Task content and job losses in the Great Lockdown

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Abstract

I examine the short-term labor market effects of the Great Lockdown in the United States. I analyze job losses by task content (Acemoglu & Autor 2011), and show that they follow underlying trends; jobs with a high non-routine content are especially well-protected, even if they are not teleworkable. The importance of the task content, particularly for non-routine cognitive analytical tasks, is strong even after controlling for age, gender, race, education, sector and location (and hence for differential demand and supply shocks). Jobs subject to higher structural turnover rates are much more likely to be terminated, suggesting that easier-to-replace employees were at a particular disadvantage, even within sectors; at the same time, there is evidence of labor hoarding for more valuable matches. Individuals in low-skilled jobs fared comparatively better in industries with a high share of high-skilled workers.

JEL Codes: D22, E32, J23, J24, M51.

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1 Introduction

The COVID-19 pandemic and the associated non-pharmaceutical interventions (NPIs) to contain it have rendered a massive shock on the global economy. In the United States, an unprecedented 22 million people applied for unemployment benefits over the space of 4 weeks, an almost 30-fold increase over the previous 4-week period.

Substantial policy measures have been enacted in virtually all advanced economies, and the United States presents an interesting case, in that policy measures were designed to support workers, through a large expansion of unemployment benefits, rather than jobs, which was the case in a number of countries in Europe which implemented employment support measures, such as wage subsidies. At this early stage, employment losses at the level of the United States have not been reported elsewhere.

At first glance, the reaction may appear excessive to what is likely to be a temporary shock. On the one hand, firms may fire workers to reduce costs in the face of dwindling revenue, particularly if they have other liabilities close to maturity, or because the uncertainty has increased their risk aversion. On the other hand, search costs for good job-worker matches are high, and labor shedding is inefficient; one would then expect that firms shed their hardest-to-replace workers last.

In this paper, I investigate the drivers of short-term job losses in the United States as a result of COVID-19 and the "Great Lockdown" recession. I focus on the United States both because it represents the more extreme case of labor market shock, partially because it is well-known to represent the most dynamic labor market in the world (Elsby et al. 2013), but also because it provides high-frequency public use micro-data.

I use CPS micro-data, and consider all exits from employment; that is, I consider individuals who were employed in February or March 2020, and look at monthly transitions (and hence only use the continuing sample of the CPS). I group together all transitions out of employment, including out of the labor force, as it is likely that a number of exits from employment are erroneously recorded as exits from the labor force precisely because of the force from the shock.[1]

[1]The standard definition of unemployment as individuals not working but looking for work is misleading in a context where individuals are forced to stay at home. Overall, the number of individuals outside the labor force rose by 8.7 million in April relative to February.

I focus on the role of structural drivers of employment losses, and in particular the task characteristics of jobs, using the task content framework of Acemoglu & Autor (2011). While other papers (e.g. Cajner et al. 2020, Chetty et al. 2020, Cowan 2020) have also studied worker transitions in response to the COVID-19 shock, the task framework is useful in examining whether and why certain workers were more affected than others. The task framework looks at jobs as a collection of tasks, which require certain skills to be completed, hence breaking down the skill content of each job. It can provide a comprehensive framework for analyzing employment losses, by considering job characteristics, and shed light on the types of jobs that were most affected, going beyond demographics, education or sectoral effects. The task framework is particularly suited to studying the pandemic shock, due to the pronounced differences it is expected to have had on workers depending on the relationship of the tasks they perform to technology, location, and other actors. For instance, the most salient effect of COVID-19 on the labor markets is the rise of teleworkability, as individuals switch to working from home.[2] While we expect individuals in teleworkable occupations to be less affected, other issues may matter, such as the relative supply of particular skills. The task framework can help in analyzing these issues.

I further examine whether firms were less likely to layoff hard-to-replace employees. Labor hoarding (Guerrieri et al. 2020) may be optimal if the shock is expected to be temporary and labor search is subject to high costs. Put another way, firms may be less likely to destroy high-value matches if they can afford to keep them until the recovery, even at a short-term cost. By contrast, the uncertainty and possible credit tightening caused by the shock may lead employers to layoff easy-to-replace employees (or sever low quality-matches in general) in order to reduce costs. I use a simple measure based on average monthly frequency of turnover, which has the advantage of being easily and transparently estimated with a large sample, for both sectors and occupations.

I find strong evidence that job loss patterns resemble underlying trends. Task content is of central importance; in particular, individuals in jobs with a high non-routine cognitive analytical (NRCA) and personal (NRCP) content are especially well-protected, even if their jobs are not teleworkable. The importance of the task content, particularly for non-routine cognitive analytical tasks, is strong even after controlling for age,

[2] Bryniolfsson et al. (2020) report that half of previously employed workers work from home, 70% of which used to commute.

gender, race, education, sector and location. Results are robust to controlling for the extent of local lockdowns (at the CBSA level) using high-frequency data on people movements and credit card payments. These results are consistent with the findings of Cajner et al. (2020), who use administrative payroll data to find much larger employment declines for lower paid workers. Furthermore, I find patterns consistent with labor hoarding for workers in NRC-intensive jobs; controlling for the average turnover rate at the sector or occupation level wipes out any role for task content for all job types, except for those intensive in non-routine cognitive tasks. This also possibly implies a role for preemptive layoff for easy-to-replace workers. I also find an important role for complementarities for NRCA-intensive jobs; in industries with a large concentration of such jobs, lower skilled workers are less likely to lose employment than individuals in similar occupations in other industries, even after controlling for sectoral characteristics.

The results are consistent with the work of Jaimovich & Siu (2020) and Hershbein & Kahn (2018), who show that job polarization, the switch away from routine jobs towards non routine cognitive and manual jobs that has characterized labor markets in advanced economies for the past three decades (Autor 2015), occurs largely in recessions, when routine jobs are disproportionately destroyed; Jaimovich & Siu (2020) also show that polarization implies jobless recoveries, as routine jobs are permanently lower. Foote & Ryan (2015) further show that middle-skill workers are predominantly employed in volatile sectors.[3] While it is too early to tell what the implications of COVID-19 are, let alone whether the short-term effects of the shock will be persistent, a corollary of that research could be that structural changes in employment also take place primarily in recessions (Burger & Schwartz 2018). For instance, it is less costly (in the sense of foregone sales) to implement organizational changes in downturns and new firms are likely to operate with newer technology vintages than older firms.[4]

[3] It should be noted that structural change, in particular polarization, has not been found to be associated with jobless recoveries in advanced economies outside the United States (Graetz & Michaels 2017). For the Great Recession, in particular, a number of commentators (e.g. Rothstein 2017) have argued for a protracted weak demand explanation for the slow recovery.

[4] There are already news reports of sharp organizational changes brought forward as a result of the crisis. Carphone Warehouse, a large UK phone retailer announced that it would cut 2900 jobs and close all 531 standalone stores, citing changes to the industry unrelated to COVID-19 (Warrington 2020). At the same time, other organizations have halted large reorganizations, which could have a smoothing effect on the shock. HSBC announced postponement of a massive global overhaul in order to be able to function smoothly during the crisis (Crow 2020).

I finally briefly consider whether a major reallocation shock is under way. Indeed, certain sectors, related to home consumption and leisure, are booming. Barrero et al. (2020) provide anecdotal evidence of substantial hiring sprees in booming sectors, and even exchanges by firms in affected sectors to reallocate workers to booming firms. They then provide direct evidence of an important reallocation effect of the shock; using high frequency firm-survey data, they report three jobs created for every ten destroyed, a large number given the unprecedented overall contraction. They also construct a forward-looking reallocation measure, using firm employment expectations, and document a sharp rise in expected reallocation. I examine whether such a phenomenon can already be detected by publicly available data. There is no meaningful change in the share of workers switching occupations or industries within the month, suggesting that any major reallocation would be taking place within occupations or industries. Furthermore, while I confirm the relative creation and destruction magnitudes in aggregate data, by comparing the hire and separation rates in the Job Openings and Labor Turnover Survey (JOLTS), I note that the hire rate is similar to historical averages, suggesting that evidence of a major reallocation shock may be premature until new data is released.

2 Data

The primary data source is the Basic Monthly Sample (BMS) from the Current Population Survey (CPS), the primary source of information for the US labor market. I use primarily the 2012-2020 sample, to focus on recent trends. I also rely on data going back to 2005 for some exercises.

I base my analysis of task content on the job skills measures created by Acemoglu & Autor (2011). They use data from the O*NET (Occupational Information Network) study, which provides survey-based measures of work abilities (e.g. manual dexterity), activities (e.g. thinking creatively), work context (e.g. face-to-face discussion) and skills (e.g. social perceptiveness) for each occupation. They classify each occupation according to six tasks, collected in three broad groupings: non-routine cognitive (NRC), routine (R), and non-routine manual (RM), approximating the top, middle and lower ends of the skills distribution (conventionally defined by a one-on-one mapping of wages to skills). Each of these is further broken down into two subgroups: non-routine cognitive analytical (NRCA) and personal (NRCP), routine cognitive (RC) and manual (RM), and non-routine manual physical (NRMPH) and personal (NRMPE).[5] It has been long recognized that a simple high-, middle-, and low-skill categorization may be insufficient to capture the intricacies of the labor market. Figure A1 in the appendix shows a mapping between skills, tasks and occupations.[6]

The proxy for teleworkability is the index created by Dingel & Neiman (2020), at the occupation level. They also use responses to the O*NET survey, and based on questions relating to work context and activities of an occupation, such as working outdoors or handling objects or machinery, they classify the feasibility of working from home, for each occupation, creating a binary indicator equal to 1 for teleworkable occupations. Teleworkable jobs include all or most jobs in computer and mathematical, education, legal, business and management occupations, and opposite for building, food preparation, construction and production occupations. The mapping from O*NET to CPS is not one-to-one, so for a few CPS code with multiple values I take the average (across 4-digit codes) and recode the indicator to 1 if the average value is above 0.5, and 0 otherwise.

