Remote work wanted?
Evidence from job postings during COVID-19*

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Abstract

As the COVID-19 pandemic pushed firms to comply with social distancing guidelines, the relative demand for work that could be performed from home was expected to increase. However, while employment in "remotable" occupations was relatively resilient during the pandemic, online job postings -which measure demand for new hires- for these occupations dropped disproportionately. This apparent contradiction is not explained by prior job "churning" in "non-remote" jobs, nor by the recomposition of the labor market across economic sectors. The underperformance of postings in "remotable" jobs during the pandemic concentrates in essential occupations and occupations with high returns to experience.

Keywords: COVID-19, Remote work, Labor markets.

JEL Codes: J21, J23

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1 Introduction

The nature of social distancing policies in response to COVID-19 is supposed to produce diverging outcomes for workers performing "remotable" and "not-remotable" activities, namely those who can work from home and those who can not. Indeed, as millions of workers have started working from home, the expectation is that the demand for remotable jobs should be more resilient during the pandemic, translating into relatively less layoffs and more hiring efforts. Consistent with this expectation, Mongey et al. (2020) show that, during the first months of the COVID-19 lockdown, high-teleworkability occupations experienced less layoffs, highlighting potential distributional concerns around the response to the pandemic.[1] Similarly, Forsythe et al. (2020) show that, as of mid April 2020, remotable occupations had lower numbers of layoffs than non-remotable occupations. Nevertheless, they find that the latter had relatively better numbers in online vacancy postings.

Our paper addresses this apparent contradiction in detail. We evaluate the evolution of employment and job postings around the "remotability" of work in the U.S. during the pandemic up to the end of 2020. Consistent with the findings in Forsythe et al. (2020), remotable occupations in the U.S. show relative resilience in employment in the first months of the pandemic. Nevertheless, the gap in employment between remotable and not-remotable occupations had largely closed by the Fall of 2020. When it comes to job postings, we find a much wider and sustained gap in the opposite direction. While the employment outperformance of remotable occupations starts with the onset of 2020, their postings underperformance starts in April -one month after President Trump's National Emergency declaration- and has remained relatively stable between June and December of 2020.

We study a number of possible drivers behind the pattern of employment resilience with hirings erosion in remotable work under COVID-19. A first potential explanation is that, as businesses started to reopen, they attempted to hire back workers for not-remotable jobs that faced the bulk of layoffs at the onset of the lockdowns. However, we

[1] Building on the Dingel and Neiman (2020) definition of teleworkable occupations.

find that our results are robust to controlling for layoffs in an occupation in recent months, suggesting that the high "churning" of not-remotable jobs is not a likely driver behind these results. Moreover, we find that our estimates of the postings gap are unaffected when we analyze postings data within economic sectors of the economy, suggesting that they are not the result of an industrial recomposition of the labor market during the pandemic.

A key potential explanation has to do with essential activities, which rely in not-remotable tasks that must continue -or are likely to expand- during a pandemic. While essential activities explain the remotable underperformance in job postings, they do not explain their overperformance in employment. Returns to experience may also explain the divergence in employment and postings performance, as valuable experience that can be deployed at a distance may only accumulate with in-person interactions (i.e. close mentoring and supervision, building of trust and rapport, etc.), which cannot develop during lockdowns. While high returns to experience explain the employment overperformance or remotable jobs, they only partly explain their postings underperformance. Moreover, employment and hiring patterns in an occupation may depend on whether such occupation is complementary to not-remotable co-workers, as the remotability of a job may not prevent a drop in its demand if this is mostly complementary to not-remotable jobs affected by social distancing. However, we find no statistical heterogeneity in the employment or postings performance of remotable occupations along this dimension.

We further study the spatial heterogeneity in the underperformance of remotable job postings during the COVID-19 pandemic between American cities. We find that while effects seem strongest in larger and richer coastal cities, they appear orthogonal to the relevance of remote work and accommodation activities in a city. Overall, these findings should be considered by policy-makers at all levels of government in evaluating potential responses to stimulate the rehire of workers affected by the COVID-19 pandemic: While non-remotable occupations experienced the bulk of job losses at the peak of the pandemic, it is not obvious that nudging workers to perform remotable tasks will improve their future employment prospects. Since an important part of this policy responsibility falls on local authorities facing stringent budgetary pressures as a result of the pandemic, we believe the findings are of special relevance to city-level policy-makers.

This paper expands the literature on labor demand patterns along the remotability dimension of work during COVID-19. Dingel and Neiman (2020) provide a classification of occupations according to the technological possibility to perform them from home. Dey et al. (2020) contrast this metric with pre-pandemic records from the American Time Use Survey (ATUS) and finds that 30% of workers in remotable occupations had engaged in remote work, while only 4% of workers in non-remotable occupations did the same. Bartik et al. (2020) find that this measure of suitability for remote work is an accurate predictor for the industry-level adoption of remote work during the pandemic. Brynjolfsson et al. (2020) conduct two surveys on representative samples during COVID-19, finding that about 50% of the workforce was working from home in early May and that 35% of the workforce stopped commuting in the shift to remote work. Papanikolaou and Schmidt (2020) show that industries relying in not-remotable work faced larger declines in employment, revenue, stock market performance, and default rates during the pandemic. Almagro and Orane-Hutchinson (2020) find that occupations with the highest share of remote workers were less associated with the diffusion of COVID-19 in New York City with the roll-out of stay-at-home orders, while Mongey et al. (2020) document that workers in low-remotability occupations are less educated, have lower incomes, have fewer liquid assets and are less likely to be home-owners. Our findings suggest that having these workers transitioning to remotable occupations would not necessarily have improved their employability outcomes during the COVID-19 pandemic.

The paper continues as follows: Section 2 explains the main sources and variables utilized in our assessments. Section 3 presents descriptive and econometric analysis documenting the contradiction in employment and job postings patterns along the remotability dimension. Section 4 discusses whether the potential explanations mentioned above capture the apparent contradiction between employment and hiring attempts. Section 5 shows the spatial distribution of our estimates across American cities, and section 6 shows how employment and postings patterns have evolved during 2021. Section 7 concludes.

2 Data

Our empirical strategy consists on evaluating the differences in the recent changes in employment and job postings between remotable and not-remotable occupations, controlling for potential confounders and exploring heterogeneities across relevant occupational attributes. Our main data sources are the monthly estimates of employment by occupation from the Current Population Survey (CPS) and the monthly series of job postings by occupation from Burning Glass Technologies (BGT), both complemented by multiple occupational attributes derived from publicly available sources.

Employment

We measure the changes of employment by occupation using IPUMS Current Population Survey (CPS) microdata from January 2018 to December 2020.[2] To get the number of workers by occupation for each month, we aggregate the weighted number of employed respondents by Occupational Census Code using the composite weight that replicates published BLS labor force estimates.[3] Although the CPS has smaller sample size than other sources of monthly employment estimates like the Current Employment Statistics (CES), it is the source that allows the calculation of occupation-level employment estimates. This quality makes the CPS one of the most relevant public datasets to disentangle the recent labor market shifts.[4]

Lagged separations

Aside from employment status, the Current Population Survey (CPS) captures information on the reason of unemployment, weeks unemployed since the last job, and the last occupation held when employed. The reason of unemployment allows us to identify

[2] Flood et al. (2020)

[3] Starting from January 2020, the CPS switched its occupational classification scheme from 2010 Occupational Census Code to 2018 Occupational Census Code (OCC2010 and OCC2018, respectively). In order to make occupational counts comparable before and after this change, we turned OCC2018 into OCC2010 using the Census Bureau Occupation Code List Crosswalk, producing a set of 452 comparable occupations across both periods.

[4] See for example: Forsythe et al. (2020), Mongey et al. (2020), Ding et al. (2020).

job losses, definition that includes layoffs, terminations of temporary work arrangements and other types of separations. Once respondents are classified by separation status and occupation, we identify the month of the separation by subtracting the number of weeks in unemployment from the first week of the incumbent month. Finally, we aggregate the composite individual weights of each separated respondent by occupation (OCC2010) and month of separation in order to create monthly estimates of job separations by occupation. Since most of the job separations correspond to layoffs, we'll refer to the term separations and layoffs interchangeably.

