test testing the null hypothesis that the $\beta^{p,k}$ and $\beta^{n,k}$ coefficients are equal, separately for each month of the horizon considered. The effects that we estimate are statistically different from each other at all horizons except impact, regardless of the pandemic severity indicator used.

Next, we estimate alternative specifications. We start by checking the robustness of our baseline estimates to different lag specifications and estimate three alternative specifications where, in turn, (i) we include four rather than two lags of the explanatory variables, (ii) we do not include forward shock variables, and (iii) we include two lags of the one-period change in advertised telework. Point estimates from these alternative specifications are shown in Annex Figure A.2, together with baseline estimates and baseline confidence bands. All the new estimates fall within our baseline confidence bands, indicating that our results do not depend on the lag structure used. Next, we estimate an alternative specification in which we rely on two-way clustered (country and time) rather than Driscoll-Kraay standard errors to obtain 90% confidence bands (Annex Figure A.3). The new confidence bands are slightly larger than our baseline, but the results are still highly statistically significant.

We also estimate an alternative specification in which we additionally control for the severity of the pandemic in terms of health outcomes (both contemporaneous and lagged), measured through the incidence of COVID-19 fatalities and one in which we also include health care occupations in the sample. Estimates from these alternative specifications, shown in Annex Figure A.4, are close to and not statistically different from our baseline. As additional exercise, we estimate Equation (1) using the incidence of COVID-19 fatalities as the main pandemic severity indicator, rather than as a control variable. We do so to check that our results are robust to using a pandemic severity indicator that does not focus on mobility. The new results confirm our baseline findings: an increase in pandemic severity substantially raises advertised telework in occupations where this is feasible, while a decrease does not undo the prior increase (Annex Figure A.5).

Next, we control the sensitivity of our results to the specific measure of pandemic severity used in the model. Particularly, we use the government response index, which also accounts for health mandates, instead of the stringency index and the frequency of visits to workplaces and visits to entertainment venues, as alternative measures of mobility. Point estimates from these alternative specifications are close to and not statistically different from our baseline (Annex Figure A.6).

One potential concern with our results could be that they might reflect unobserved trends in telework across occupations at the sub-national level, which would not be captured by our country-time fixed effects, and not be detected using our test for whether pre-trends are parallel on average. Such trends, for example, could arise from seasonality in telework intensity that differs across sectors, or from country-specific trends in high and low telework potential occupations; and they could become problematic if they systematically correlated with exposure to changes in pandemic severity. To test for such potential spurious correlation, we conduct a placebo test in which we regress the observed changes in telework *before* the pandemic on 12-month *future* changes in pandemic severity (essentially shifting back the pandemic by one year into the past). The results from this placebo, shown in Annex Figure A.7, are generally flat and not statistically significant.

Finally, another potential concern with our results could be that the lack of a response to an easing of pandemic severity is because employers expect the pandemic to worsen again in the future. It is close to impossible to rule out this explanation completely but we try to address this concern by estimating the effect of an easing of pandemic severity before and after the start of the vaccination campaign, which may have had an impact on the expectations about the future unfolding of the pandemic.[9] The results, shown in Annex Figure A.8, are very similar to our baseline: regardless of whether we consider the period before or after the start of the vaccination campaign, we find that an easing of pandemic severity does not have any differential effect on advertised telework.

3.3. IMPLICATIONS FOR THE INCREASE IN TELEWORK ACROSS COUNTRIES

Our results suggest that the pandemic may have permanently unlocked the potential to telework in occupations where telework is actually feasible. But what does this imply for the evolution of telework across countries? First, just because the pandemic unfolded differently across countries – in some it constituted a bigger shock than in others – we should expect advertised telework to have increased more in countries which were hit the most by COVID-19, other things equal. Second, since countries differ substantially in terms of telework potential, given the same pandemic shock, telework is likely to have increased more in those with higher potential. To get an idea of how differently the pandemic impacted telework across countries, we perform a simple back-of-the-envelope calculation, using (i) our occupation-level impulse-response coefficients, (ii) the country-level overall increase in pandemic severity, as well as (iii) country shares of jobs that can be done from home, calculated by Dingel & Neiman (2020).[10]

Under some conservative assumptions, we calculate that the pandemic may have increased the share of job postings advertising telework by about 6 percentage points in the average country. Looking across

[9] The start of the vaccination campaign is country-specific. Since the start of the vaccination campaign has been slow in most countries, we define the start of the vaccination campaign to be the month in which the total number of vaccine doses per 100 inhabitants surpassed 10.