To measure occupation- and sector-specific match quality, I take the CPS basic monthly micro-data files from 2005-2015 and calculate, for each occupation and industry, the share of workers that is laid-off every month. I take the median monthly value for each year to account for seasonality and then average them over the entire 15-year period in order to sweep away cyclical forces.[7] This measure, which does not include job-to-job transitions, is a proxy for the ease with which firms can replace their employees, and hence for the average job-specific match quality (for each sector and occupation). The downside of this measure is that it may be higher for declining industries. As an auxiliary indicator, I also use the gross worker flow rate, given by the

[5]Measures for each task are standardized, then summed and the sum is standardized again.

[6]Acemoglu & Autor (2011) do not explicitly use the NRMPE category in their paper, only define it in their code. I further use the refinement of Dias da Silva et al. (2019), who exclude management and professional occupations (Census codes 10 to 3599), as medical professions were ranked highly in NRMPE, as well as NRCP, making distinction between the two groups difficult. The NRMPE category is designed to capture in-person services, which are thought to be a growing part of the new economy.

[7]Median estimates are preferable to seasonally adjusted estimates because seasonal industries will have a higher turnover on an annual basis. I also compute instead seasonally adjusted estimates and the results are qualitatively similar.

sum of transitions out of employment, transitions into employment, and job-to-job transitions, as a share of total employment, for the industry or occupation. Job-to-job transitions are calculated as the share of workers who remain employed in consecutive months but report that they are not working for the same employer, following Fallick & Fleischman (2004). [8]

The sample is composed of individuals aged 15 or over. As the interest of this paper is on employment losses, I focus on transitions from employment to non-employment, and hence use the panelized version of CPS, using the approach of Nekarda (2009).[9] The main dependent variable (ENE) is equal to zero for individuals who work at time t-1 and remain employed at time t, and 1 for those who work at t-1 but do not at t. This implies that people who drop out of the labor force are also included, to get a more complete measure of transitions outside of employment. I only exclude individuals who voluntarily leave their jobs.[10] Focusing on those formally unemployed (individuals without work but seeking to work) may be substantially misleading in this case. Indeed, employment in April 2020 fell by 24.7 million relative to February (in seasonally unadjusted terms), but unemployment rose by 16.3 million, meaning that roughly a third of job losers exited the labor force.[11] Invariably, this choice comes with some issues, seasonality being a clear one, as workers in seasonal industries may drop out from the labor force in the low seasons; however, this should be controlled for using industry dummies and month dummies.

I work with two-level NAICS sectors, and group some similar sectors together, as some have too few observations in each month to record transitions out of employment. I end up with 35 different sectors (down from 51 used in the detailed group two-digit classification in CPS). I cluster standard errors at the occupation level, though results change little if I cluster at the sector-level instead.

[8]There is a large number of respondents who are employed in consecutive months yet as reported as "not in universe" for this question, but it is impossible to know why.

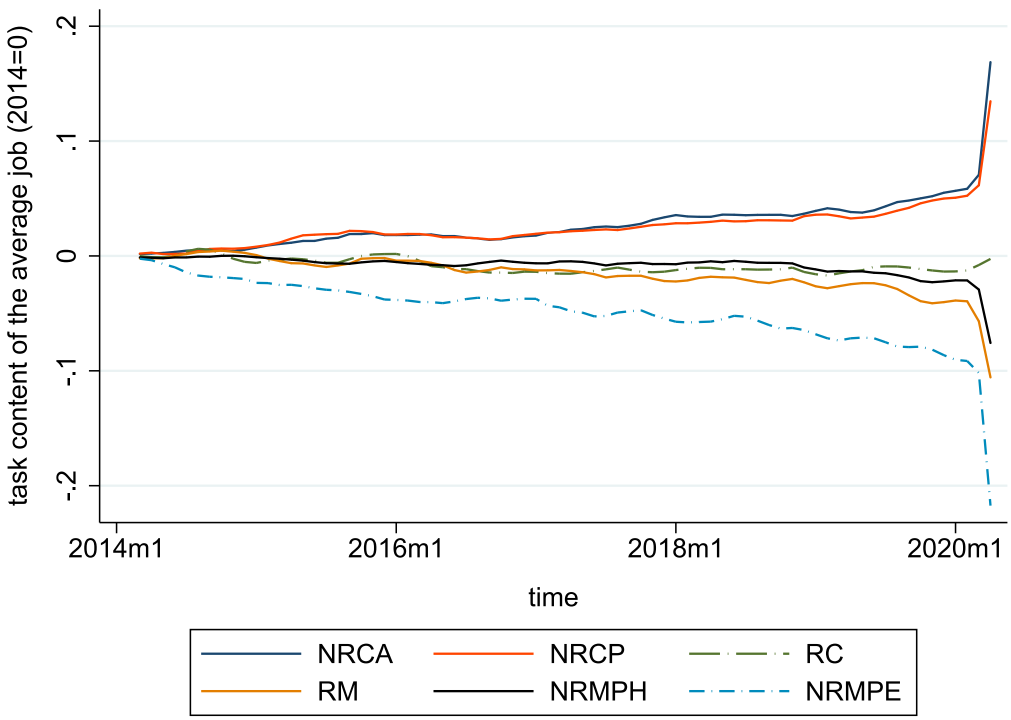
[9]I panelize using the code of Kevin Rinz, available at `kevinrinz.github.io/data.html`.

[10]Individuals who were let go and found a new job are not considered as having transitioned. This is related to the well-known time aggregation bias in CPS data (Shimer 2012), but is not a concern in this case, as I am interested in how the shock affected transitions out of employment. If individuals manage to find another job within the month, this would imply that the industry/occupation where this worker is employed is resilient enough to the shock. Exceptions are cases where individuals change occupations/industry, or individuals transitioning voluntarily to other jobs.

[11]The BLS noted that correcting for the excess transitions out of the labor force would increase the unemployment rate in April by almost 5 percentage points. See here.

CPS is a rotating panel, where households are recorded for four consecutive months, and where leakages from one month to other are around 6%; as such, while for two adjacent months the matching is around 70%, it is less than 50% for non-consecutive months (Rivera Drew & Warren 2014). As such, I prefer to study transitions from February to March and March to April. With such a large increase in unemployment, I expect effects in April to be mostly cumulative, justifying this approach.

Figure 1: Evolution of task content of the average worker



Notes: Each line shows the content of the average job for the specific task at each point in time. Task indices are standardized, so the scale is in standard deviation form Sample is from January 2015 to April 2020. Seasonally adjusted using X13-Seats. All series set to 0 in January 2014, and shown in 3-month moving averages until February 2020, in order to smooth the series. The adjusted and unadjusted trends are indistinguishable before March 2020.

The main result is previewed with graphical evidence in Figure 1, where I plot, for the 2014-2020 period, the content of the average job for each of the six tasks, across all jobs in the US economy. Each index is standardized, so the scale is in standard deviation form. Jobs intensive in non-routine cognitive tasks have been on a long-run upward trend for the past few years. For these the trend accelerated in 2019, and rose substantially in March and April 2020. The opposite is true for all types of manual tasks, while the average RC task content has been mostly flat for the past five years.

These patterns indicate an increase in the share of jobs intensive in tasks typically associated with high skills, a flat profile for middle skills, and a reduction for low skills. As such, this is not indicative of job polarization. Figure 2 replicates and extends to recent years results from Autor (2015), and shows (smoothed) changes in employment shares and wages at different intervals for each occupational skill percentile (in 1980, a conventional starting point for such analyses). Unlike the 2007-2012 period, where job losses due to the financial crisis occurred in the middle of the distribution, the recovery period of 2012-2018 exhibits a positive linear relationships between skills and relative employment growth. At the same time, wage gains were relatively broadly shared. This could be indicative of skill bias, together with an increase the relative supply of high skills, preventing the skill premium from rising, as was the case in the 1970s (Katz & Murphy 1992). This is purely a conjecture though, and beyond the scope of the paper to study. Clearly though the more recent period is not associated with an increase in job polarization, but rather an evolution in employment shares increasing in skill.

3 Estimation

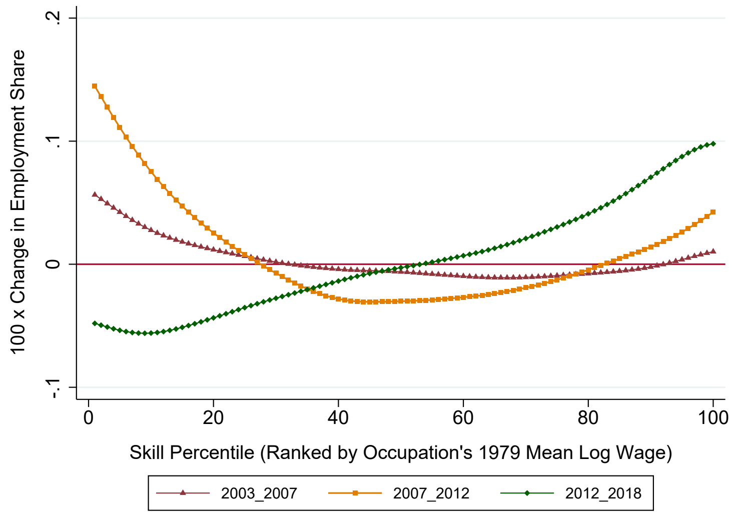
3.1 Task content of occupations

In this section, I examine how the probability of leaving employment depends on the task characteristics of the job, using the task indicators of Acemoglu & Autor (2011). For ease of interpretation, I convert the continuous task index to a dummy variable, equal to 1 for occupations whose values of the index is above the 80^{th} percentile of the index, and zero otherwise.[12] Recall that the dependent variable is ENE, which is equal to 1 for individuals transitioning out of employment, and 0 if they remain employed. I run several models where I regress ENE on the binary task indicator, dummies for March and April 2020, and the interaction of the task indicator with the pandemic month dummies. I run models for each of the task indicators separately.