Job postings

We use Burning Glass Technologies' proprietary data on job postings to track new job openings by month and occupation. Burning Glass Technologies (henceforth BGT) is a labor market analytics company that collects online job vacancies posted across multiple job boards and company websites on a daily basis. Each collected job vacancy goes through a proprietary cleaning process that, among others, identifies its location and assigns it the occupational code that better fits its title and description. We count all the postings per occupation and month, where occupations are classified by Standard Occupation Classification (SOC) and the month corresponds to the date the posting was published.

Merge of employment and postings data

The CPS encodes occupations with Occupational Census Codes (OCC2010), while the BGT job posting series and most public sources showing occupational information use the Standard Occupation Classification (SOC 2010). In order to make both sources comparable, we crosswalk both the OCC2010 and SOC 2010 into an intermediate system called SOCXX, which is a less granular version of SOC 2010 compatible with both schemes.[5]

[5]This occupational classification constitutes a revised version of the SOC codes available in the Census Bureau Occupation Code List Crosswalk and is made up of 446 occupations in total, while the 2010 Standard Occupation Classification System used in the OEWS 2018 has 808.

The combined panels of employment and job postings include 424 of these SOCXX occupations in total, but just 364 are common across both datasets.[6] Our findings are based on this final set of 364 occupations, which accounts for 99.5% of new job postings and 98.6% of employment in February 2020.

Teleworkability

In order to identify teleworkable occupations, we rely on the procedure developed by Dingel and Neiman (2020) using surveys from the Occupational Information Network (O*NET). This approach identifies occupations that can't be performed remotely based on the importance attached to specific items of O*NET's Work Context and Work Activities questionnaires, answered by small samples of labor specialists and workers.[7]

According to this approach, work activities suggesting that an occupation is not teleworkable include working directly with the public, having constant physical movement, constantly moving objects, and regularly operating, inspecting, or repairing machinery (including vehicles). Similarly, work contexts indicating that remote work is unfeasible include working outdoors the majority of the time, dealing with violent people at least once a week, rare use of email, frequent use of protective equipment, and frequent exposition to minor injuries, diseases or infection.

Occupations where at least one of these work contexts and activities are reported as "very important" are considered non-teleworkable, while the rest is considered teleworkable. Dingel and Neiman (2020) estimate that 37% jobs in the United States could be performed from home, which is close to the share of workers who teleworked in May (35%) and June (31%) according to the supplemental Covid-19 related questions added to the Current Population Survey[8].

This variable, originally computed at the O*NET SOC level, is later aggregated into an intermediate Standard Occupation Classification (SOCXX) compatible with CPS

[6] Table A4 shows a breakdown of the occupations with missing estimates of employment and job postings.

[7] In the 24.2 O*NET database release, the median occupation had 25 respondents in the work context questionnaire and 26 respondents in the Work Activities Questionnaire.

[8] See https://www.bls.gov/cps/effects-of-the-coronavirus-covid-19-pandemic.htmMayJune

monthly employment estimates by occupation. Since in most of the cases this is a many-to-one merge, we label a SOCXX as teleworkable when it is only made up of teleworkable O*NET SOC occupations.

As a result, we end up 83 remotable occupations, accounting for 26% of employment in February 2020 (see table A4), the five largest of these being Secretaries and Administrative Assistants, Office Clerks, General and Operation Managers, Teachers, and Computer Scientists and System Analysts.

Median wage

Median annual wages come from the BLS Occupational Employment and Wage Statistics 2018 (OEWS). It is initially available at the 2010 Standard Occupation Classification (SOC 2010) level, so to aggregate it into our intermediate occupational classification scheme SOCXX, we take the average of the median wage across each of the incumbent SOCs 2010, using the OEWS 2018 total employment estimates as the weighting variable.

Typical education requirements

Data on occupations' educational requirements comes from the BLS employment projections database 2018.[9] This variable shows the education level most workers need to enter a job at an occupation, ranging from "No formal education credential" to "Doctoral or professional degree". Each occupation is associated with a single kind of entry-level educational attainment, and this information is initially available at the SOC 2010 level. Therefore, we process the variable to make it compatible with our revised classification scheme (SOCXX). In most of cases, each revised occupational code SOCXX is composed by SOC 2010 of equal educational requirements, but there are exceptions. In those cases, we keep the educational requirement accounting for the largest share of employment of each revised occupational code SOCXX, based on OEWS 2018 total employment estimates.

[9]See Education and Training by occupation, accessed in April 2020.

Employment in essential industries

We calculate the share of total employment of each occupation allocated in essential NAICS industries using Delaware and Minnesota State's list of essential industries and the 2018 OEWS industry-occupation staffing patterns. Once we have the share of employment in essential industries of each occupation, we classify as essential those occupations with more than 50% jobs allocated in these sectors.

Under this definition, 222 occupations in our panel are essential, accounting for 65% of employment and 74% of postings as of February 2020 (see table A6). 61 essential occupations are teleworkable, including occupations like Secretaries, and Computer Software Engineers, while 161 are non-teleworkable, including occupations like Cashiers, Registered Nurses, and Truck Drivers.

Returns to experience

We estimate the returns to experience of each occupation by performing a Mincer-like regression on microdata from the IPUMS American Community Survey 2018 (ACS). The ACS collects information on each respondent's employment status, occupation,[10], education attainment, age and total pre-tax wage and salary income.

After creating an estimate of potential years of work experience following the formula $Age - Years\ of Education - 6$,[11] we fit the log-linear model in equation 1:

$$\log W_r = \beta_1 Ex_r + \sum_{o=2}^{O} \phi_o + \sum_{o=2}^{O} \alpha_o Ex_r * \phi_o + \beta_2 Ed_r + \beta_3 G_r + \epsilon_r \tag{1}$$

Where $\log W_r$ is the natural logarithm of the reported wage of respondent r, Ex_r is the potential years of work experience, Ed_r is the educational level, G_r is the gender, and ϕ_o is a binary indicator for occupation o. α_o captures the marginal compensation to an additional year of potential experience for occupation o. We use the $\hat{\alpha_o}$ estimates as our

[10]IPUMS USA, by Ruggles et al. (2020) provides occupational information by 2010 Census Occupational Codes. We apply a crosswalk to aggregate occupations at the intermediate Standard Occupational Code (SOCXX) level before running the Mincer regressions.

[11]We calculate the variable years of education by looking at the highest year of schooling attained or the highest academic degree achieved. The variable ranges from 1 to 18, which correspond to 1st grade and Doctoral degree, respectively.

measure of the return to experience in occupation o.

We split occupations by the median value of $\hat{\alpha_o}$ to identify high and low returns to experience occupations. 175 occupations are classified as high-returns to experience, accounting for 48% of employment and 52% of postings in February 2020 (see table A6). 41 of these are teleworkable while 134 are not. Within high-return occupations, the largest teleworkable ones are Office Clerks, Computer Scientists, Computer Software Engineers, and Teacher Assistants, while largest non-teleworkable are Retail Salespersons, Food Preparation and Serving Workers, and Cashiers.

Average share of non-remotable co-workers

In order to get a metric on occupations' complementarity to non-remote work, we use the 2018 OEWS industry-occupation staffing patterns and the Dingel and Neiman (2020) definition of remotable occupations to calculate the average share of non-remotable co-workers by occupation depicted in equation 2.

$$NRsh_o = \frac{\sum_{i=1}^{I}(NRsh_i - sh_{io} * (NR_o)) * E_i^o}{\sum_{i=1}^{I} E_i^o} \tag{2}$$

This equation captures the share of other non-remotable jobs for the average industry employing workers in occupation o. First we calculate the share of non-remotable workers in each industry ($NRsh_i$) and then we take its weighted average by occupation, where the share of non-remotable jobs subtracts each occupation's share for a industry (sh_{io}) if that occupation is itself non-remotable ($NR_o = 1$). Consistently, this variable measures the prevalence of non-remotable co-workers for a given occupation, regardless of whether the occupation itself is remotable or not.