[10] Relative to simply looking at changes in the share of teleworkable job postings over the pandemic, our approach has three advantages. First, it corrects for pre-pandemic trends. Second, it only captures the increase in telework directly attributable to the pandemic. Third, it provides comparable estimates across countries. This is important because the representativeness of certain occupations in online job postings may differ across countries. For instance, imagine two countries that have the same labor market structure, but in which occupations with a high telework potential are overrepresented in the first one and underrepresented in the second one. One would observe a larger increase in the share of teleworkable job postings in the first country than in second as a response to the same pandemic shock just because occupations with a high telework potential are overrepresented in the first country. A drawback of our approach is that we lose five countries, for which data on telework potential is not available: Australia, Canada, Israel, Japan, and New Zealand.

countries, the increase in advertised telework as a result of the pandemic may range between 3 percentage points in Mexico and about 10 percentage points in Luxembourg. The low increase in Mexico is even though the pandemic, as measured by our indicators, was more severe there than in several other countries. Hence, the small increase in advertised telework can be mainly attributed to its low share of teleworkable jobs (22 percent, according to Dingel & Neiman, 2020). By contrast, the large increase in Luxembourg is due to a combination of the pandemic being quite severe and the share of teleworkable jobs being high in Luxembourg (over 60 percent).

Table 1. The share of job postings advertising telework across countries

	Predicted increase relative to the U.S. due to the pandemic (ratio, back-of-the-envelope calculation)	Predicted increase due to the pandemic (% points, back-of-the-envelope calculation)	Level in 2019 (% points, Indeed vacancies)
Mexico	0.7	2.9	0.6
U.S.	//	4.1	2.8
Spain	1.1	4.7	2.8
Germany	1.2	5.1	3.3
Sweden	1.2	5.1	1.4
Italy	1.3	5.2	1.2
Poland	1.3	5.4	5.4
U.K.	1.4	5.8	2.8
Switzerland	1.5	6.2	1.9
Austria	1.6	6.4	3.1
Ireland	1.6	6.5	2.6
Belgium	1.6	6.6	1
Netherlands	1.6	6.6	1.1
France	1.6	6.6	1.5
Luxembourg	2.3	9.5	1.6
Average	1.4	5.8	2.2

Note: The table reports predicted increases in country shares of job postings advertising telework over the March 2020 to September 2022 that was directly due to the pandemic. Values are obtained from the back-of-the-envelope calculation illustrated in Annex B. Values for Australia, Canada, Israel, Japan and New Zealand are not available due to lack of data on country shares of jobs that can be done from home (Dingel & Neiman, 2020).
Sources: own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data

Table 1 reports the predicted increase in the share of job postings advertising telework attributable to the pandemic in each country, as calculated through our back-of-the-envelope calculation, as well as the share of remote job postings in overall Indeed online before the pandemic, as a reference point. The almost 6 percentage point increase in the share of remote job postings in the average country means that the pandemic may have more than tripled the share of advertised telework in job postings (from a little more than 2 percentage points before the pandemic).[11] Annex B provides more details regarding the back-of-the-envelope calculation.

4. CONCLUSION

In this paper, we document a substantial increase in the share of job postings that advertise telework. Using a triple differences identification strategy, we show that increases in pandemic severity raise advertised telework, with no subsequent declines during periods of easing severity. Overall, these results suggest that telework is here to stay, especially in countries where tight mobility restrictions during the pandemic and a large fraction of teleworkable jobs in overall employment triggered large increases in telework during 2020-21.

Given the likely persistence of telework in countries where it has increased significantly during the pandemic, public policies need to make the most of its potential productivity and welfare-enhancing effects. In particular, public policies need to focus on ensuring that workers have access to an appropriate working environment (e.g. ICT equipment, office space and childcare); facilitating the diffusion of best practice managerial practices (e.g. shift from presenteeism to output-oriented assessment of worker productivity); and ensuring that there are no blind spots in terms of access to a fast, reliable and secure IT infrastructure (e.g. in rural areas and for low-income workers) (OECD, 2020).

[11] This is a conservative estimate since occupations with high potential to telework might be overrepresented in Indeed vacancies and hence the 2.2 percentage points share of teleworkable job postings in Indeed data in the average country might overstate the extent of teleworkable job postings before the pandemic.