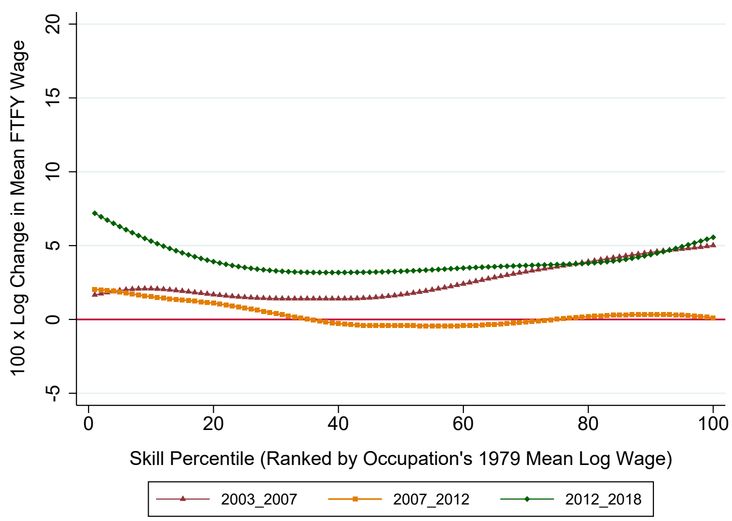
[12]Results are qualitatively very similar with the continuous indicator as well.

Figure 2: Smoothed employment and wage changes by occupational skill percentile

(a) Employment



(b) Wages



Notes: Calculated using 2003, 2006-2008, 2012, and 2014-2018 American Community Survey Integrated Public Use Microdata Series (IPUMS) files. The top figure plots changes in employment shares by 1980 occupational skill percentile rank using a locally weighted smoothing regression (bandwidth 0.75). The bottom figures plots similarly defined log wage changes for full-time, full-year workers. Skill percentiles are measured as the employment (annual hours) weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. Consistent occupation codes for Census years 1980, 1990, and 2000, and 2008 are from Autor (2015).

More formally, the model I study is:

$$\begin{aligned} ENE_{ijo,t} = \alpha_0 + & \alpha_1 task_{ijo,t-1} + \alpha_2 task_{ijo,t-1} \times Mar20_t + \alpha_3 task_{ijo,t-1} \times Apr20_t \\ & + \alpha_4 Mar20_t + \alpha_5 Apr20_t + \alpha_6 \Theta_{ijo,t-1} + \gamma_j + \delta_t + \epsilon_{ijo,t}, \end{aligned} \tag{1}$$

where $ENE_{ij,t}$ denotes the outcome for individual i in sector j, in occupation o, at time t, $task_{ijo,t-1}$ is the binary indicator for whether the individual is in a job with a high intensity of the given task at time t-1, $Mar20$ and $Apr20$ are indicators for March and April 2020, γ_j are sector dummies, δ_t are time dummies, $\Theta_{ijo,t-1}$ are lagged individual controls, and $\epsilon_{ij,t}$ is the error term. Recall that the sample is limited to individuals employed in the previous month.

As such, I examine whether task intensity matters in general for transitions out of employment, and whether the COVID-19 shock altered any prevailing pattern. Of course, losing one's job at any given month could have little consequences for one's employment trajectory, but it is important to control for time-invariant patterns, to avoid conflating them with pandemic effects. All regressions include monthly dummies to control for seasonality, and some specifications also include sector-time dummies. Individual controls include age and its square, gender, and an indicator for whether the person is Caucasian. The education variable is categorical for less than high-school, high-school/GED graduate and college graduate. This model is similar to the one used by Cajner et al. (2020).

Results are given in Table A1 in the Appendix; I report here the main coefficients in graphical form for convenience, using the odds ratio coefficient from a logistic regression, for the specification with all controls and sector-time fixed effects, for the March and April samples from 2012-2020. As the probability of losing employment rose so much in April 2020, the odds ratio, which gives the relative odds of losing employment for each value of the binary variable, has the desirable feature of scaling responses, which is convenient for a graphical representation.[13]

Each set of lines in Tables A1 responds to regression results from (1) for each of the

[13] The downside of logistic regressions is that convergence is problematic when including a large set of fixed effects (e.g. with sector-time dummies), which is why linear probability models are preferred as a baseline.

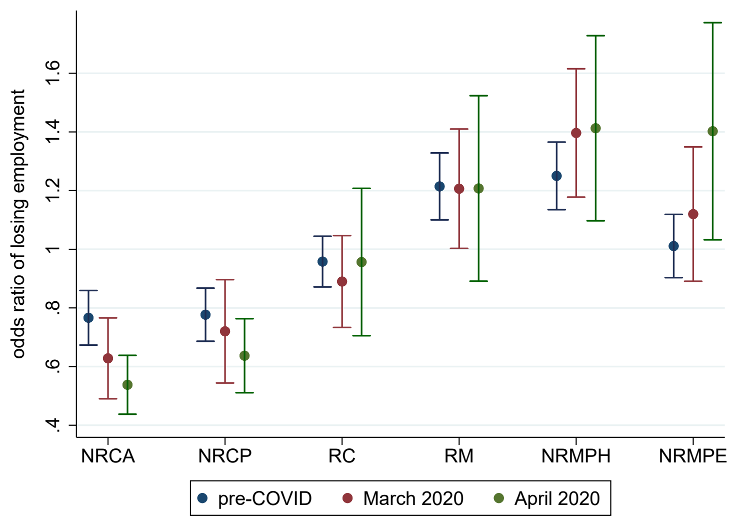
six task indices. It reports the α_1, α_2 and α_3 coefficients, and each column lists results from alternative specifications. For ease of interpretation, the task-COVID interaction coefficients are given in additive form to the pre-COVID coefficient, hence capturing the total effect of the pandemic shock.

The first set of results consider the role of the non-routine cognitive analytical (NRCA) content of the job. NRCA content is an important predictor of employment losses - individuals with high NRCA occupations have a 3pp lower probability of losing employment in March 2020. What is more, the effect remains strong even when demographics, education and job intensity are taken into account. Column 4 further shows results after controlling for industry-month fixed effects, which is the easiest way through which I can control for differential demand shocks, most notably those related to exposure to social distancing. The coefficient changes little and remains highly significant. This is a key finding: individuals with NRCA-intensive jobs were more protected from the pandemic shock irrespective of the industry they worked in.

NRCA content is more important for the non-teleworkable occupations (column 5). A large part of this is driven by sector-specific effects, as the inclusion of industry fixed-effects reduces substantially the magnitude of the NRCA coefficient, though it is still statistically significant. This suggests that, for the subset of teleworkable occupations, sectoral differences account for almost half of the effect, possibly indicating again that industries abundant in NRCA jobs were hit comparatively less. Of course, industry fixed effects remove time-invariant effects as well, which could be particularly important regarding job-sector-specific match value. High-NRCA individuals may be more dear to their firms, possibly due to high job-specific match surplus, or relatively low supply of the particular skills they have. For teleworkable occupations, by contrast, while NRCA-intensity by itself is less important than for non-teleworkable ones, the coefficient does not change after controlling for sector fixed-effects. Even within the subset of teleworkable jobs and within industries, individuals in NRCA-intensive occupations are less likely to be hit by an employment loss, which indicates that such a supply story is likely to hold.

The pre-COVID coefficient shows that individuals in NRCA-intensive jobs are always less likely to transition out of employment in any given month. At the same time, this effect is magnified in March, and the coefficient on the task-COVID interaction term is

Figure 3: Odds ratio coefficient of ENE on task content



Notes: Odds ratio coefficients with 95% confidence intervals from logistic regressions of the probability of losing employment to a binary of high-task content, its interaction with a COVID dummy, relevant covariates and time-sector fixed effects. Sample is composed of February to March and March to April transitions from 2012-2020.

statistically significantly different from the pre-COVID coefficient. In the pre-COVID sample, individuals in jobs with high-NRCA content were 2pp less likely to transition out of employment, relative to a baseline probability of 4% for other individuals. In March, those in high-NRCA jobs were 3pp less likely to lose their jobs, while 5.5% of those in low-NRCA jobs lost their jobs. This is strong evidence that the pandemic shock served to exacerbate existing patterns, in particular providing for employment protection for jobs with high NRCA content. This pattern survives across all specifications for NRCA.

For April, the results are very similar, only now the magnitude of the coefficients is substantially higher, because the loss of employment in the aggregate is three times higher than March. Figure 3 shows graphically odds ratio coefficients of a logistic regression of the specification with fixed effects (column 4).[14] The blue dots give estimates for α_1, the red dots for α_2, and the green dots for α_3. As these are scaled (relative to the probability of losing employment for the baseline group), they help with inter-

[14]The coefficients come from regressions only including March and April for 2012-2020, as the inclusion of sector-time dummies renders the estimation unstable.

preting the magnitudes. I see that the role of NRCA task content in protecting from employment losses is even higher in April, where individuals in these jobs had 40% lower odds of losing their jobs than others.