We classify occupations with values of $NRsh_o$ above the median as highly complementary of non-remote workers. This group is conformed by 168 occupations accounting for 53% of employment and 50% of postings in February 2020 (see table A6). Among these, 41 can be worked from home and 127 can not. Remotable occupations highly complementary of non-remotable work include Secretaries, Office Clerks, Teachers, and Sales Representatives in Wholesale and Manufacturing. Conversely, examples of non-remotable occupations highly complimented by non-remotable occupations include Retail Sales Persons, Cashiers, and Registered Nurses.

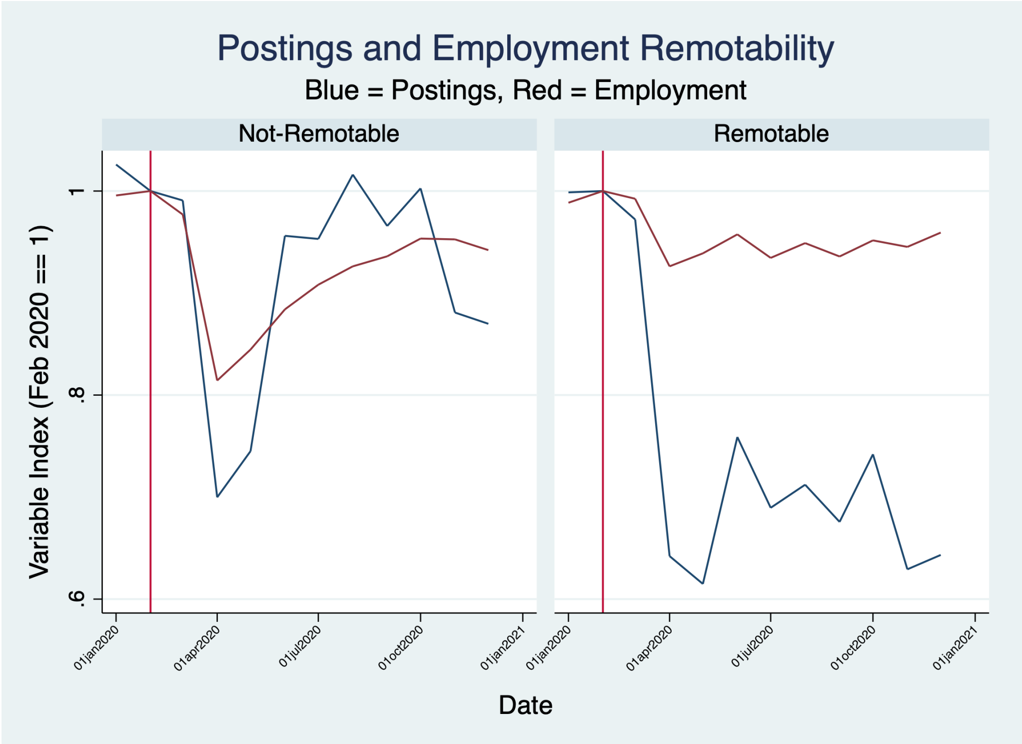
Other covariates and additional information

In the appendix, we provide descriptions for additional possible determinants of employment and postings patterns along the remotability dimension during the COVID-19 pandemic. Table A7 provides a short summary description of all relevant variables. Table A4 provides a description of employment and postings along the remotability of occupations in February 2020. Finally, tables A5 and A6 provide summary statistics for all the variables considered in our study.

3 Employment, postings and the remotability of work:

Figure 1 shows the contradictory pattern in the evolution of employment and postings along the "work-from-home" dimension. As expected, employment in remotable occupations was relatively resilient in comparison to employment in not-remotable occupations at the beginning of the pandemic. By April, remotable employment had fallen by about 5%, while not-remotable employment fell by almost 20%. However, this pattern starts reversing in May and by September the gap in employment has almost closed. The picture changes when looking at job postings. By April, the drop in postings was smaller for not-remotable occupations by almost 30 percentage points. By September, postings in not-remotable occupations were back to pre-pandemic levels, while postings in remotable occupations were still about 30% below February postings levels. While there was a general slide in job postings in November, the gap in remotable postings still hovered around 20 percentage points by the end of the year.

Figure 1: Postings, Employment and "Remotability" of Work under COVID-19



Notes: Figure shows the index of employment and postings (base February 2020) for remotable and non-remotable occupations. Employment is shown in red lines, while posting is shown in blue lines.

To study the statistical significance of the association between changes to employment and postings under COVID-19 and the remotability of different occupations, we perform a difference-in-differences model that estimates coefficients for the following equation:

$$Y_{ot} = \alpha * R_o * Post_t + \sum_{k=1}^{K} \beta^k * X_o^k * Post_t + \phi_o + \phi_t + \epsilon_{ot} \tag{3}$$

Where Y_{ot} marks the value of the index of employment or job postings for occupation o at month t.[12] R_o is a binary variable that marks whether occupation o is remotable according to Dingel and Neiman (2020), and $Post_t$ is a binary variable that marks whether month t is after President Trump's National Emergency Declaration of March 13, 2020. X_o is a matrix of K co-variate controls. ϕ_o and ϕ_t identify occupation and month fixed effects, and ϵ_{ot} is the error term. α is our main coefficient of interest. We estimate this model using monthly data on occupation-specific employment and postings levels between

[12]Indexes are calculated with the base month in February 2020, which was the last month before the Presidential Declaration of Emergency.

January 2018 to December 2020. In assessing the statistical significance of our estimates we cluster standard errors at the occupation level.

Table 1 shows estimates of α for both the change in the employment and job postings indexes during COVID-19. Columns (1) and (5) do not include any controls, columns (2) and (6) add occupation and month fixed effects, columns (3) and (7) add controls for the wage and education profiles of occupations interacted with the COVID-19 period, and columns (4) and (8) remove education and wage controls and include one-month and two-month lags in estimated separations in each occupation and their interaction with the COVID-19 period.

Our results confirm the visual intuition from figure 1: While the change in the employment index in remotable occupations outperformed that of not-remotable occupations by about 15 percentage points, the postings index of remotable occupations underperformed that of not-remotable occupations by about 14 percentage points. Both coefficients drop after controlling for the wage and education profiles of the different occupations, and the statistical significance of the employment gap is not robust to such controls. Both results are robust to controlling for lagged separations, which suggests that the contradicting patterns in the employment and postings gaps cannot be explained away by higher "job churning" in not-remotable occupations that experienced greater job separations earlier in the pandemic.[13]

[13]We incorporate the estimated separations lags to control for the possibility that occupation job churning explains the patterns in the data. Because estimated separations at the occupation level change every month, the variable is not absorbed by the occupation fixed effects. Table A1 provides a more flexible set of controls that interact lagged separations with the COVID-19 period and the remotability of work to explain changes in the postings index. Results are largely unaffected.

Table 1: Difference in Differences Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Employment Index				Postings Index			
Remote × Post	0.150	0.145	0.0752	0.135	-0.137	-0.137	-0.0821	-0.133
	(0.0495)	(0.0460)	(0.0513)	(0.0428)	(0.0283)	(0.0283)	(0.0311)	(0.0278)
Months	36	36	36	34	36	36	36	34
Occupations	364	364	364	364	337	337	337	337
R-squared	0.004	0.711	0.712	0.713	0.010	0.427	0.432	0.413
Panel FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Wage-Education Controls	No	No	Yes	No	No	No	Yes	No
Lagged Separations Controls	No	No	No	Yes	No	No	No	Yes

Notes: Standard errors in parentheses clustered at the occupation level. Lagged separation controls consist on occupation-month estimates of worker separations during the previous month, reconstructed from the CPS.

