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# WHICH WORKERS BEAR THE BURDEN OF SOCIAL DISTANCING?

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Thanks to Gianluca Violante and Greg Kaplan for making available their codes. Our measures at the three digit occupation level are available on our websites. The views expressed in this study are those of the author and do not necessarily reflect the position of the Federal Reserve Bank of New York, the Federal Reserve System, or the National Bureau of Economic Research. Replication code is available on the authors' websites.

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**ABSTRACT**

Using data from O∗NET, we construct two measures of an occupation's potential exposure to social distancing measures: (i) the ability to conduct that job from home and (ii) the degree of physical proximity to others the job requires. After validating these measures with comparable measures from ATUS as well as realized work-from-home rates during the pandemic, we employ the measures to study the characteristics of workers in these types of jobs. Our results show that workers in low-work-from-home and high-physical-proximity jobs are more economically vulnerable across various measures constructed from the CPS and PSID: they are less educated, of lower income, have fewer liquid assets relative to income, and are more likely renters. Consistent with the idea that high physical proximity or low work-from-home occupations were more exposed to the Coronavirus shock, we show that the types of workers predicted to be employed in them experienced greater declines in employment during the pandemic. We conclude by comparing the aggregate employment losses in these occupations to their employment losses in the 2008 recession, and evidence that these occupations were disproportionately exposed to the pandemic shock, and not just comprised of more cyclically sensitive workers.

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# 1 Introduction

A key response to the Coronavirus pandemic was 'social distancing', the reduction of in-person contact with others. This was reflected in both policy responses - through the shutdown of various businesses - and in behavioral responses - through the voluntary curtailing of face-to-face activities (Alexander and Karger (2020),Goolsbee and Syverson (2021)). Such social distancing reduces the spread of the virus, but can reduce labor demand in occupations that cannot be performed remotely or require a high degree of physical-proximity.

Understanding which occupations can be performed remotely or require high degrees of physical proximity is crucial for understanding the economic consequences of the epidemic.[1] In particular, to the extent that workers vary systematically across these jobs, social distancing will have systematically different effects across individuals. Therefore, understanding how individuals vary across these occupations is important for policy makers interested in formulating targeted worker assistance programs. Our paper documents that workers employed in these pandemic-exposed occupations are disproportionately likely to be economically vulnerable. For example, workers who cannot work remotely are 40 percentage points more likely to lack a college degree and 23 percentage points more likely to earn less than the median wage.

Focusing on the US[2], we combine multiple data sources to study how individuals vary across occupations that differ in the labor demand exposure to social distancing.[3] We measure an occupation's exposure by (i) a job's ability to be performed at home and (ii) its required degree of physical proximity to others. To this end, we merge *individual-level* data from the Bureau of Labor Statistics' *Current Population Survey* (CPS) and the *Panel Study of Income Dynamics* (PSID) with a version of the Dingel and Neiman (2020) classification of an occupations' capacity to work from home as well as a measure of physical proximity in the workplace. We construct these two measures using *occupation-level* data from the Department of Labor's *Occupational Information Network* (O*NET) data.[4] We show that despite being negatively correlated, some outlier occupations such as those related to education are both high work-from-home and high physical-proximity, hence relatively more affected if social distancing policies become targeted.

We validate the measures of work-from-home and physical-proximity using data from the *Amer-*

[1]As an example of the former in practice, our measures are used by Baqaee et al. (2020b) to construct a "GDP-to-Risk" index which measures which sectors provide the largest improvement to output for a marginal increase in R0. Indeed, Governor Andrew Cuomo's policy for NY State consists of a Phase I reopening with *Construction* and *Manufacturing* jobs, which the state views as *low risk* and highly essential.

[2]While our analysis focuses on classifying occupations within the United States, more recent work has broadened the Dingel and Neiman (2020) analysis to developing countries (Gottlieb et al. (2021)), highlighting that tasks may be better suited to measure a jobs ability to be done from home rather than an occupation.

[3]We do not consider the *labor supply* effects of policies such as the CARES Act.

[4]In these occupation-level data, occupational classifications are finer than those available in the individual-level data. To make the data conformable we develop a cross-walk that allows us to use the Bureau of Labor Statistics' *Occupation Employment Statistics* (OES) to employment weight O*NET measures within the coarser occupations defined in the CPS. Code is available on request.

*ican Time Use Survey* (ATUS) and the CPS.[5] The O*NET-based work-from-home measure is designed to capture whether a job *could feasibly* be done from home and is based on the types of activities conducted at work (e.g. heavy lifting, working outdoors etc). Nonetheless, we show that, across occupations, the measure is highly correlated with the share of time working that is spent at home in ATUS in 2018. Moreover, we show that the O*NET physical-proximity measure is correlated with the reported fraction of time spent working alone in ATUS in 2018. The correlation of our measure with pre-pandemic measures of actual time spent working from home and the actual number of people one works with is reassuring. Additionally, using data that has become available since the start of the pandemic in the supplemental questions to the CPS, we show that workers employed in jobs that our measures predict can be performed from home were indeed more likely to telecommute during the pandemic.