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ANNEX A: Additional tables and figures

Table A.1. Occupation categories

High telework potential		Mid telework potential		Low telework potential	
Information Design & Documentation	100%	Scientific Research & Development	77%	Personal Care & Home Health	9%
Software Development	100%	Civil Engineering	76%	Hospitality & Tourism	6%
Education & Instruction	99%	Architecture	71%	Retail	5%
Insurance	99%	Banking & Finance	67%	Chemical Engineering	4%
Mathematics	98%	Logistic Support	67%	Physicians & Surgeons	4%
Project Management	97%	Real Estate	63%	Beauty & Wellness	4%
IT Operations & Helpdesk	97%	Medical Information	59%	Driving	2%
Legal	96%	Sports	52%	Veterinary	2%
Management	96%	Industrial Engineering	50%	Agriculture & Forestry	1%
Social Science	96%	Arts & Entertainment	44%	Construction	1%
Marketing	95%	Customer Service	37%	Installation & Maintenance	1%
Childcare	90%	Mechanical Engineering	30%	Production & Manufacturing	1%
Media & Communications	90%	Therapy	24%	Food Preparation & Service	0%
Sales	87%	Community & Social Service	19%	Dental	0%
Accounting	86%	Aviation	18%	Nursing	0%
Human Resources	86%	Security & Public Safety	16%	Medical Technician	0%
Electrical Engineering	84%	Mining	11%	Pharmacy	0%
Administrative Assistance	83%	Loading & Stocking	11%	Cleaning & Sanitation	0%

Information Design & Documentation	100%	Scientific Research & Development	77%	Personal Care & Home Health	9%
Software Development	100%	Civil Engineering	76%	Hospitality & Tourism	6%
Education & Instruction	99%	Architecture	71%	Retail	5%
Insurance	99%	Banking & Finance	67%	Chemical Engineering	4%
Mathematics	98%	Logistic Support	67%	Physicians & Surgeons	4%
Project Management	97%	Real Estate	63%	Beauty & Wellness	4%
IT Operations & Helpdesk	97%	Medical Information	59%	Driving	2%
Legal	96%	Sports	52%	Veterinary	2%
Management	96%	Industrial Engineering	50%	Agriculture & Forestry	1%
Social Science	96%	Arts & Entertainment	44%	Construction	1%
Marketing	95%	Customer Service	37%	Installation & Maintenance	1%
Childcare	90%	Mechanical Engineering	30%	Production & Manufacturing	1%
Media & Communications	90%	Therapy	24%	Food Preparation & Service	0%
Sales	87%	Community & Social Service	19%	Dental	0%
Accounting	86%	Aviation	18%	Nursing	0%
Human Resources	86%	Security & Public Safety	16%	Medical Technician	0%
Electrical Engineering	84%	Mining	11%	Pharmacy	0%
Administrative Assistance	83%	Loading & Stocking	11%	Cleaning & Sanitation	0%

Note: The table lists the different occupation categories that we consider and their telework potential (measured as the share of jobs that can be done from home).
Source: Own calculations based on Dingel & Neiman (2020) and Indeed data.

Table A.2. List of keywords indicating advertised telework

Keywords for location, job title and description	Keywords for job title and description
"home office"	"lavoro a distanza"
"werk van thuis"	"lavoro in remoto"
"remoto"	"lavoro da remoto"
"télétravail"	"lavoro da casa"
"lavoro da casa"	"lavorare remotamente"
"remote"	"lavorare da remoto"
"en remoto"	"da remoto"
"home based"	"smart working"
"desde casa"	"smartworking"
"jobba hemifrån"	"テレワーク"
	"在宅ワーク"
	"内職"
	"自宅での勤務"
	"在宅型ワーク"
	"自宅から勤務"
	"thuiswerken"
	“werk van thuis”
	"werken vanuit huis"
	"zdalna"
	"w domu"
	"z domu"
	"telepraca"
	"praca zdalna"
	"trabalho remoto"
	"100% remoto"
	"trabalho de casa"
	"teletrabalho"
	"trabalhar remotamente"
	"arbeta på distans"
	"arbeta hemifrån"
	"arbete på distans"
	"arbete hemifrån"
	"distansarbete"
	"jobb på distans"
	"distansjobb"
	"jobba på distans"
	"jobba hemifrån"
	“jobb hemifrån"
	"arbeta på avstånd"
	"מרחוק"
	"עבודה בבית"
	"עבודה מרחוק"
	"לעבוד מרחוק"
	"לעבוד מהבית"
	"עבודה מהבית "