Results are roughly similar for non-routine cognitive personal (NRCP) jobs, with the coefficient being negative and statistically significant across most specifications, with the exception of the subsample of teleworkable jobs, and for non-teleworkable jobs once controlling for sector fixed-effects. Intuitively, for jobs that can be executed remotely, NRCP elements are less relevant. The estimated coefficients are also larger in magnitude for the COVID-19 period, but by a smaller margin than NRCA, however the difference becomes statistically significant in April for all specifications.

Individuals in jobs with a high content of routine cognitive (RC) element fared better only once controlling for demographics, as they have substantially lower educational attainment than individuals in NRC-intensive jobs, and in particular for the non-teleworkable jobs. In this case as well, the magnitude is substantially higher than for the pre-COVID sample, but similar qualitatively. This may be somewhat surprising as these jobs are typically administrative and clerical (Acemoglu & Autor 2011), and are thought to be at-risk for automation. At the same time, such occupations that have still survived previous automation waves may be substantially more difficult to automate at the margin. The focus is on monthly transitions out of employment, making it difficult to discern long-term patterns. Moreover, sector-specific effects seem to drive all of the variation, and, in any case, any effect is wiped out in April.

On the other hand, routine manual (RM) and, especially, non-routine manual physical (NRMPH) jobs were at a clear disadvantage. This is likely to reflect the fact that these jobs are typically executed with physical presence, while requiring little training and have low match value; as such, they are hit both with supply and demand shocks. Again though, such patterns were clearly present for the pre-COVID sample as well. These effects are not driven by sector-specific shocks, which could be indicative of supply forces. Indeed, the coefficient for NRMPH in April becomes much larger once controlling for sector-specific effects. This is indeed consistent with employers cutting NRMPH-intensive jobs to reduce operating expenses in the face of uncertainty shocks, as such positions are relatively easy to fill-in once uncertainty recedes.[15]

[15]The very high coefficient of the NRMPH index for teleworkable occupations is due to the fact that

Finally, individuals employed in occupations with a high non-routine manual personal (NRMPE) content did not differ from average, irrespective of the specification. Note again that I have removed management and professional jobs from this group; otherwise the coefficient would indicate they had fared relatively better, especially in April, and in particular for non-teleworkable jobs, as the majority of them would have been in medical occupations, which were in particularly high demand due to the pandemic shock.

To recap, I find that non-routine cognitive jobs were substantially less affected by the pandemic shock. High NRCA jobs have enjoyed a premium in the form of additional job security. Individuals in routine cognitive jobs were also somewhat protected, at least given their relatively lower educational attainment, but in this case sectoral-specific effects drive the results. On the other hand, manual jobs, particularly non-routine manual physical jobs, were especially affected. In all these cases, the pandemic shock exacerbated preexisting patterns. It should be noted that the COVID-19 shock does not resemble an automation shock as such, but rather a skill-biased shock, in that lower skills seems to have been disproportionately affected. At the same time, social distancing measures necessitate labor substitution technologies by firms, and it is unclear whether this will remain once the shock passes. Finally, the results are consistent with the analysis of Cajner et al. (2020), who focus on separations by wage groups, and find that sectoral effects (which account for the differential shocks of the pandemic) played a relatively minor role.

An interesting parallel to this analysis is how the pattern of separations relates to that in the Great Recession. To investigate this, I run the baseline model (1) on a sample covering only the COVID-19 Shock (February-April 2020) and the Great Recession (October 2008-December 2009). The Great Recession started in December 2007, but it was relatively mild at its early stages, and non-seasonally adjusted employment was rising until late Summer 2008. As such, I start the after the Lehman shock, when the recession became especially deep and unemployment started to climb fast.

Results are shown in table 1. Starting with NRCA, in the Great Recession individuals employed in high-NRCA jobs had 29% lower odds of losing their job relative to others. This effect was magnified substantially during the pandemic, with indi-

the sample is very small, as this category only includes three occupations.

viduals in these jobs having 32% lower odds of losing their job relative to the Great Recession. As such, the protection individuals in NRCA jobs received was then substantially higher in the current recession relative to the Great Recession. There could be a number of reasons behind this result, most prominently the fact that the Great Recession was a large protracted demand shock, with employment falling continuously for over a year, while the COVID-19 shock was sharper but much shorter. Firms are hence perhaps less likely (in relative terms) to let go of their higher skilled workers in the current recession, expecting a faster increase in demand.

Workers in NRCP-intensive jobs were similarly less likely to lose their jobs in the Great Recession, but this effect remained the same in the pandemic. More interestingly, workers in RC-intensive occupations were not more likely than the rest to separate in the Great Recession, and this did not change in the current recession. Given that this group never recovered from its losses in the Great Recession, it then seems that such occupations were not disproportionately hit, but rather new jobs were not created once the recovery started. By contrast, while individuals in RM jobs were substantially more likely to be separated in the Great Recession, the difference is much weaker, and not statistically significant, for the COVID-19 episode. At the same time, this group did recover from the Great Recession, but slowly.

For NRMPH-intensive jobs, results are similar with RM jobs, as those groups overlap to some extent. Finally, by far the largest difference is in the NRMPE group, which was hit the hardest in the COVID-19 shock, as it mostly comprises of high-contact personal service jobs. In the Great Recession, this was group was not affected differently than average (and also recovered faster).

The recovery from the Great Recession was also slow (even though the expansion was the longest on record). It took almost 8 years from its peak (October 2009 to March 2017) for unemployment to reach its pre-crisis trough of 4.4%, and even though it fell as low as 3.6% in February 2020, the employment rate never recovered, due to a persistent decline in the participation rate. (Jaimovich & Siu 2020) have shown that the employment losses from the Great Recession were substantially heavier for routine occupations; they argue that the loss of routine jobs and the delayed adjustment of workers to new jobs can explain the jobless recovery. Routine cognitive occupations (using the definition of Jaimovich & Siu 2020), in particular, never recovered, staying

Table 1: The Great Lockdown versus the Great Recession

	(1) NRCA	(2) NRCP	(3) RC	(4) RM	(5) NRMPH	(6) NRMPE
index $\times GR$	-0.007***	-0.008***	-0.004	0.012***	0.012***	-0.000
	(-3.75)	(-4.33)	(-1.63)	(3.91)	(3.88)	(-0.15)
index $\times Mar20$	-0.013***	-0.011**	-0.005	0.007*	0.012***	0.006
	(-4.05)	(-2.49)	(-1.30)	(1.82)	(3.00)	(1.13)
index $\times Apr20$	-0.073***	-0.063***	0.008	0.037**	0.043***	0.053**
	(-8.30)	(-5.69)	(0.48)	(2.10)	(2.69)	(2.44)
N	678522	678522	678522	678522	678522	678522
Dem/phics	X	X	X	X	X	X
Education	X	X	X	X	X	X
Sector FE	X	X	X	X	X	X

The dependent variable is a dummy equal to 1 if an individual lost their job, 0 otherwise, for those employed in the previous month. Index is a dummy equal to 1 for occupations above the 80^{th} percentile of each task index. Each column shows results from regressing the dependent variable on the respective task indicator (index), period dummies, their interactions, and controls (demographics, education controls, sector fixed effects. The task indicators are denoted as defined in section 2. Errors clustered at the occupation level. The sample is October 2008-December 2009 and March-April 2020.

flat close to their trough of around 33 million throughout the recovery, while routine manual occupations reached their pre-Recession levels by 2018, despite a deeper fall. More generally, they argue that all recessions since 1991, when polarization was already under way, have been characterized by such a pattern.

The nature of the two shocks and the speed of transmission are completely different, but to the extent that jobless recoveries are a structural feature of polarized labor markets, it could be instructive to compare the two episodes in that regard once the dust settles and, in particular, recalls have run their course.

3.2 The role of turnover

In the previous section I showed evidence that occupational task content is an important predictor of job losses. While individuals with higher skills clearly fared better, it is still unclear whether this is because they are in relatively short supply, or whether there is also a role for firm-specific human capital in driving these results. Search and matching frictions are large in the labor market, and employers may be willing to hoard labor in the face of a temporary shock in order to avoid losing hard-to-replace workers; at the same time, they may respond to uncertainty shocks by laying off workers who skills are in abundance and have little job-specific match capital.

I test this hypothesis by augmenting the baseline model with a turnover indicator:

$$ENE_{ijo,t} = \alpha_0 + \alpha_1 index_o + \alpha_2 turnover_{j/o} + \alpha_3 \Theta_{ijo,t-1} + \gamma_j + \epsilon_{ijo,t}, \tag{2}$$

As before, I run separate regressions for each of the task indices, in binary form. The first indicator is given by the share of workers laid off in the median month each year, averaged from 2005 to 2015, at either the occupation or the sector level. While this more directly measures the ease of replacement of employees, it would also be higher for declining occupations and industries. As such, I use an additional indicator in the form of total turnover rate, given by gross worker flows in and out of an industry or occupation over employment.[16]

Results are shown in Table 2, for each of the six task categories; columns 1-3 show results for the layoff rate, and columns 4-6 for total turnover. All models include demographics and education controls.[17] I focus on April transitions only, as over 90% of employment losses are recorded in April data.