A key question is whether changes in employment and postings indexes only show alterations along the remotability dimension after COVID-19. Finding such balanced trends before COVID-19 would confirm that our estimates are driven by the effects of the pandemic on labor demand patterns along the remotability of work. To do so, we estimate the following model:

$$Y_{ot} = \sum_{m=1}^{M} \alpha^m * R_o * 1[t = m] + \phi_o + \phi_t + \epsilon_{ot} \tag{4}$$

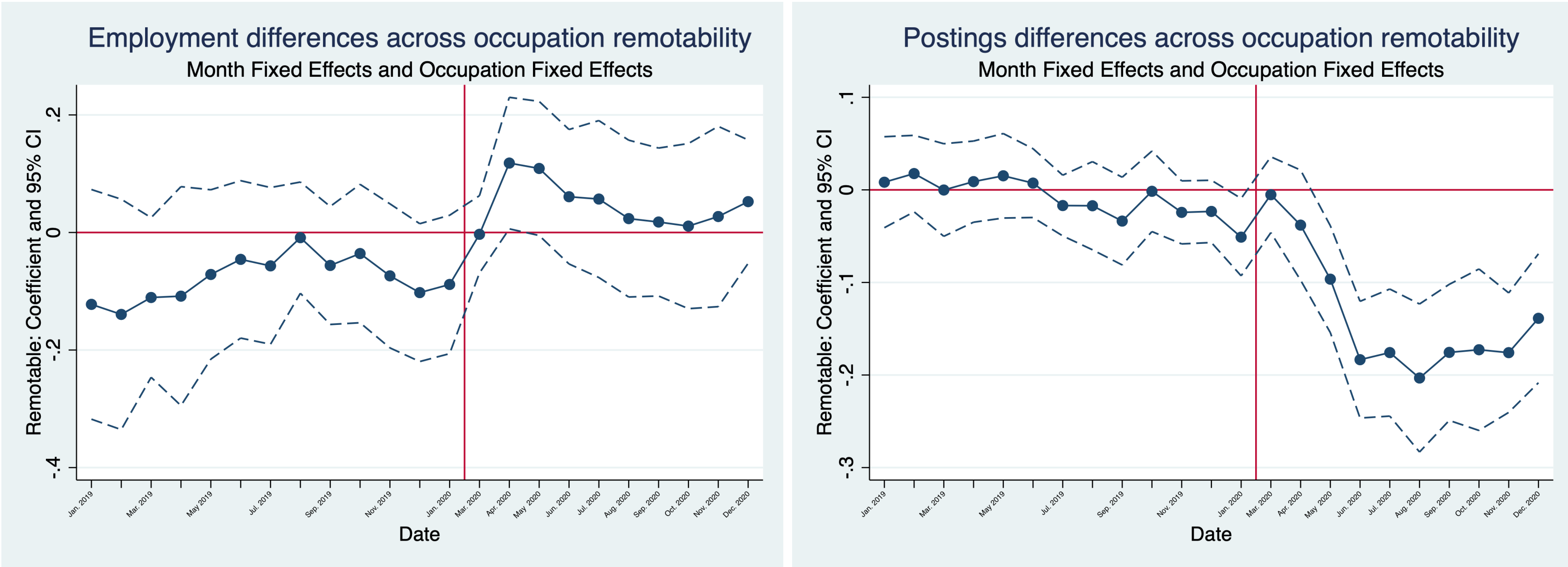
Where $1[t = m]$ is a binary variable for each month in our data. We expect values of α^m to be close to 0 before the COVID-19 period and change afterwards. We again cluster standard errors at the occupation level.

Figure 2 shows our point estimates and 95% confidence intervals for α^m.[14] Panel A suggests that coefficients were negative before the COVID-19 period, but remained largely unaltered for the whole period before the start of 2020. This suggests that employment adjustments along the remotability margin started a month prior to President Trump's National Emergency declaration. Panel B suggests that trends in postings between remotable and not-remotable jobs remained balanced until March, and that postings in remotable activities only started underperforming in April.

[14] While we use data starting from January 2018 in fitting the model, the figures only show estimates starting in January 2019 so that figures capture the COVID-19 period with sufficient space. Conclusions regarding parallel trends do not change after considering the full set of coefficients.

Figure 2: Event Study Figures

(a) Employment (b) Postings



Notes: Figures show event study estimates for the difference in the relevant index between remotable and non-remotable occupations in each month. Estimates are calculated controlling for month and occupation fixed effects.

A potential concern about our results is that they may be driven not by a relative change in employers' efforts to procure remote workers, but by a relative contraction in activities that rely on such work. While many of the industries most affected by the pandemic rely heavily on in-person work, it is still the case that the ideal specification would account for variation in outcomes between remotable and non-remotable occupations within economic activities. The data necessary to assess employment patterns at this level and with the necessary periodicity is unavailable. However, BGT data allows us to measure the monthly number of online job postings for each occupation in each of the 20 industrial sectors according to NAICS. Leveraging this data, we perform the following specification:

$$Y_{oit} = \alpha * R_o * Post_t + \phi_{oi} + \phi_{it} + \epsilon_{oit} \tag{5}$$

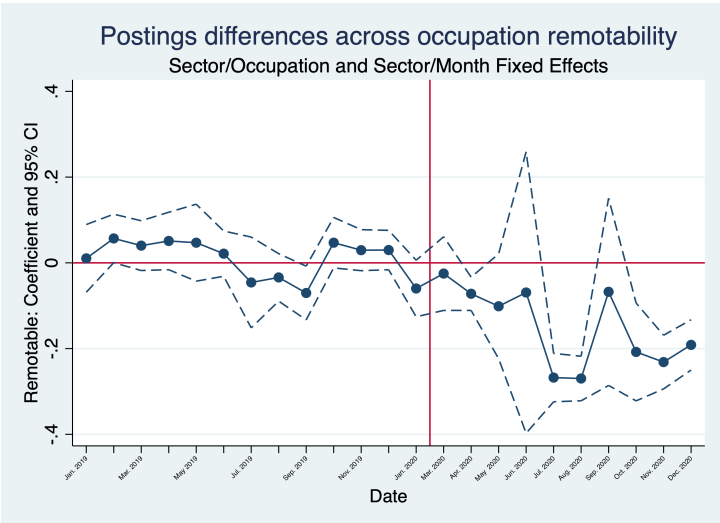
Where we now add occupation-industry fixed effects (ϕ_{oi}) and industry-month fixed effects (ϕ_{it}). This specification allows us to estimate the value of α considering within-sector variation in job postings patterns which are not driven by a change in the industrial composition of the overall labor market. Table 2 shows these results iterating between using occupation and month fixed effects (column 1), adding occupation-industry fixed effects (column 2) and finally adding industry-month fixed effects (column 3). These estimates do not change meaningfully between one another, and are all at least as large as those shown in table 1. Figure 3 shows the relevant event study figure, showing again that the effect peaked at the start of the third quarter of 2020 and persisted until the end of the year. We interpret these results as confirming that the underperformance of remotable job postings during COVID is not driven by a change in the industrial composition of the labor market.

Table 2: Difference in Differences at Occupation-Industry-Month Level

	(1)	(2)	(3)
VARIABLES		Postings Index	
Remote × Post	-0.181	-0.181	-0.178
	(0.0495)	(0.0494)	(0.0504)
Observations	400,176	400,176	400,176
R-squared	0.007	0.061	0.063
Occ FE	Yes	No	No
Occ/Ind FE	No	Yes	Yes
Month FE	Yes	Yes	No
Ind/Month FE	No	No	Yes
Ind Level	Sector	Sector	Sector

Notes: Standard errors in parentheses clustered at the occupation-industry level. Sectors are defined as NAICS 2-digtis industries.

Figure 3: Event Study at Occupation-Industry-Month Level



Notes: Figure shows event study estimates for the difference in the relevant index between "remotable" and "non-remotable" occupations in each month. Estimates are calculated controlling for occupation/sector and sector/month fixed effects.

4 What drives this apparent contradiction?

We are interested in understanding what factors may be driving the contradictory patterns between employment and postings along the remotability of work. To do this, we evaluate heterogeneities in this result along occupation characteristics of interest for potential explanations. We estimate the following model:

$$Y_{ot} = \alpha_1 * R_o * Post_t + \alpha_2 * C_o * Post_t + \alpha_3 * R_o * C_o * Post_t + \phi_o + \phi_t + \epsilon_{ot} \quad (6)$$

Where C_o is an occupation characteristic of interest. α_2 captures the independent effect of this characteristic for not-remotable occupations and α_3 captures the marginal effect of the characteristic for remotable occupations. Our goal is to assess whether controlling and interacting for the characteristic explains away the independent effect of remotability when the characteristic is absent - which is captured by α_1. Now again, standard errors are clustered at the occupation level.