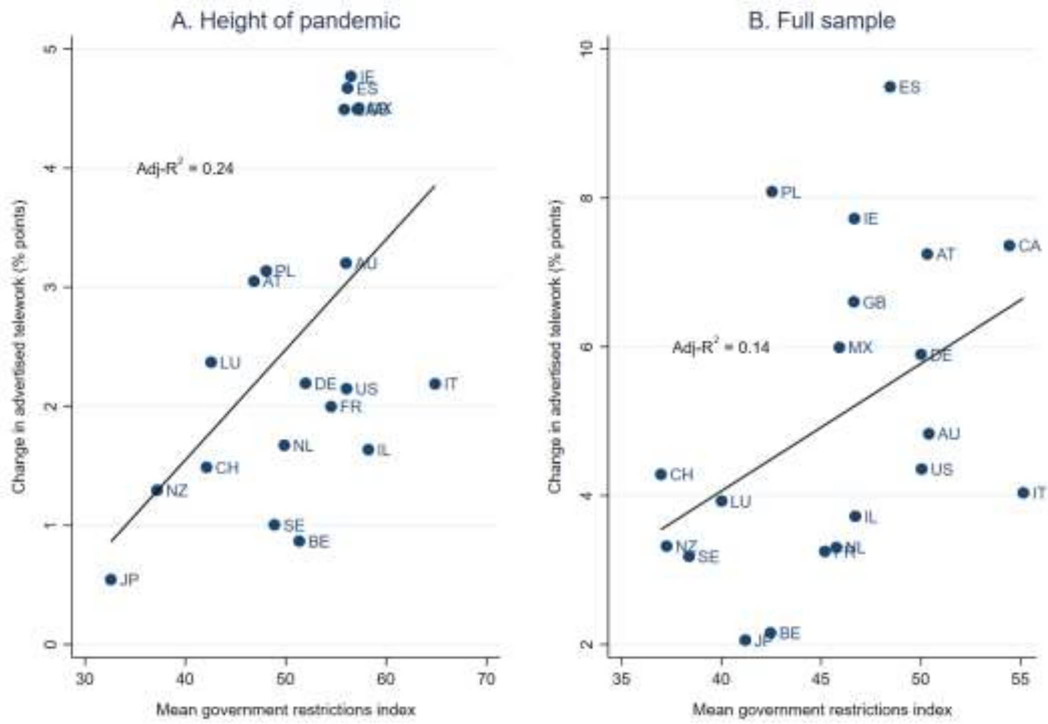
Note: The table lists the keywords that we use to identify job postings that advertise telework.
Source: Indeed.

Table A.3. Baseline results and Wald test for equal coefficients

	Impact	**1-month**	**2-month**	**3-month**	**4-month**	**5-month**
			Panel A. Oxford COVID-19 Stringency Index			
			Increase in pandemic severity			
$\widehat{\beta}^{p,k}$	0.10*	0.39***	0.35***	0.51***	0.57***	0.58***
s.e.	(0.06)	(0.06)	(0.08)	(0.09)	(0.12)	(0.13)
			Decrease in pandemic severity			
$\widehat{\beta}^{n,k}$	-0.12	-0.06	-0.14	-0.19	-0.28	-0.08
s.e.	(0.14)	(0.11)	(0.18)	(0.19)	(0.19)	(0.25)
			Wald test $\widehat{\beta}^{p,k} = \widehat{\beta}^{n,k}$			
p-value	0.92	0.01**	0.24	0.12	0.18	0.07*
			Panel B. Google mobility			
			Increase in pandemic severity			
$\widehat{\beta}^{p,k}$	0.15***	0.45***	0.65***	0.75***	0.83***	0.85***
s.e.	(0.05)	(0.06)	(0.13)	(0.19)	(0.21)	(0.21)
			Decrease in pandemic severity			
$\widehat{\beta}^{n,k}$	-0.13	-0.07	-0.02	0.05	-0.11	-0.00
s.e.	(0.13)	(0.22)	(0.26)	(0.27)	(0.28)	(0.42)
			Wald test $\widehat{\beta}^{p,k} = \widehat{\beta}^{n,k}$			
p-value	0.95	0.11	0.01**	0.00***	0.01***	0.03**