The first column includes sectoral turnover; for all six of the task indices, the coefficient on the sectoral turnover indicator is large and statistically significant, and is essentially unchanged. This shows that sectors that tend to layoff a larger fraction of their workers at a given point in time also laid off a larger fraction of their workers due to the COVID-19 shocks; the coefficient of around 5 indicates that an additional 1pp in median layoff intensity led to 5% additional layoffs in this industry.

There are several possible implications of this finding. On the one hand, this is strong confirmation of the idea that the COVID-19 shock exacerbated pre-existing patterns. Moreover, it may indicate a role for uncertainty in exacerbating the shock; as firms

[16] An improvement would be to also have information on job tenure; unfortunately, while CPS does have a biennial Job Tenure supplement, it is not, to my knowledge, available for 2020.

[17] As the measures of turnover are based on past data, I cannot include previous years in the estimation sample. However, as the previous section made clear, the COVID-19 shock was distinctly larger to allow for a separate analysis.

are uncertain about the effects of the COVID-19 shock, they may have hedged by laying off workers that they deem easier to replace once the shock recedes. A similar interpretation could hold for demand concerns. At the same time, one concern is that sectoral turnover is correlated with COVID-19 demand or lockdown shocks, and so I am only capturing these effects.

This match quality interpretation is strengthened by results in column 2, which shows results for regressions where I instead include occupational turnover, and the coefficient is largely the same. Finally, column 3 includes a sector fixed effect together with the occupation turnover variable, hence controlling for sector-specific COVID-19 shocks. The turnover coefficient changes little, suggesting that even within sectors, occupations with a higher turnover suffer more job losses.[18] The specifications with total turnover in columns 4-6 show much the same picture. In this case, adding a sectoral fixed effect to the specification with the occupation turnover leads the coefficient to fall by about a quarter, but it remains large and statistically significant.

As regards the task indices, and focusing on the specifications with occupational turnover and sector fixed effects, which provide the cleanest estimates, only the coefficient for NRCA and NRCP are statistically significant; for all other tasks, the coefficients lose much of their magnitude and are not significant. The ease with which firms can replace employees working in these tasks seems to go a long way into explaining job losses during the pandemic shock. But individuals in jobs with high intensity of non-routine cognitive tasks are less likely to lose their jobs, even controlling for occupation turnover, and even controlling for sectoral characteristics and demand shocks. This could be evidence of labor hoarding behavior for hard-to-replace employees.

3.3 The role of sectoral structure

The above analysis has indicated a central role for the NRCA-content of jobs as being an important driver of relative employment losses due to the COVID-19 shock.

[18] An alternative way of capturing local shocks is by using Google's Mobility Reports, which track people movement across several dimensions and can provide a measure of the extent of the lockdowns. Controlling for such measures at the county level in fact strengthens the main results, but reduces the sample by over 60%, as most CPS observations do not report counties, only states or metro areas. If I instead fill in missing county values with state values and using this imputed measure as a control, results change little, while the coefficient on the mobility measure has the expected sign.

Table 2: Turnover

	(1)	(2)	(3)	(4)	(5)	(6)
		Terminations			Total turnover	
nr cog anal						
index	-0.064***	-0.047***	-0.034***	-0.054***	-0.019*	-0.024***
	(-5.40)	(-4.03)	(-3.86)	(-5.15)	(-1.73)	(-2.59)
turnover	4.908***	5.951***	6.354***	1.760***	2.368***	1.682***
	(4.58)	(4.45)	(6.35)	(6.47)	(6.75)	(7.50)
nr cog pers						
index	-0.043***	-0.029**	-0.033***	-0.042***	-0.013	-0.026**
	(-3.35)	(-2.30)	(-3.10)	(-3.48)	(-1.08)	(-2.54)
turnover	5.248***	6.542***	6.566***	1.846***	2.430***	1.709***
	(5.16)	(5.02)	(7.20)	(6.88)	(7.27)	(8.55)
r cog						
index	-0.016	-0.008	0.005	-0.007	0.001	0.005
	(-0.88)	(-0.48)	(0.33)	(-0.43)	(0.06)	(0.37)
turnover	5.296***	6.892***	7.205***	1.857***	2.480***	1.831***
	(5.17)	(5.26)	(7.54)	(7.05)	(7.76)	(9.15)
r man						
index	0.023	-0.007	-0.004	0.024	-0.013	0.000
	(1.17)	(-0.30)	(-0.23)	(1.29)	(-0.62)	(0.02)
turnover	5.243***	7.150***	7.283***	1.857***	2.530***	1.820***
	(4.96)	(4.71)	(6.47)	(6.73)	(7.14)	(7.60)
nr man phys						
index	-0.001	-0.049**	-0.006	0.012	-0.032	0.008
	(-0.03)	(-2.00)	(-0.31)	(0.69)	(-1.55)	(0.49)
turnover	5.390***	8.700***	7.351***	1.865***	2.606***	1.787***
	(4.60)	(5.00)	(6.46)	(6.79)	(7.60)	(8.19)
nr man pers						
index	-0.006	-0.005	-0.017	-0.006	-0.004	-0.020
	(-0.31)	(-0.24)	(-1.37)	(-0.35)	(-0.22)	(-1.48)
turnover	5.287***	6.917***	7.035***	1.859***	2.472***	1.803***
	(5.42)	(5.26)	(7.43)	(6.84)	(7.58)	(8.87)
N	33245	33245	33245	33245	33245	33245
Dem/phics	X	X	X	X	X	X
Education	X	X	X	X	X	X
Industry Turnover	X			X		
Occupation Turnover		X	X		X	X
Sector FE			X			X

The dependent variable is a binary indicator equal to 1 if an individual lost their job, 0 otherwise, for those employed in the previous month. Turnover is the median layoff probability (cols 1-3) or total turnover rate (cols 4-6) in each year, averaged over 2005-2015, either at the industry or the occupation level. Index is a binary indicator equal to 1 for individuals whose jobs are in the top quantile of the task index in t-1, for each task type. The sample includes transitions from March to April 2020. Errors clustered at the occupation level.

In this section, I dig deeper into this issue. Somewhat surprisingly, differential demand shocks do not seem to matter much for the magnitude of the NRCA-coefficient. At the same time, there may still be a sectoral element. In particular, it is possible that because such industries are knowledge-intensive, job-specific human capital is higher, and firms would be unwilling to sever these relationships even in bad times. A corollary would be to check whether this spills over to low-NRCA jobs as well.

I do so with the following model:

$$\begin{aligned} ENE_{ijo,t} = \beta_0 + \alpha_1 lowNRCA_{io,t-1} + \alpha_2 lowNRCA_{io,t-1} \times sectorNRCA_{j,t-1} + \\ \alpha_3 sectorNRCA_{j,t-1} + \alpha_4 \Theta_{ij,t-1} + \gamma_j + \epsilon_{ij,t}, \end{aligned} \tag{3}$$

where $lowNRCA$ is the negative of the NRCA index dummy, while $sectorNRCA$ is the raw sectoral average of the NRCA index. I expect a positive α_1 and negative α_3. A negative α_2 would indicate that low-skill individuals experience fewer unemployment transitions in high-NRCA sectors. For brevity, I focus on April transitions here as well, and consider March in a final specification where I pool the pre-pandemic period as well.

Results are given in table 3. Column 1 shows results from a baseline with no controls: the α_1 and α_3 coefficients have the expected signs, and the interaction coefficient α_2 is negative and significant, confirming the above intuition. One concern is that this may simply reflect differential demand shocks, as NRCA-intensive sectors experienced lower employment losses. While sectoral NRCA intensity should control for a substantial part of this, it is important to try and purge the model of demand variation. Column 2 augments the model with sectoral fixed effects. The interaction coefficient falls by almost half in magnitude, but remains negative and significant. Column 3 further augments the model with demographics and education controls, including an indicator for urban workers, and its interaction with $sectorNRCA$. The effect may be driven by differences between urban and rural areas; rural/urban location could bias results in either direction. While high NRCA sectors are typically located in cities, rural areas were presumably less hit by the COVID-19 shock. Nevertheless, the main result is little affected by the inclusion of controls.

Finally, column 4 shows results from a regression of a pooled model for the entire

Table 3: The role of sectoral NRCA intensity

	(1)	(2)	(3)	(4)
lowNRCA× Apr20	0.1142*** (7.53)	0.1064*** (8.56)	0.0771*** (6.34)	0.0943*** (7.85)
lowNRCA× sectorNRCA × Apr20	-0.0867*** (-3.91)	-0.0452*** (-2.91)	-0.0401*** (-2.69)	-0.0412*** (-2.74)
sectorNRCA× Apr20	-0.0391*** (-3.82)			
lowNRCA × pre-COVID				0.0089*** (6.61)
lowNRCA × Mar20				0.0198*** (4.82)
lowNRCA × sectorNRCA × pre-COVID				-0.0077*** (-3.41)
lowNRCA × sectorNRCA × Mar20				-0.0121* (-1.66)
N	33245	33245	32930	4204153
Dem/phics			X	X
Education			X	X
Sector FE		X	X	
Sector-Time FE				X

The dependent variable is a binary indicator equal to 1 if an individual lost their job, 0 otherwise, for those employed in the previous month. Errors clustered at the occupation level. $lowNRCA$ is a dummy equal to 1 for occupations below the 80^{th} percentile of the NRCA index, and $sectorNRCA$ is the sectoral average of the NRCA index. The sample in columns 1-3 is April 2020; in 4 it is comprised of all months in 2012-2020.