Table 3 provides estimates for this model considering three different characteristics: 1) whether the occupation is highly demanded by *essential* industries[15], 2) whether the occupation has *high returns to experience*, and 3) whether the occupation has a *high share non-remotable co-workers* on average.[16] Panel A shows estimates on the effect on changes in the employment index, while Panel B shows estimates on the effect on changes in the postings index. Column (1) replicates the results from columns (2) and (6) in table 1. Results in Columns (2), (4) and (6) suggest that just controlling for these variables without including interaction terms to the remotability of occupations does not contribute to explaining the contradiction in the signs of our estimates for α_1 in Panel A and Panel B.

4.1 Essential occupations

Column (3) in Panel A shows that interacting essential and remotable occupations has no meaningful effect on employment estimates. However, Panel B shows that the estimate

[15]We refer to these as essential occupations in the rest of the text.

[16]These variables are all in binary format, splitting occupations in high and "low" in the median value of the underlying characteristic. Table A2 shows the same specification but using the standardized continuous value of the underlying variables. While the coefficients now need to be interpreted as the association between a 1 s.d. increase in the variable of interest and the change in the relevant outcome during COVID-19, the direction of the conclusions remain largely the same as those drawn from table 3.

of α_1 for postings now turns to 0. We find a positive effect for essential occupations that are not-remotable and a negative interaction term, both statistically significant. These results suggest that posting performance under COVID-19 was not affected by remotability in not essential occupations, but postings in not-remotable essential occupations outperformed their remotable counterparts by almost 35 percentage points.

Finding that this specification affects conclusions for postings changes under COVID-19 highlights the importance of "front-line workers". These kind of workers operate in not-remotable and essential occupations, and demand for their work increased during the pandemic. However, we observe that the effect of remotability is about the same for employment changes under COVID-19 for both essential and non-essential occupations, which suggests that the higher demand for "front-line" workers did not materialize in improved employment prospects for these occupations. An open question that results from this analysis is about the kind of frictions preventing workers from migrating into these occupations.

4.2 Returns to experience

Column (5) in Panel A shows that interacting remotability with a marker for occupations with high returns to experience cuts our estimate of α_1 almost completely. We have a negative but insignificant effect of high returns to experience in not-remotable occupations, and a positive, significant and larger coefficient on the interaction term. These results suggest that "remotability" has no differential effect on employment performance for occupations with low returns to experience, but that employment in "not-remotable" occupations with high returns to experience underperformed their remotable counterparts by about 36 percentage points.

Panel B in Column (5) shows a negative but smaller effect of remotability on postings for occupations with low returns to experience, and a null effect of high returns to experience in not-remotable occupations. The interaction term is negative, and is almost statistically significant at the 10% level. These results suggest that postings in remotable with low returns to experience underperformed with a gap of almost 9 percentage points, and that this gap was about 7 percentage points larger for occupations with high returns to experience.

Observing these parallel patterns in employment and postings suggests that employers made special efforts to retain employees performing tasks that rely on experience and can be performed at a distance, but disproportionately halted the hiring of such workers, who may be unable to acquire the necessary experience remotely.

4.3 Non-remotable co-workers

Column (7) in Panel A shows that interacting remotable occupations with a marker for whether the occupation has a high average share of not-remotable co-workers does not make a big difference on employment changes during COVID-19. Similarly, Panel B shows a negative interaction term that is not statistically significant. This result suggest that the remotability of co-workers does not explain the contradicting patterns between remotable employment and postings.

4.4 Other potential explanations

In table A3 we explore additional potential explanations under the same empirical framework. Specifically, we assess the role of occupations' education and wage profiles, whether occupations require on-the-job training, whether they usually require previous experience for hiring, whether they usually require tenure for hiring, and whether they usually appear later in workers' careers.[17] As was the case above, controlling for the different variables without introducing interaction terms does not seem to explain away the contradictions in estimates for α_1 between Panel A and Panel B. However, with the exception of training in Panel A, all estimates of α_1 remain largely unaffected in comparison to the estimate in column (1) after including interaction terms, and interaction terms are mostly statistically insignificant.

[17] Section 2 provides definitions and sources for all variables.

Table 3: Essential work, returns to experience and complementarity to in-person work

Panel A: Employment Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Remote × Post	0.145	0.138	0.131	0.155	0.0396	0.150	0.131
	(0.0460)	(0.0517)	(0.0428)	(0.0485)	(0.0469)	(0.0474)	(0.0447)
Essential × Post		0.0441	0.0421				
		(0.0565)	(0.0689)				
Remote × Essential × Post			0.0109				
			(0.0831)				
High Returns to Experience × Post				-0.0525	-0.102		
				(0.0626)	(0.0788)		
Remote × High Returns × Post					0.223		
					(0.0934)		
High Share of Non-remote Co-workers × Post						-0.117	-0.126
						(0.0645)	(0.0823)
Remote × Non-remote Co-workers × Post							0.0405
							(0.0964)
Months	36	36	36	36	36	36	36
Occupations	364	364	364	353	353	364	364
R-squared	0.719	0.719	0.719	0.720	0.721	0.719	0.719
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Postings Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Remote × Post	-0.137	-0.152	0.00146	-0.135	-0.0877	-0.142	-0.127
	(0.0283)	(0.0309)	(0.0489)	(0.0292)	(0.0367)	(0.0279)	(0.0373)
Essential × Post		0.0867	0.128				
		(0.0314)	(0.0364)				
Remote × Essential × Post			-0.214				
			(0.0609)				
High Returns to Experience × Post				-0.00327	0.0184		
				(0.0317)	(0.0391)		
Remote × High Returns × Post					-0.0930		
					(0.0576)		
High Share of Non-remote Co-workers × Post						0.115	0.123
						(0.0313)	(0.0393)
Remote × Non-remote Co-workers × Post							-0.0315
							(0.0560)
Months	36	36	36	36	36	36	36
Occupations	337	337	337	327	327	337	337
R-squared	0.443	0.447	0.450	0.441	0.442	0.447	0.447
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses clustered at the occupation level. All regressions include occupation and month fixed effects. Panels A and B show regressions on occupations' employment and job postings index (base February 2020) that explore heterogeneities across remotability and three potential confounders. Essential occupations are those with more than 50% jobs allocated in "essential" industries. Occupations with "high returns to experience" are those with an above-the-median estimate of the marginal wage return to each additional year of work experience, based on the ACS 2018. Occupations with a "high share of non-remote co-workers" are those with an above-the-median share of non-remote co-workers, as measured by joining the OEWS industry-occupation matrix with the remotability indicator.