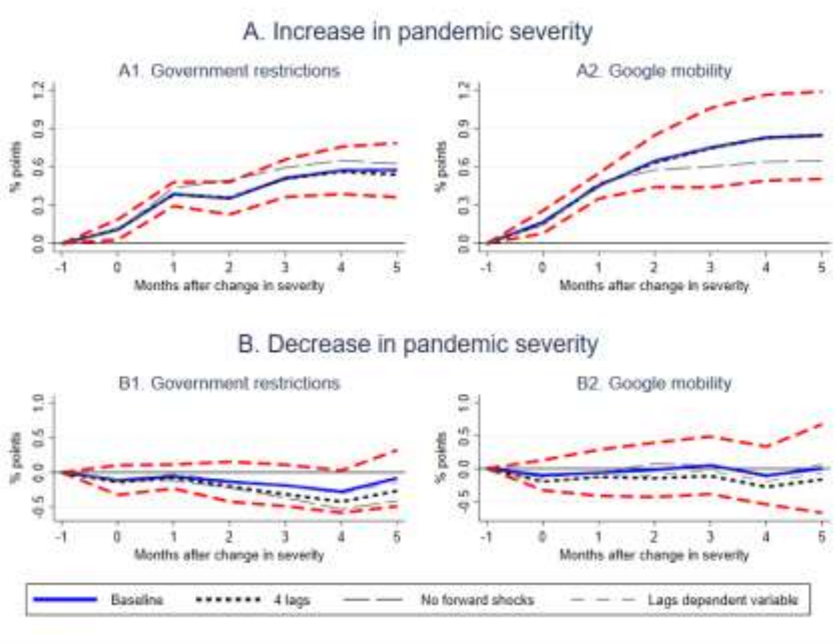
Note: The table reports the $\widehat{\beta}^{p,k}$ and $\widehat{\beta}^{n,k}$ coefficients and their standard errors (in parenthesis) estimated from Equation 1, as well the p-value of a Wald test testing the null that $\widehat{\beta}^{p,k} = \widehat{\beta}^{n,k}$.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data.

Figure A.1. Share of job postings advertising telework and government restrictions, by country



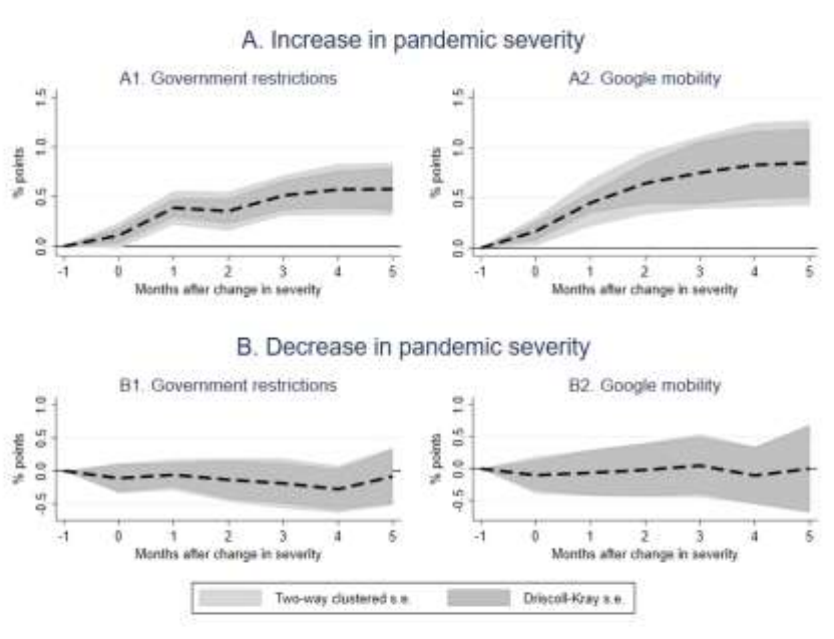
Note: The figure plots changes in country shares of job postings advertising telework and average values of the Oxford COVID-19 Government Response Stringency Index. Panel A plots 2020 average minus 2019 average, where Panel B plots 2020-2022 averages minus 2019 averages. Country shares of job postings advertising telework are obtained by aggregating over the different occupations using their shares in a country's overall job postings as weights.
Source: Own calculations based on Hale et al. (2021) and Indeed data.

Figure A.2. Robustness checks on baseline results – econometric specification



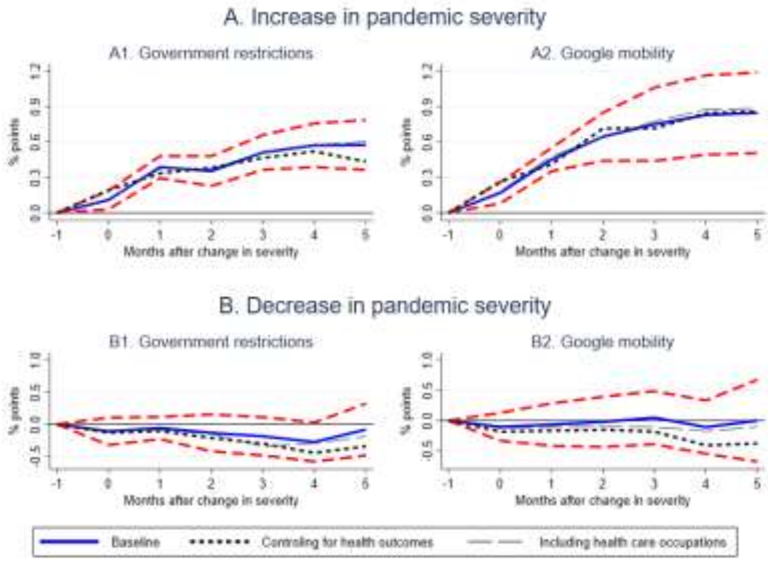
Note: The figure reports impulse response functions showing different estimates of the baseline results obtained from alternative specifications of Equation 1. Blue solid and red dashed lines report respectively point estimates and 90% confidence intervals from the baseline specification, as in Figure 4. Short-dashed, long-dashed and point-dashed lines report point estimates respectively obtained including 4 lags (instead of 2) of the explanatory variables, not including forward explanatory variables and including 2 lags of the 1-period change of the share of job postings advertising telework. For additional notes refer to the note to Figure 4.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data.