2012-2020 sample, with appropriate interaction terms for the variables of interest. As before, coefficients for March and April are given in additive form relative to pre-COVID values. In this case as well, these patterns held in the pre-COVID sample, but at a substantially smaller degree. In terms of its relative magnitude, it appears that employment losses from the pandemic shock are scaled up versions of usual patterns. The triple interaction coefficient of interest retains its size and significance even for March, and is substantially larger in April.

These results suggest a complementarity between high- and low-skilled workers in sectors with a relatively high share of NRCA-intensive jobs. Aghion et al. (2017) present evidence of such a channel for innovation; the wage premium earned by employees of innovative firms is higher for low- than high-skilled employees. They build a model to rationalize their finding, and one prediction of the model is that in fact worker quality is more firm-specific for low- than high-skill workers, implying longer job tenures for low-skilled employees in innovative firms, as firms will invest more resources to train them.

3.4 Controlling for economic activity with high-frequency data

In the previous exercises, I controlled for differential shocks using different combinations of fixed effects, which provide a transparent means of controlling for such issues, at the cost of losing variation. An alternative way of accounting for local economic activity is by using some of the newly released high-frequency data. In this section, I revisit the analysis of the previous sections using two such datasets. The first is Google's Mobility Reports, which track people's using GPS data. They track people's movement across several dimensions relative to pre-COVID values and reports percentage changes in visits, providing a proxy for the extent of the lockdowns. The best coverage and most relevant variables for my purposes are given by the retail and recreation (RER) and workplaces (WORK) indices; for instance, March 22 saw a 44% reduction in visit to retail and recreation places relative to the January 3-February 6 average. The second source is the spending data of the Opportunity Insights Economic Tracker project of Chetty et al. (2020), which track credit/debit card payments at the zip code level, as collected by a private provider, capturing around 10% of total transactions, with a higher representation of expenditure on accommodation, food and retail. The authors show that this data tracks aggregate spending quite well. The measure I use the percentage change in total spending relative to January (SPEND).

I aggregate county-level data to the core-based statistical area (CBSA) level (using population weights), because county of residence is reported for only around a third of respondents. This likely implies a substantial loss of variation; Chetty et al. (2020) report very large variations in spending changes even across adjacent zip codes. Both datasets come in daily frequencies; I aggregate daily data in lower frequencies following the timing of CPS interviews, and so April values reflect averages from 12 March to 11 April. I use binary values of the RER, WORK and SPEND variables, set to 1 for counties with above median values of each respective variable.

I estimate a variant of (1) for April only, with sectoral fixed effects and all controls

Table 4: High-frequency controls

	(1)	(2)	(3)	(4)	(5)	(6)
Non-routine cognitive						
		analytical			personal	
index	-0.063***	-0.068***	-0.074***	-0.052***	-0.057***	-0.058***
	(-5.64)	(-6.70)	(-7.01)	(-4.08)	(-5.01)	(-4.76)
high	-0.028***	-0.032***	-0.044***	-0.025***	-0.028***	-0.037***
	(-4.47)	(-4.34)	(-5.75)	(-4.25)	(-3.73)	(-4.98)
index× high	0.015	0.027***	0.039***	0.003	0.014	0.015
	(1.33)	(2.66)	(3.85)	(0.26)	(1.34)	(1.41)
Routine						
		cognitive			manual	
index	-0.003	-0.008	0.000	0.034	0.035*	0.037*
	(-0.17)	(-0.53)	(0.02)	(1.52)	(1.72)	(1.73)
high	-0.025***	-0.026***	-0.033***	-0.023***	-0.023***	-0.032***
	(-4.18)	(-3.78)	(-4.73)	(-4.02)	(-3.23)	(-4.61)
index×high	-0.000	0.010	-0.008	-0.011	-0.013	-0.015
	(-0.02)	(0.61)	(-0.49)	(-0.74)	(-0.93)	(-1.02)
Non-routine manual						
		physical			personal	
index	0.058***	0.059***	0.060***	0.047*	0.060***	0.064**
	(2.85)	(2.91)	(2.79)	(1.89)	(2.63)	(2.36)
high	-0.018***	-0.019***	-0.028***	-0.025***	-0.019***	-0.027***
	(-3.18)	(-3.04)	(-4.38)	(-4.51)	(-3.20)	(-4.57)
index×high	-0.038***	-0.034*	-0.034*	0.002	-0.028	-0.037*
	(-2.61)	(-1.73)	(-1.82)	(0.12)	(-1.50)	(-1.89)
N	23997	25103	25103	23997	25103	25103
SPEND	X			X		
WORK		X			X	
RER			X			X

The dependent variable is a dummy equal to 1 if an individual lost their job, 0 otherwise, for those employed in the previous month. Index is a dummy equal to 1 for occupations above the 80^{th} percentile of each task index, and high is a dummy equal to one for above median values of SPEND, WORK and RER, as denoted. Each panel shows results from regressing the dependent variable on the respective task indicator (index), the respective activity indicator (high), their interactions, and controls (demographics, education controls, sector fixed effects. Errors clustered at the occupation level. The sample is April 2020.

included. Results are given in table 4. Each panel reports results from each pair of broad task categories: NRC analytical and personal in the top panel, R cognitive and manual and the middle panel, NR physical and personal in the bottom panel. The task indicator is denoted as $index$ and the activity indicator denoted as $high$ (standing for high levels of activity, even though it fell in almost all areas).

The coefficient for $high$ is negative and significant for all activity indicators. In areas with above median levels of (relative) activity, transitions out of employment were around 3pp smaller. The effect is largest for the RER indicator, which is likely to cover mostly employees in related industries. This is consistent with the results of Chetty et al. (2020), who report that more affluent localities exhibited a larger reduction in both spending and employment; their data only cover low income employment.

This view is reinforced by results for non-routine manual jobs, where the index-high interaction coefficient is positive and significant for most specifications. This implies that the likelihood of transitioning out of employment is further mitigated for individuals in these occupations in high activity areas, relative to others. Especially for the non-routine manual occupations, the separation rates is equal to other occupations, on average, in high activity areas, as the three coefficients sum to zero. On the other hand, the index-high interaction is positive and significant for the WORK and RER indicators for NRCA-intensive jobs, meaning that the relative protection such jobs offer is smaller in high activity areas. The interactions are small and not significant for the other task indicators, suggesting that individuals in these occupations fared similarly (relative to other occupations) in high and low activity areas.

Overall, controlling directly for changes in economic activity does not materially change our results, but does provide more subtle insights for the professions that were affected the most (non-routine manual) and the least (non-routine cognitive analytical) from the shock, showing that these effects were driven primarily by areas where activity slowed down by more. These controls cannot answer whether demand or supply effects are driving the results, as either could contribute to lower activity.

3.5 Is there a reallocation wave under way?

The scale of job losses in the United States as a result of the COVID-19 have given rise to a debate regarding the extent to which jobs lost can be recovered. A combination of search costs, defaults, uncertainty and structural change may imply the permanent loss of many jobs, as well as a long delay in creating new jobs. The results of Barrero et al. (2020) certainly point towards such a story. Using survey data, they show an increase in *expected* excess reallocation (sum of creation and destruction minus net employment change) of 2.4 times relative to pre-pandemic averages, at the firm level. They document that for every 10 jobs lost, 3 have already been created. Combing their results with historical data on recalls, they estimate that 42% of staffing reduction will lead to permanent job losses.

Even though the vast majority of layoffs in April are listed in CPS as temporary, other sources also indicate that a substantial part of these matches may be destroyed. For instance, although 91% of UI claimants in California expected to be recalled to their jobs in the late March, this figure had fallen to 69% by early May.[19]

The large reallocation patterns reported by Barrero et al. (2020) occur at relatively high frequencies, substantially increasing the time-aggregation bias of CPS. What the CPS can shed light on, however, is whether there is a noticeable shift of workers across occupations or sectors. This could include employed workers who switch employers or unemployed workers who take up a new job in a different occupation or sector relative to their previous employment. An increase in the fraction of workers who switch occupation or industry would point to increased reallocation. I calculate occupation and industry switchers as the fraction of workers who switch in adjacent months, both for continuing workers and for entrants from unemployment (as CPS codes the last known industry and occupation for unemployed workers). [20] I extend the sample to May, when employment rose substantially, and could give an additional data point for reallocation. I exclude individuals recalled from a temporary layoff; while Fujita (2018), in a similar exercise, does include them, the spike in recalls from temporary layoffs in May would bias the switching rate downwards. I calculate job-to-job transitions as the share of workers who are employed in consecutive months but switch employers from one month to the other.

I plot these measures in figure 4. The blue and red lines show the (non-seasonally unadjusted) shares of workers employed in a given month who switch occupations (4-digit level) and sectors (2-digit level) relative to the previous month. There is no clearly discernible increase for either series. Following an upward trend coinciding

[19]Source: California Policy Lab.

[20]Focusing only on workers employed in consecutive months yields a qualitatively very similar picture. Comparing the same month across years is complicated, as occupation codes changed in 2020, resulting in a discrete jump in January. As such, an analysis of consecutive months, removing January 2020, is more informative. I also remove June and July 2015, which exhibit a very large spike in the share of individuals who switch occupations and industries.

with the recovery, the share of workers employed in consecutive months that switch occupations has hovered around 7% since 2016, and 4.5% for industries. The green line shows the occupation switching rates using the coarse 22 CPS major occupation classification, to correct for the erroneous switches problem notes by Fujita (2018). The coarse switching rate is naturally lower, but the pattern is very similar, and also shows little movement during the COVID-19 shock. Finally, the yellow line shows the share of job-to-job transitions. Again, the measure is around 2% across the horizon considered, and does not move perceptibly in April or May.[21] Note that purpose here is only to see whether there is a spike in switching in April, not to analyze cyclical properties of these series, which is why I only plot non-seasonally adjusted rates.