5 Where are these trends strongest?

We now explore the distribution in the postings underperformance of remotable occupations across cities in the United States.[18] We perform city-specific difference-in-differences estimations on the job postings of all different occupations, evaluating the differential performance of remotable occupations during the COVID pandemic. More specifically, we estimate the following equations:

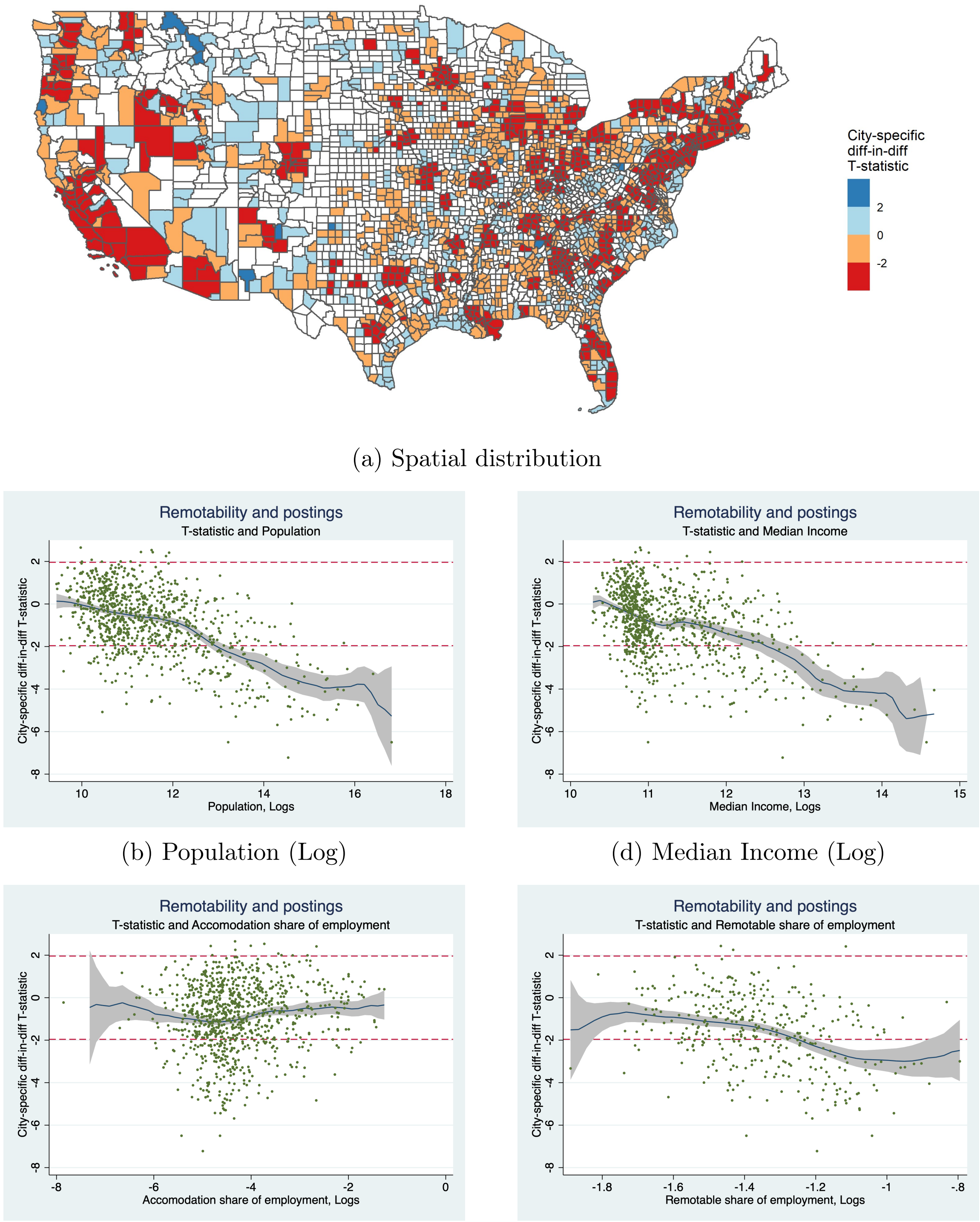
$$Y_{ot}^{c} = \alpha^{c} * R_{o} * Post_{t} + \sum_{k=1}^{K} \beta_{c}^{k} * X_{o}^{k} * Post_{t} + \phi_{o} + \phi_{t} + \epsilon_{ot}^{c} \tag{7}$$

Where Y_{ot}^{c} marks the value of the index of job postings for occupation o at month t in city c.[19] The coefficient of interest in each of the city-specific regressions is now α^{c}. Figure 4 shows the spatial distribution of the t-statistics of the α^{c} estimates, and how they associate with key baseline city characteristics: Size, Median Income, and the share of remotable occupations and the accommodation sector in the local labor market. We find that the postings underperformance of remotable occupations is strongest in larger and richer coastal cities, while it seems orthogonal to the baseline share of accommodation sector or remotable jobs in each local economy.

[18] We focus only on postings because monthly employment measures from CPS would be too imprecise if grouped at the occupation-city level.

[19] Indexes are calculated using the pre-COVID average number of postings for occupation o in city c.

Figure 4: Distribution of t-statistics of city-specific estimates of α^c



(a) Spatial distribution

(b) Population (Log)

(d) Median Income (Log)

(c) Share Accommodation (Log)

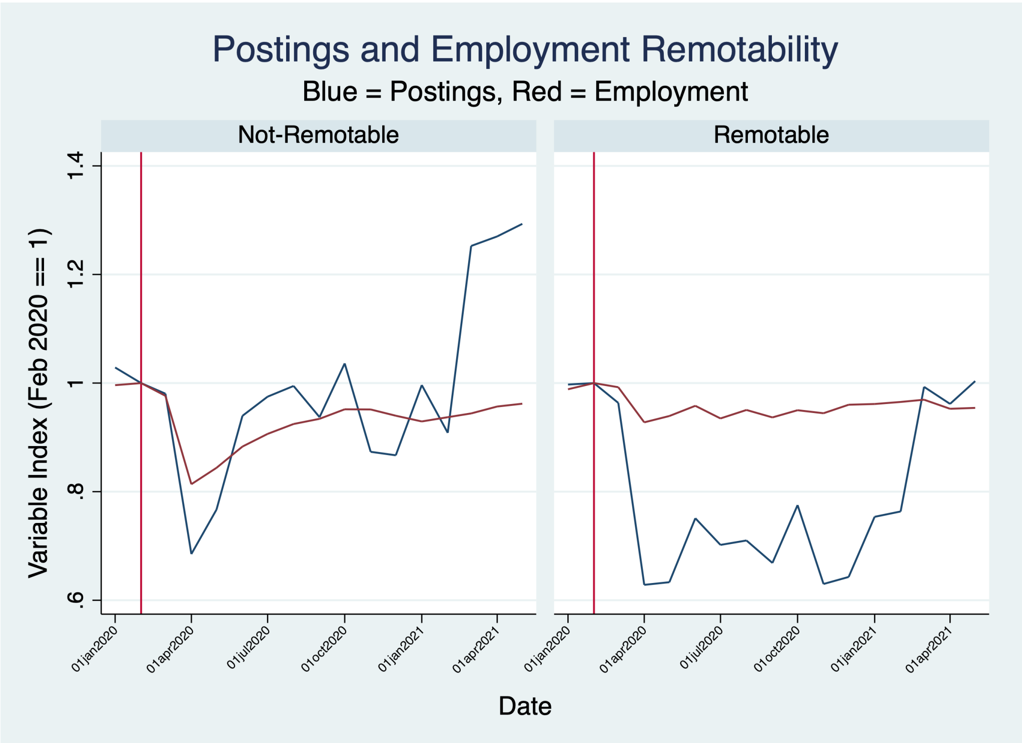
(e) Share remotable (Log)

Notes: Panels show the correlation of the t-statistics of remotability on the job postings index of 915 core-based statistical areas (CBSA) with different city-level covariates. Panel A shows its spatial distribution in a county-level map. Panel B, C, D, and E shows its correlation with population, share of jobs in accommodation industries, median income, and share of remotable jobs, respectively (all in log scale).

6 Converging back to normal?

Given the rapid roll-out of vaccination efforts, the US started reopening most sectors of the economy at the beginning the second quarter of 2021. Given ongoing debates on whether remote work patterns implemented during the COVID-19 will persist into the future or not, we now expand our analysis to the first 5 months of 2021. Figure 5 shows updated employment and postings trends for remotable and non-remotable occupations. Employment levels seem to have converged back to pre-pandemic levels for both remotable and non-remotable occupations. Remotable postings converged back to pre-pandemic levels at the end of the first quarter of 2021. Interestingly, while non-remotable postings had recovered before the start of the year, they have continued to grow beyond pre-pandemic levels. While this result may not be sustained beyond the full reopening of the economy, it continues to mark a postings gap between remotable and non-remotable occupations.

Figure 5: Postings, Employment and "Remotability" of Work by May 2021



Notes: Figure shows the index of employment and postings (base February 2020) for "remotable" and "non-remotable" occupations. Employment is shown in red lines, while posting is shown in blue lines.