Figure A.3. Robustness checks on baseline results – standard errors



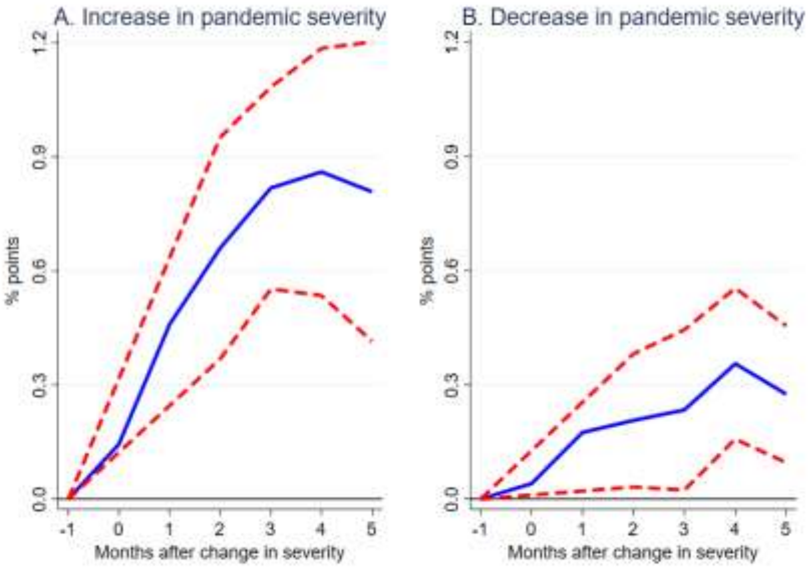
Note: The figure reports impulse response functions showing different baseline point estimates and 90% confidence bands obtained from two different sets of standard errors. Dark grey areas report confidence bands obtained using Driscoll-Kray standard errors, as in Figure 4. Light grey areas report confidence bands obtained using two-way clustered (country and time) standard errors. For additional notes refer to the note to Figure 4.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data.

Figure A.4. Robustness checks on baseline results – sample and control variables



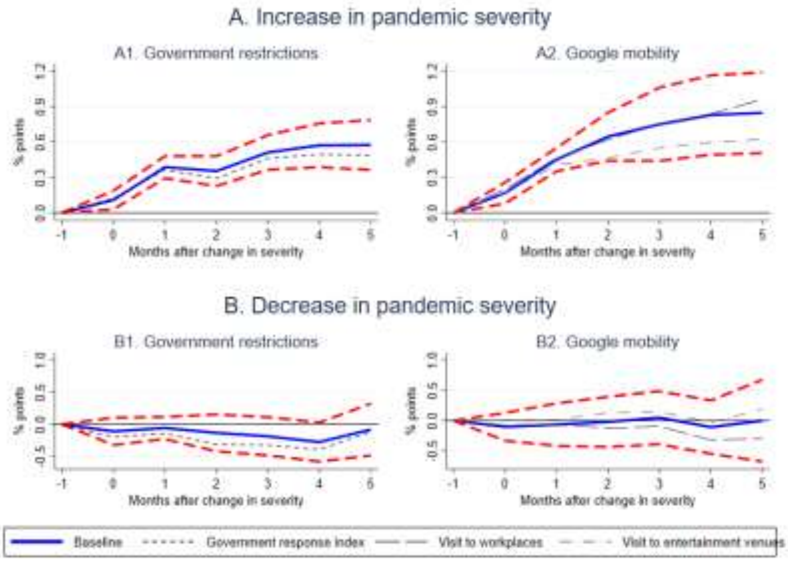
Note: The figure reports impulse response functions showing different estimates of the baseline results obtained from alternative specifications of Equation 1. Blue solid and red dashed lines report respectively point estimates and 90% confidence intervals from the baseline specification, as in Figure 4. Short-dashed lines report point estimates obtained including positive and negative changes in per capita COVID-19 fatalities (contemporaneous values, 2 lags and as forward variables). Long-dashed lines report point estimates obtained including all occupations in the sample (see Footnote 3 for more details). For additional notes refer to the note to Figure 4.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data.