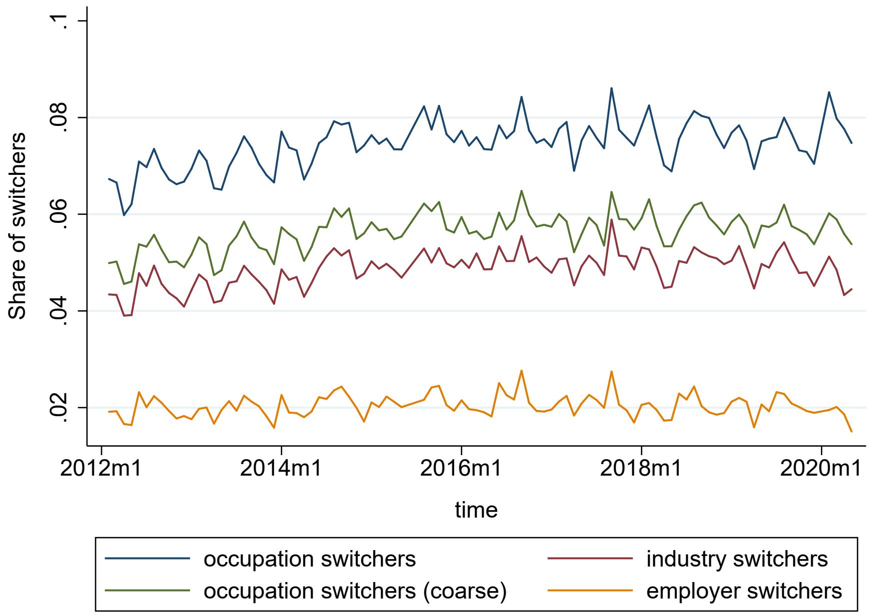
There are a number of caveats to this analysis. First, this is not a properly defined measure of reallocation, as it focuses exclusively on the sub-sample of those currently employed, hence ignoring job losers who did not find a new job within the month. Second, it is well-known that vast majority (85-90%) of reallocation occurs within industries and localities (Davis & Haltiwanger 1992), and Barrero et al. (2020) give an excellent illustration of this phenomenon. At the same time, given the size of the shock, I expect that such a major reallocation shift should have involved at least some movement in the series plotted in figure 4. A final major caveat to this analysis compared to Barrero et al. (2020), is that it is based on data for an on-going shock. By contrast, Barrero et al. (2020) rely on a forward-looking measure, and argue that such a measure is preferable in this context, because creation lags destruction in major reallocation shocks for at least a year.[22] What this exercise can say though is that, to the extent that a large realignment of the workforce is already underway, it is occurring largely within industries and occupations.

An alternative source of information on reallocation in high frequencies is JOLTS, a survey of 16,000 establishments designed to capture worker flows in the US labor market. Table 5 shows seasonally adjusted sectoral hire and separation rates for the

[21]This measure can also include workers who are laid off and find a job prior to the CPS interview. The denominator consists only of individuals with a valid response to the relevant question, as a large number of eligible interviewees have missing values for this question, for unknown reasons. However, the stable value around 2% is consistent with estimates by Bosler & Petrosky-Nadeau (2016) with different data.

[22]Note also that the higher sampling bias (due to an increase in non-response rates) in CPS may be especially acute in this case.

Figure 4: Share of workers switching occupations and sectors



Notes: The chart shows the share of workers employed in consecutive months who switch occupations (4-digit, blue line) or sectors (2-digit, red line) from one month to another. The green line uses the CPS 22-occupation classification. The yellow line shows the share of workers who switch employers. The sample includes all CPS Basic Monthly Sample files from 2012-2020.

non-farm private economy. A number of issues stand out.

First, hires kept their pace relatively unabated in March, but separations increased by a factor of 2.5 relative to February. Non-farm private sector hire rate fell modestly, to 3.7%, from 4.2% in February. Seasonal adjustment may be misleading given the size of the shock; the fall in the non-seasonally adjusted hire rate was ever smaller, at 0.1pp. The separation rate, by contrast, rose substantially, from 4% to 11.1%. The layoff rate (which excludes quits) rose from 1.4% to 8.8%. Both rates fell in April, but relative to February, the relative change in the separation rate is still larger (in log points).

Second, sectoral differences in the change in hiring behavior is relatively muted. Hiring in fact increased in non-durable manufacturing and fell by only 0.2pp in retail; on the other hand, it fell substantially in entertainment and in accommodation and food services. The dispersion of the change in hiring rates across sectors was relative compressed overall; the upshot is that, while hiring was curbed, it was still taking

Table 5: Hires and Separation Rates by sector, February-April 2020

	Hire rate				Separation rate			
	(1) Feb	(2) Mar	(3) Apr	(4) Δ	(5) Feb	(6) Mar	(7) Apr	(8) Δ
Mining	3.4	2.7	1.7	-1.2	2.8	6.0	10.4	5.4
Construction	5.1	5.1	2.9	-1.1	4.7	9.9	11.9	6.2
Durable manuf	2.4	2.0	2.0	-0.4	2.3	5.9	6.7	4.0
Nondurable goods manuf	2.9	2.9	3.7	0.4	2.8	6.9	5.3	3.3
Wholesale trade	2.6	2.3	2.2	-0.4	2.6	4.2	4.7	1.8
Retail trade	5.2	4.9	5.1	-0.2	5.2	10.6	8.8	4.5
Transportation/utilities	4.1	3.8	3.2	-0.6	4.1	8.1	6.8	3.4
Information	3.3	2.6	1.3	-1.4	3.0	3.7	5.6	1.7
Finance and insurance	2.5	2.3	1.6	-0.6	2.3	2.6	1.7	-0.2
Real estate	3.4	2.9	1.5	-1.2	2.5	7.7	10.7	6.7
Professional and business services	5.1	5.1	3.5	-0.8	5.0	8.0	6.4	2.2
Education	2.5	2.4	2.0	-0.3	2.4	8.6	8.7	6.3
Health care	3.2	2.8	2.4	-0.6	2.9	6.9	6.1	3.6
Arts and entertainment	6.8	5.2	1.9	-3.3	6.3	24.5	25.6	18.8
Accommodation and food services	6.4	3.9	3.9	-2.5	6.1	34.1	23.0	22.5
Other services	3.8	2.8	2.4	-1.2	3.7	16.4	19.0	14.0
Total private non-farm	4.2	3.7	3.0	-0.9	4.0	11.1	8.7	5.9

Source: JOLTS. Sample includes all monthly data from February to April 2020, in non-seasonally adjusted form, except for the bottom line. The hire and separation rates are defined as hires or separation over employment, multiplied by 100. Columns 4 and 8 show the difference between the average value for March and April relative to February.

place, and in fact remained higher than its trough of 3.1% in June 2009, in March and slightly below in April.

Third, there are enormous differences across sectors in separations. The dispersion of the change in the rate is an order of magnitude higher relative to hires. Entertainment and accommodation and food services, in particular, experienced separations of over half of their February employment, given their particular exposure to the pandemic shock; on the other hand, for the finance and insurance and insurance sector, separations in fact fell in April, and total employment shrank by only 0.7% relative to February.

Fourth, the ratio of hires to separations is 0.34 for both months, almost identical to the survey findings of Barrero et al. (2020). At the same time, the hire rate is relatively close to its long-term sample average of 4%.[23] This is an interesting finding in

[23]Davis et al. (2010) noted that earlier renditions of JOLTS underestimated gross workers flows in

its own right; while the ratio of separations to hires was typically around 1, reaching a maximum of 1.25 in April 2009, it jumped to 3 in March and 2.9 in April, but this was mostly driven by the separation rate: relative to February, the log change in the separation rate was 8 times larger than the log change in the hire rate in March, and 2.3 times in April. As such, while the surprisingly strong pace of hiring in the face of such a large shock may indeed indicate the emergence of a large reallocation wave, the fact that the hire rate is so close to its usual level implies this conclusion could be premature. On the other hand, a disproportionate fraction of hires comes from young firms; given the large reduction in business formation and the tighter borrowing constraints small firms face, it is possible that the aggregate hire rate may in fact mask an increasing hire rate for large firms, which could indeed imply higher reallocation. Future data releases will likely shed light to this puzzle.

4 Conclusion

I examined the pattern of short-term job losses from the COVID-19 shock in the United States, using the task approach to labor markets. This framework can shed light on what types of jobs were most affected from the shock, and which ones were most resilient, offering a complementary analysis of the labor market effects of the shock to work using granular data to more precisely capture the demography, geography and scale of the shock (Cajner et al. 2020, Chetty et al. 2020). I find that job task content is an important predictor of job losses, even controlling for demographics, education, industry, teleworkability and local economic activity. The coefficients on the task content indicators become insignificant once I control for occupational turnover (which proxies for the ease of replacing workers), except for indicators for jobs intensive in non-routine cognitive (NRC) tasks; this suggests that layoffs followed usual patterns, but firms hoarded workers with NRC skills.