7 Conclusion

This paper documents a statistically robust contradiction in the evolution of employment and job postings during COVID-19 along the "remotability" of work. While employment in "remotable" jobs has shown resilience during the pandemic, postings in such occupations have shrunk disproportionately. Importantly, these patterns are robust to controlling for lagged job separations and for tests observing postings patterns within industrial sectors of the economy, suggesting that the underperformance of remotable postings during COVID-19 is not explained by prior layoffs or by an industrial recomposition of the labor market.

We analyze potential explanations for this inconsistency, and find that postings for not-remotable positions outperform those of remotable jobs only if these are essential. However, we do not observe this pattern in employment dynamics, suggesting that a high demand for front-line workers has not been met in terms of employment. Moreover, Employment in remotable jobs only outperforms in occupations with high returns to experience, but the remotable underperformance in postings also appears strongest in occupations with high returns to experience. This suggests that employers aimed to retain workers with valuable experience that can work remotely, but halted the hiring of workers that would need to gather such experience at a distance. Finally, the postings gap was greatest in larger and richer coastal cities.

These findings uncover a relevant divergence between employment and hiring along the remotability dimension of work during the COVID-19 pandemic: Hiring efforts and employment retention efforts did not moving consistently along the remotability dimension of work. Given the ongoing policy efforts to stimulate the rehire of laid-off workers, as well as the potentially growing relevance of remote work, additional research on this apparent contradiction is necessary.

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Appendix

Table A1: Flexible controls for lagged separations

	(1)	(2)	(3)	(4)
VARIABLES	Postings Index			
Remote × Post	-0.137	-0.133	-0.141	-0.120
	(0.0283)	(0.0278)	(0.0290)	(0.0300)
Separations (1 Month Lag)		-1.52e-06	-1.74e-06	-2.85e-06
		(8.59e-07)	(7.56e-07)	(8.07e-07)
Remote × Separations (1 Month Lag)			7.21e-07	4.14e-06
			(3.76e-07)	(9.14e-07)
Remote × Post × Separations (1 Month Lag)				-3.54e-06
				(8.83e-07)
Separations (2 month Lag)		-1.67e-06	-1.71e-06	-2.19e-06
		(6.97e-07)	(6.86e-07)	(9.39e-07)
Remote × Separations (2 Month Lag)			2.91e-07	2.21e-06
			(2.12e-07)	(1.01e-06)
Remote × Post × Separations (2 Month Lag)				-1.93e-06
				(1.09e-06)
Months	36	34	34	34
Occupations	337	337	337	337
R-squared	0.443	0.426	0.427	0.425
Panel FE	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses clustered at the occupation level. Lagged separation controls consist on occupation-month estimates of worker separations reconstructed from the CPS, which asks respondents' reason of unemployment and their ongoing number of weeks unemployed.

Table A2: Heterogeneities considering continuous variables

Panel A: Employment Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Remote × Post	0.145	0.136	0.139	0.154	-0.0557	0.0549	0.0306
	(0.0460)	(0.0468)	(0.0636)	(0.0479)	(0.0848)	(0.0365)	(0.242)
Essential Industry Share × Post		0.0673	0.0676				
		(0.0304)	(0.0346)				
Remote × Essential Share × Post			-0.00257				
			(0.0537)				
Returns to Experience × Post				-0.0505	-0.0922		
				(0.0599)	(0.0740)		
Remote × Returns × Post					0.207		
					(0.0909)		
Avg. NR Share of Co-workers × Post						-0.412	-0.417
						(0.161)	(0.191)
Remote × Non-remote Share Post							0.0280
							(0.277)
Months	36	36	36	36	36	36	36
Occupations	364	364	364	353	353	364	364
R-squared	0.719	0.719	0.719	0.720	0.721	0.719	0.719
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Postings Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Remote × Post	-0.137	-0.150	0.0404	-0.135	-0.0500	-0.0594	-0.108
	(0.0283)	(0.0296)	(0.0662)	(0.0291)	(0.0555)	(0.0347)	(0.227)
Essential Industry Share × Post		0.0932	0.119				
		(0.0290)	(0.0321)				
Remote × Essential Share × Post			-0.174				
			(0.0640)				
Returns to Experience × Post				-0.00596	0.0112		
				(0.0272)	(0.0318)		
Remote × Returns × Post					-0.0860		
					(0.0534)		
Avg. NR Share of Co-workers × Post						0.359	0.348
						(0.118)	(0.136)
Remote × NR Share × Post							0.0556
							(0.246)
Months	36	36	36	36	36	36	36
Occupations	337	337	337	327	327	337	337
R-squared	0.443	0.448	0.450	0.441	0.442	0.446	0.446
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses clustered at the occupation level. All regressions include occupation and month fixed effects. Panels A and B show regressions on occupations' employment and job postings index (base February 2020) that explore heterogeneities across remotability and three potential confounders. The "essential share" is the share of jobs in an occupation allocated in "essential" industries. Returns to experience measures of the marginal wage returns to each additional year of work experience in a given occupation, based on mincerian-like regressions fit on the ACS 2018. The "share of non-remote co-workers" is the average share of non-remote workers in the industries where a given occupation is required, measured after joining the OEWS industry-occupation matrix with the remotability indicator.

Other potential explanations

Table A3 tests additional explanations to the divergence of remotable occupations' employment and job postings indexes. This section describe each of variables tested in this supplementary analysis.

Work experience in related occupations, and typical on-the-job training:

The BLS employment projections database 2018 includes related work experience requirements and typical on-the-job training for each SOC 2010 occupation. The work experience in related occupations variable shows the length of the work experience in related occupations that is commonly considered necessary to fill-in certain roles, or that otherwise is commonly accepted as substitute for other types of training or education. The variable takes the values "None", "Less than 5 years" and "5 years or more". On the other hand, the variable of typical on-the-job training shows the kind of training or preparation processes typically needed to attain competency in the job position once the candidate gets the job. The variable can take six values, ranging from "None" to "Long term on-the-job training", which involves either more than twelve months of training, or a combination of related work experience and formal classroom instruction. Just as in the case of entry-level educational requirements, each occupation has one level of experience and training associated. In order to aggregate these variables for each of our revised occupational codes (SOCXX), we keep the value with the largest share of employment according to the OEWS 2018 employment estimates.

Average tenure and average position in workers' careers:

Lastly, we estimate occupations' average tenure and average career position using resumes' data compiled and sorted by Burning Glass Technologies (BGT). Based on a sample of 800,000 resumes and with information of occupational codes, starting and ending years, and chronological position in the worker's career, we compute the average tenure of each occupation and the average in-career position of the occupation.