Figure A.5. Robustness checks on pandemic severity indicator – incidence of COVID-19 fatalities



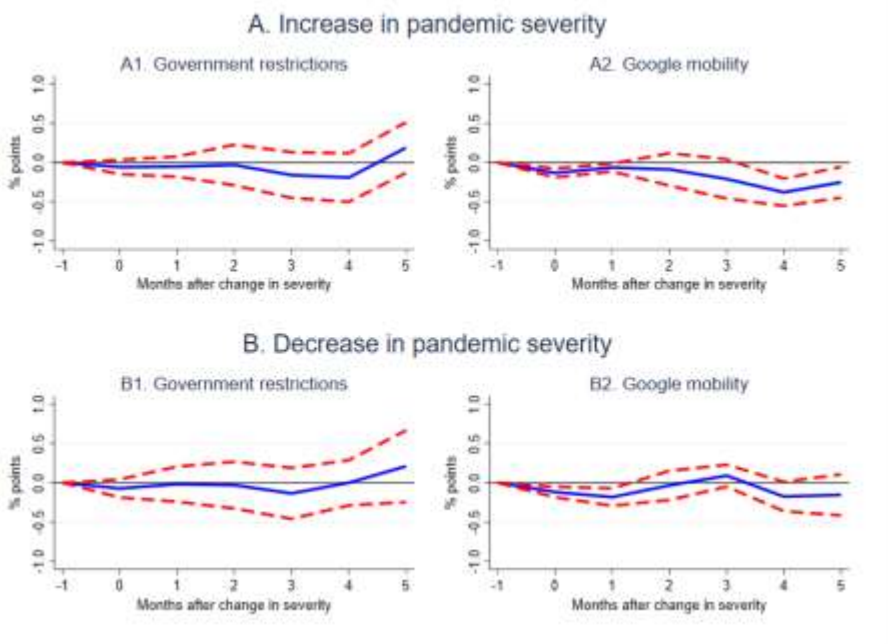
Note: The figure reports impulse response functions showing estimates of the baseline results obtained from an alternative specification of Equation 1, in which changes in per capita COVID-19 fatalities are used as pandemic severity indicator. For additional notes refer to the note to Figure 4.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021) and Indeed data.

Figure A.6. Robustness checks on pandemic severity indicator –government response index and alternative Google Mobility indicators



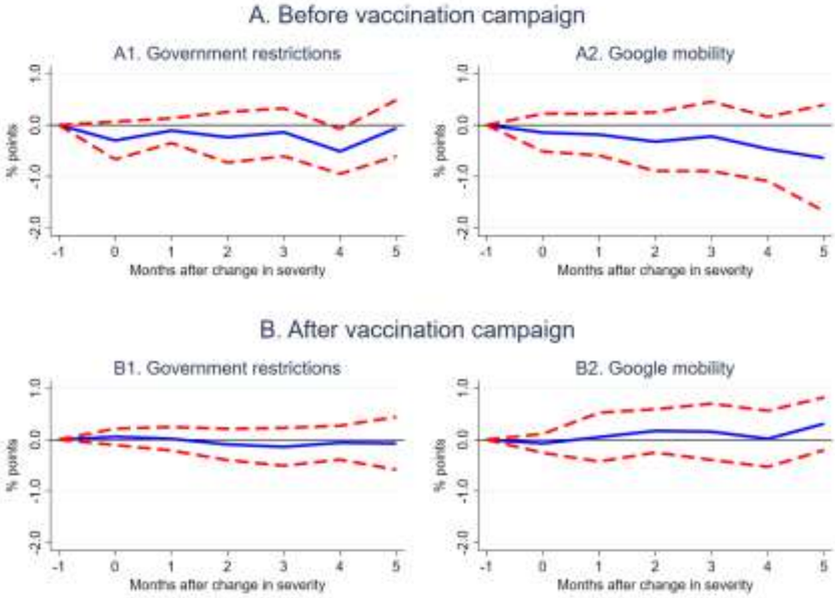
Note: The figure reports impulse response functions showing different estimates of the baseline results obtained from alternative specifications of Equation 1, in which different pandemic severity measures are used. Blue solid and red dashed lines report respectively point estimates and 90% confidence intervals from the baseline specification, as in Figure 4. Short-dashed lines report point estimates obtained using the government response index rather than the stringency index as a measure of government restrictions. Long-dashed and dot-dashed lines report point estimates obtained using visit to, respectively, workplaces and entertainment venues as alternative Google mobility indicators. For additional notes refer to the note to Figure 3.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data.