I also take a stab at gauging whether reallocation patterns can already be seen in publicly available data, CPS and JOLTS. In CPS I show that there is discernible uptick in the share of workers switching occupations, while, from JOLTS, I find that the hire

public use files. Following their recommendations, BLS revised the methodology in 2009 and moderated the discrepancy, though differences remain.

rate moved much less than the separation rate, and remains relatively close to its historical average, at only 0.1pp below its trough in the Great Recession, even though unemployment is currently much higher. Taken together with the results of Barrero et al. (2020), these findings imply that reallocation may have yet to take off, but if it has, it is taking place within occupation and industries. At the same time, it is important to note that at least some of the reallocation away from contact-intensive sectors (hospitality, personal services) is likely to be temporary, until vaccines become available and relevant investments take place (e.g. separating panels, germ-resistant surfaces). This makes it more likely that there will be a protracted underutilization of resources, relative to even a gradual reallocation shock, and hence a larger scope for demand-supporting policies. More broadly, the surprisingly small change in the hire rate in the face of a massive increase in the separation and layoff rates is an important area for future work.

Overall, it remains to be seen whether the patterns identified in this paper will persist. A new burgeoning literature, an offspring of the slow recovery from the financial crisis, argues for structural change as taking place in recessions and amplifying them (Chodorow-Reich & Wieland 2020, Jaimovich & Siu 2020). While COVID-19 is a singular shock, and past experience may not be especially useful, it has arguably already ushered in a wave of substantial technological diffusion and paradigm-shifting change in work patterns. Baldwin (2020) lays out the argument that the jobs that will survive are those relying on social cognition and interpersonal skills, which artificial intelligence or offshoring cannot handle, precisely the type of transition expected before the COVID-19 shock.

More speculatively, there is some evidence that such transition may have been foreshadowed by financial markets: Pagano et al. (2020) show that not only has portfolio reallocation taken place away from stock firms in sectors heavily exposed to the pandemic, towards resilient stocks, but that highly resilient firms substantially outperformed low-resilience firms for the six years prior to the pandemic. They speculate that investors may have been pricing such a risk, but another possibility is technological; given that the currently dominant technologies are also more resilient to the pandemic, firms on the forefront of production or intensive usage of these technologies were both possibly enjoying higher stock returns before the COVID-19 shock and were in a better position to withstand the shock, for instance by transitioning to a new work paradigm or having sufficient cash buffers.

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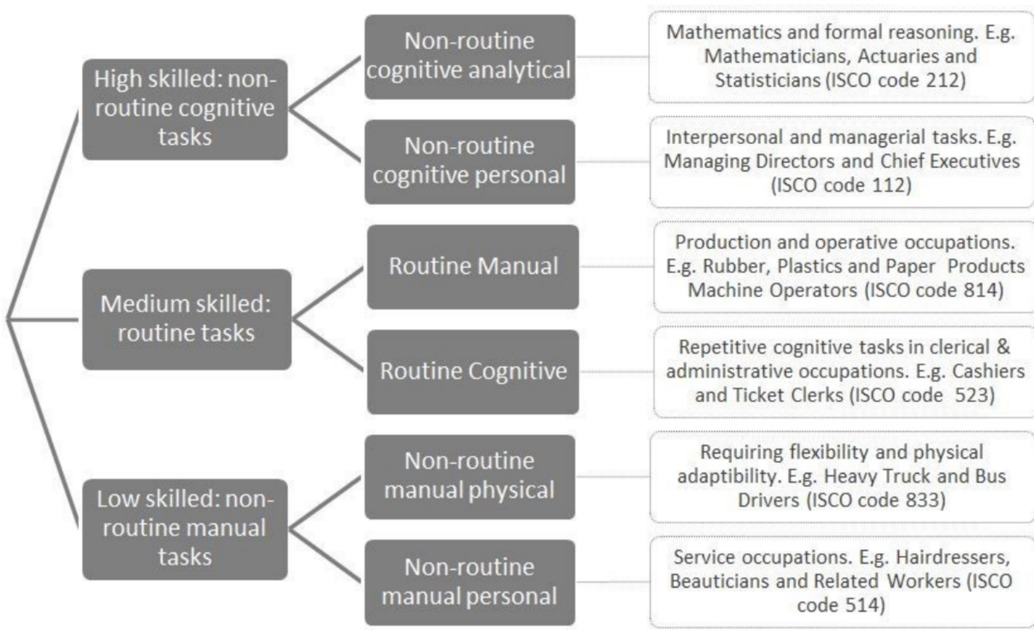
A Appendix

Figure A1: Mapping of skills, tasks and occupations



Source: Dias da Silva et al. (2019).

Table A1: Regressions for task content

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Non-TW	Non-TW	TW	TW
nr cog anal								
pre-covid	-0.021***	-0.014***	-0.005**	-0.005***	-0.024***	-0.008***	-0.004	-0.004**
	(-6.86)	(-5.72)	(-2.22)	(-3.71)	(-7.64)	(-4.54)	(-1.29)	(-2.18)
March	-0.030***	-0.023***	-0.015***	-0.014***	-0.043***	-0.019***	-0.013**	-0.013***
	(-6.53)	(-5.57)	(-3.73)	(-4.15)	(-6.33)	(-3.65)	(-2.25)	(-2.71)
April	-0.120***	-0.113***	-0.105***	-0.073***	-0.100***	-0.036	-0.068***	-0.054***
	(-8.38)	(-8.21)	(-7.70)	(-8.35)	(-3.57)	(-1.33)	(-4.44)	(-4.67)
nr cog pers								
pre-covid	-0.018***	-0.011***	-0.005**	-0.006***	-0.026***	-0.014***	-0.001	-0.003*
	(-6.09)	(-4.73)	(-2.22)	(-4.28)	(-8.99)	(-6.16)	(-0.21)	(-1.80)
March	-0.021***	-0.014***	-0.008*	-0.012***	-0.028***	-0.018*	-0.002	-0.009*
	(-4.22)	(-3.33)	(-1.92)	(-2.69)	(-3.90)	(-1.73)	(-0.43)	(-1.74)
April	-0.086***	-0.079***	-0.074***	-0.063***	-0.094***	-0.070***	-0.028*	-0.037***
	(-5.51)	(-5.30)	(-5.01)	(-5.77)	(-2.69)	(-2.62)	(-1.90)	(-2.94)
r cog								
pre-covid	-0.000	-0.005*	-0.005***	-0.002	-0.004	-0.003	-0.003	0.001
	(-0.06)	(-1.81)	(-2.67)	(-1.17)	(-0.48)	(-1.12)	(-0.78)	(0.59)
March	-0.006	-0.011**	-0.011***	-0.005	-0.015	-0.009**	-0.004	0.002
	(-0.94)	(-2.38)	(-2.73)	(-1.30)	(-1.50)	(-1.99)	(-0.57)	(0.29)
April	-0.000	-0.005	-0.005	0.008	-0.032	-0.014	0.037*	0.043**
	(-0.01)	(-0.21)	(-0.24)	(0.47)	(-0.97)	(-0.60)	(1.65)	(2.33)
r man								
pre-covid	0.017***	0.016***	0.006**	0.008***	0.010*	0.011***	0.021*	0.021**
	(3.42)	(4.56)	(2.14)	(3.94)	(1.96)	(4.72)	(1.87)	(2.05)
March	0.017***	0.016***	0.007	0.008**	0.008	0.010*	0.017	0.020*
	(2.72)	(2.94)	(1.39)	(1.97)	(1.16)	(1.96)	(1.44)	(1.79)
April	0.061***	0.060***	0.051**	0.038**	0.010	0.009	0.134**	0.116**
	(2.82)	(2.97)	(2.56)	(2.16)	(0.35)	(0.43)	(2.36)	(2.25)
nr man phys								
pre-covid	0.009**	0.016***	0.008***	0.008***	0.001	0.010***	0.014***	0.017***
	(2.08)	(4.73)	(2.78)	(3.96)	(0.25)	(3.81)	(4.13)	(4.29)
March	0.011*	0.018***	0.010*	0.013***	-0.000	0.016***	0.045***	0.050***
	(1.75)	(3.34)	(1.94)	(3.36)	(-0.03)	(3.62)	(5.67)	(5.07)
April	0.024	0.031*	0.023	0.044***	-0.033	0.011	0.027	0.051***
	(1.25)	(1.74)	(1.30)	(2.75)	(-1.30)	(0.60)	(1.61)	(3.44)
nr man pers								
pre-covid	0.006	0.000	-0.001	0.001	-0.002	-0.003	0.006	0.005
	(1.13)	(0.10)	(-0.30)	(0.27)	(-0.38)	(-1.20)	(0.64)	(0.97)
March	0.012	0.007	0.005	0.006	0.006	0.005	0.004	0.004
	(1.45)	(0.94)	(0.77)	(1.15)	(0.63)	(0.76)	(0.29)	(0.50)
April	0.093***	0.087***	0.086***	0.053**	0.076*	0.054**	0.035	0.007
	(2.67)	(2.62)	(2.59)	(2.45)	(1.82)	(2.07)	(0.83)	(0.37)
N	4204153	4204153	4204153	4204153	2505587	2505587	1698566	1698566
Dem/phics		X	X	X	X	X	X	X
Education			X	X	X	X	X	X
Sector-Time FE				X		X		X

The dependent variable is an indicator equal to 1 if an individual lost their job, 0 otherwise, for those employed in the previous month. Each panel shows results from regressing the dependent variable on the respective task indicator, interacted with time dummies. The task indicator is a binary equal to 1 for individuals whose jobs are in the top quantile of the task index in the previous month, for each task type. Regressions include monthly dummies. Errors clustered at the occupation level. TW columns include the subsample of teleworkable occupations, and opposite for Non-TW. Sample is 2012-2020.