Table A3: Other potential explanations

Panel A: Employment Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Remote × Post	0.145	0.0726	0.132	0.0964	0.157	0.118	0.0326	0.141	0.164	0.146	0.145	0.0884	0.211
	(0.0460)	(0.0509)	(0.0650)	(0.0410)	(0.0877)	(0.0447)	(0.0538)	(0.0441)	(0.0534)	(0.0460)	(0.0596)	(0.0441)	(0.108)
College × Post		0.156	0.187										
		(0.0613)	(0.0824)										
Remote × College × Post			-0.110										
			(0.0997)										
High Wage × Post				0.167	0.183								
				(0.0601)	(0.0720)								
Remote × High Wage × Post					-0.0873								
					(0.0983)								
Training Required × Post						-0.112	-0.155						
						(0.0541)	(0.0695)						
Remote × Training × Post							0.173						
							(0.0883)						
Experience Required × Post								0.0380	0.0774				
								(0.0380)	(0.0508)				
Remote × Experience × Post									-0.120				
									(0.0695)				
Tenure Required × Post										0.0385	0.0379		
										(0.0473)	(0.0583)		
Remote × Tenure × Post											0.00282		
											(0.0859)		
Late Career × Post												0.152	0.179
												(0.0609)	(0.0703)
Remote × Late × Post													-0.168
													(0.117)
Months	36	36	36	36	36	36	36	36	36	36	36	36	36
Occupations	365	365	365	365	365	365	365	365	365	365	365	365	365
R-squared	0.711	0.712	0.712	0.712	0.712	0.711	0.711	0.711	0.711	0.711	0.711	0.712	0.712
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Postings Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Remote × Post	-0.137	-0.0813	-0.120	-0.112	-0.158	-0.113	-0.0915	-0.129	-0.140	-0.137	-0.157	-0.103	-0.128
	(0.0283)	(0.0308)	(0.0451)	(0.0284)	(0.0525)	(0.0287)	(0.0319)	(0.0283)	(0.0334)	(0.0283)	(0.0356)	(0.0276)	(0.0565)
College × Post		-0.123	-0.144										
		(0.0322)	(0.0413)										
Remote × College × Post			0.0718										
			(0.0615)										
High Wage × Post				-0.0881	-0.101								
				(0.0319)	(0.0377)								
Remote × High Wage × Post					0.0659								
					(0.0622)								
Training Required × Post						0.115	0.126						
						(0.0298)	(0.0372)						
Remote × Training × Post							-0.0422						
							(0.0573)						
Experience Required × Post								-0.0781	-0.0976				
								(0.0311)	(0.0427)				
Remote × Experience × Post									0.0581				
									(0.0565)				
Tenure Required × Post										-0.0794	-0.0959		
										(0.0305)	(0.0380)		
Remote × Tenure × Post											0.0686		
											(0.0553)		
Late Career × Post												-0.0908	-0.0960
												(0.0322)	(0.0370)
Remote × Late × Post													0.0320
													(0.0648)
Months	36	36	36	36	36	36	36	36	36	36	36	36	36
Occupations	337	337	337	337	337	337	337	337	337	337	337	337	337
R-squared	0.427	0.432	0.432	0.430	0.430	0.433	0.433	0.428	0.428	0.429	0.429	0.430	0.430
Panel FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses clustered at the occupation level.

Table A4: Breakdown of Remotability, Employment and Postings
Values from February 2020

Sub-sample	Occupations	Share of occupations	CPS Employment estimates	Share of employment	BG job postings	Share of job postings
Positive Employment (Feb, 2020)	364	85.85%	153,933,141	98.61%	3,297,217	99.49%
Positive Postings (Feb, 2020)	337	79.48%	151,867,823	97.28%	3,297,217	99.49%
—Non-Remotable	281	66.27%	112,954,162	72.36%	2,093,220	63.16%
—Remotable	83	19.58%	40,978,979	26.25%	1,203,997	36.33%
Always 0 Postings	48	11.32%	2,175,212	1.39%	—	—
Always 0 Employment	12	2.83%	—	—	17,007	0.51%
Total in both sources	424	100.00%	156,108,353	100.00%	3,314,224	100.00%

Notes: This table reports the relevance on employment and postings of the occupations included in the employment and postings regressions (first and second row), while also showing their breakdown by remotability (third and fourth row). Rows five and six show the weight of the occupations with no available postings and employment estimates, and row seven shows the universe of occupations captured across both datasets. Estimates of employment and postings correspond to February 2020.

Table A5: Descriptive Statistics (Continuous variables)

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Number of jobs (in thousands)	364	422.893	651.389	1.474	62.883	166.314	470.350	5,007.759
Job postings (in thousands)	364	9.058	20.394	0.000	0.696	2.624	8.178	175.085
Number of layoffs (in thousands)	364	8.513	19.892	0.000	0.000	0.000	7.316	158.280
Annual median wage 2019 (in thousands)	364	59.134	30.853	22.140	36.348	49.521	74.097	210.976
Share of jobs in essential industries	364	0.546	0.308	0.000	0.319	0.580	0.796	1.000
Returns to experience	353	0.013	0.008	−0.015	0.009	0.013	0.017	0.045
Avg. Share of Non-remote Co-workers	364	0.739	0.127	0.222	0.648	0.764	0.830	0.977

Notes: This table reports the distribution of the continuous variables tested as controls in the postings and employment regressions. The column N shows the number of occupations with available estimates of these variables and employment in February 2020. Additional columns show the summary statistics of each variable in February 2020.

Table A6: Descriptive Statistics (Discrete variables)

	Occupations	Remotable Occupations	Other Occupations	Employment share	Postings share
Median wage					
Below (0)	182	21 (12%)	161 (88%)	50.68%	42.11%
Above (1)	182	62 (34%)	120 (66%)	49.32%	57.89%
At least Bachelors' degree					
Not usually required (0)	250	27 (11%)	223 (89%)	65.43%	54.53%
Usually required (1)	114	56 (49%)	58 (51%)	34.57%	45.47%
Essential occupations					
Not essential (0)	142	22 (15%)	120 (85%)	34.38%	25.17%
Essential (1)	222	61 (27%)	161 (73%)	65.62%	74.83%
Returns to experience					
Low (0)	178	37 (21%)	141 (79%)	47.74%	45.02%
High (1)	175	41 (23%)	134 (77%)	48.25%	51.59%
Missing (—)	11	5 (45%)	6 (55%)	4.01%	3.38%
Share of "non-remote" coworkers					
Low (0)	196	42 (21%)	154 (79%)	46.69%	49.62%
High (1)	168	41 (24%)	127 (76%)	53.31%	50.38%
Tenure					
Low (0)	260	59 (23%)	201 (77%)	71.61%	75.73%
High(1)	104	24 (23%)	80 (77%)	28.39%	24.27%
Timing of occupation					
Late in career (0)	182	18 (10%)	164 (90%)	41.99%	24.71%
Early in career (1)	182	65 (36%)	117 (64%)	58.01%	75.29%
Related experience					
Not usually required (0)	311	64 (21%)	247 (79%)	78.51%	81.37%
Usually required (1)	53	19 (36%)	34 (64%)	21.49%	18.63%
Training					
Not usually required (0)	137	47 (34%)	90 (66%)	46.98%	54.33%
Usually required (1)	227	36 (16%)	191 (84%)	53.02%	45.67%

Notes: This table reports the distribution of occupations, employment and postings at the intersection of remotability and different occupational attributes. The employment and posting estimates correspond to February 2020.

Table A7: Variable description

Variable	**Source**	**Original aggregation**	**Description**	**Format**
Teleworkable	O*NET database 24.2 and Dingle and Neiman (2020)	6-digits Standard Occupation Classification (SOC)	Equal one if occupation is teleworkable.	Binary
Annual Median Wage	2018 Occupational Employment Statistics (OES)	6-digits Standard Occupation Classification (SOC)	Median Annual Wage in 2018	Continuous
Education requirement	BLS Employment Projections Database 2018	6-digits Standard Occupation Classification (SOC)	Education level achieved by surveyee	Binary (1 = Bachelor or higher)
Work Experience	BLS Employment Projections Database 2018	6-digits Standard Occupation Classification (SOC)	Keep the work experience level accounting for the largest share of employment	Binary
On the job training	BLS Employment Projections Database 2018	6-digits Standard Occupation Classification (SOC)	Keep the training level accounting for the largest share of employment	Binary
Essential occupation	Own calculations using the 2018 Occupational Employment Statistics (OES) and Delaware and Minnesota classifications of essential industries	4-digits North American Industry Classification System (NAICS) and 6-digits Standard Occupation Classification (SOC)	Share of employment in essential industries.	Binary and continuous
“Not-remote” co-workers	Own calculations using O*NET database 24.2 and the 2018 Occupational Employment Statistics (OES)	4-digits North American Industry Classification System (NAICS) and 6-digits Standard Occupation Classification (SOC)	Share of “not-remote” workers for NAICS, and of average co-workers for SOC	Binary and continuous
Returns to experience	American Community Survey and Own Calculations	2010 Occupational Census Codes	Occupation-specific estimates of returns to experience	Binary and continuous
Average Tenure	Own calculations using Burning Glass Technologies’ resume data	6-digits Standard Occupation Classification (SOC)	Average tenure length of the occupation in years	Binary and continuous
Median occupational rank	Own calculations using Burning Glass Technologies’ resumes data	6-digits Standard Occupation Classification (SOC)	Median position of the occupation in workers’ resumes	Binary and continuous

Notes: This table summarises the source, aggregation method, and format of the set of occupational attributes tested as plausible drivers of the performance of employment and postings, including remotability.