Figure A.7. Robustness checks on baseline results – placebo test



Note: The figure reports impulse response functions showing placebo estimates of the differential effects of changes in pandemic severity on the share of job postings advertising telework in occupations with high and low potential to telework estimated from Equation 1 but using different series for the pandemic severity indicators, obtained shifting the values backwards by 12 months. For additional notes refer to the note to Figure 4.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data.

Figure A.8. Effects of a decrease in pandemic severity before and after the start of vaccination



Note: The figure reports impulse response functions showing estimates of the differential effects of a one standard deviation decrease in pandemic severity on the share of job postings advertising telework in occupations with high and low potential to telework before and after the start of the vaccination campaign. Estimates are obtained from an alternative specification of Equation 1 in which the pandemic severity indicators are interacted with 0/1 dummies to define the periods before and after the start of the vaccination campaign. The vaccination campaign is defined to have started after the inoculation of at least 10 doses per 100 inhabitants. For additional notes refer to the note to Figure 4.
Source: Own calculations based on Dingel & Neiman (2020), Hale et al. (2021), Google Mobility Reports and Indeed data.

ANNEX B: Back-of-the envelope calculation

In what follows, we describe how we calculate the increase in the share of job postings advertising telework attributable to the pandemic in each country. Relative to relying on a more direct approach that consisted of simply looking at changes in the share of teleworkable job postings over the pandemic period, our calculation has three advantages. First, it corrects for pre-pandemic trends. Second, it only captures the increase in telework directly attributable to the pandemic. Third, it provides estimates that are comparable across countries. This is particularly important because there may be issues in the representativeness of certain occupations in online job postings and these may be different across countries. For instance, imagine two countries with the same labor market structure. Assume that occupations with a high telework potential are overrepresented in the first country and underrepresented in the second one. It follows that one would observe a larger increase in the share of teleworkable job postings in the first country than in the second as a response to the same pandemic shock, just because occupations with a high telework potential are overrepresented in the first country.

Our calculation is as follows. We start from the coefficients that we estimated for the differential effect of an increase in pandemic severity over the 5-month horizon. Next, for each country we sum up the positive changes in the pandemic severity over the entire pandemic period and source the share of jobs that can be done from home as estimated by Dingel & Neiman. For each of the two pandemic severity indicators, and for each country, we then calculate the change in advertised telework that can be directly attributed to our measures of pandemic severity by multiplying our estimated coefficients (not normalized) with the sum of positive changes in pandemic severity and the share of jobs that can be done from home. In other words, for each country i, and for each pandemic severity indicator, we calculate the following statistics:

$$\Delta telework = \hat{\beta}^{p,k} * \left(\sum_{t=1}^{T} x_t^p\right) * p$$

where $\hat{\beta}^{p,k}$ is the coefficient estimated from Equation 1, x_t^p is the variable capturing positive changes in pandemic severity and p is the share of jobs that can be done from home as calculated by Dingel & Neiman (2020).

The numbers that we calculate in this way are only a fraction of the real increase in advertised telework in each country, since they only measure the direct effects through the changes in pandemic severity as measured by the specific indicators that we employ. However, they can be used to get an idea of the differences in the effect of the pandemic on advertised telework across countries. We find that the increase in advertised telework caused by the pandemic was the smallest in Mexico (equal to about 64% of the increase in the U.S., which we take as our reference country) and the largest in Luxembourg (about 220% of the increase in the U.S.).

To have a sense of the absolute increase in advertised telework across countries attributable to the pandemic, we again take the U.S. as a reference country.[12] For this country, we then calculate (i) the actual increase observed in our data over the pandemic period and (ii) a no-pandemic counterfactual increase that we obtain extrapolating the pre-pandemic trend in advertised telework over the pandemic period. Subtracting (ii) from (i), we then obtain the observed increase in advertised telework that we can attribute to the pandemic. Next, we calculate, for the U.S., the ratio of the observed increase in advertised telework to the increase that we obtain through our back-of-the-envelope calculation above. Finally, for each country, we scale the increase calculated in Equation (2) by the ratio just calculated for the U.S. This gives us the predicted increase in advertised telework in each country (middle column of Table 1).

[12] We take the U.S. as reference country because potential representativeness issues in online job postings should be smaller in this country.