With validated occupation-level measures in hand, we present our main results in two steps. First, we study how individual characteristics of workers vary across these types of occupations. Our main result is that workers in occupations that are more likely to be affected by social distancing policies are workers we would consider more economically vulnerable. Workers in these occupations are less likely to have a college degree and are less likely to have health insurance provided by their employer. They are less likely to be white, less likely to work at a large firm, and less likely to be born in the United States. Workers in low work-from-home occupations also have disproportionately low levels of liquid assets, which is especially important for policies that provide liquidity to households. We also show that these effects are monotonic: occupations that score *relatively lower* (higher) in terms of the work-from-home (personal-proximity) measure, are *even more* economically vulnerable.[6]

Second, we turn to employment outcomes and study employment changes across the February, April, and August 2020 CPS surveys. Occupations that rank low in the work-from-home measure and high in the physical-proximity measure experienced larger employment declines relative to pre-pandemic February-April changes. A direct corollary of our earlier analysis is that more vulnerable workers did indeed experience larger declines in employment. For example, non-college educated workers experienced a 15 ppt larger decline in employment relative to those with a college degree from February to April; this difference decreased to just 10 ppt by August as establishments reopened. We show that employment losses for workers in low work-from-home and high physical proximity occupations during the pandemic far exceeded the losses during the 2008 recession. This suggests that *exposure* to the COVID shock is partly responsible for the employment outcomes we document, and not just the fact that more exposed occupations tend to employ more workers that

[5] **?** use Swedish vacancy data to show that job seekers redirect their search towards high work-from-home occupations during the pandemic. Their measure of an occupations' ability to be done from home is based on the ATUS data.

[6] When we compare the top quartile of occupations by the work-from-home measure, to the bottom quartile of occupations by the work-from-home measure, we find that the estimated treatment effects are larger. When we compare the third quartile of occupations by this measure, to the second quartile of occupations by this measure, we find that the estimated treatment effects are smaller but still statistically significant in all cases.

are sensitive to downturns more generally.

Our results have clear implications for economic inequality and public policy responses to the pandemic. First, our results provide guidance as to how income replacement and liquidity injection policies may be targeted. Indeed the various programs enacted through the CARES Act may have stemmed much of the wage losses associated with job loss in these occupations. Second, since low work-from-home and high physical-proximity workers tend to have lower incomes and lower liquidity, the marginal social cost of income support is low, while the marginal private benefits are high. Social benefits are also high: such workers have higher propensities to consume out of transfers, and high disease transmission risk if they do work. Third, the correlation between low work-from-home and high physical-proximity jobs creates a double-edged sword for workers. It induces a correlation between *economic risks* under tight social distancing and *health risks* under relaxed social distancing. Already more economically vulnerable workers are disproportionately exposed to unemployment now, and infection in the future, suggesting the need for on-going policy interventions.

**Literature.** Since the start of the pandemic, the literature surrounding the theory and economic consequences of social distancing has boomed. On the empirical side, Dingel and Neiman (2020) use the Occupational Employment Statistics (OES) to ask the important question of what fraction of employment and income is accounted for by jobs that can be done from home. Leibovici et al. (2020) conduct a similar analysis, instead considering low physical-proximity occupations rather than high work-from-home occupations.[7] Both use the O*NET to classify occupations, and then employment and income data from the OES to study the geographic distribution of employment and income accounted for by types of jobs. Our focus here is on understanding the characteristics of the underlying workers that comprise employment in these jobs, validating the measures by showing they are consistent with measures from other datasets, and verifying that they are indeed correlated with post-outbreak outcomes.[8] This requires integrating the O*NET data with data containing worker characteristics, such as the CPS and the PSID.

While we validate our measures with both pre-pandemic time use data and data on telecommuting collected during the pandemic, several authors have conducted their own surveys to collect information on teleworking. For example, Adams-Prassl et al. (2020) run a survey in the UK, US and Germany, and find that jobs with mostly WFH tasks saw smaller declines in wages and employment. Similarly, Bick et al. (2020) conduct a survey in the US and confirm that 35 percent of workers telecommuted in May 2020.

Finally, on the theory side, several papers have studied the macroeconomic and distributional

[7] St. Louis Federal Reserve, *On the Economy* blog:
https://www.stlouisfed.org/on-the-economy/2020/march/social-distancing-contact-intensive-occupations

[8] Lekfuangfu et al. (2020) also use O*NET data to characterize jobs, but appeal to factor analysis to define high and low work from home or physical proximity jobs. Applying their measures to Thailand, they also study worker characteristics within different types of jobs, with a focus on how couples are sorted into these jobs.

consequences of the pandemic using our data on occupational characterizations as inputs. For example, Akbarpour et al. (2020) use a heterogeneous agent model to evaluate targeted social distancing policies, and discipline their model using our data on an industry's WFH ability. Similarly, Kaplan et al. (2020) develop a macro-SIR ("susceptible, infected, recovered") model with occupational heterogeneity disciplined by our estimates. Baqaee et al. (2020a) also develop an epidemiological model disciplined by our data to think about various reopening strategies.

**Overview.** Section 2 describes how we construct our measures of work-from-home and physical-proximity using the O*NET and OES data. We compare the two measures across occupations, and validate each against comparable measures constructed from the pre-pandemic ATUS data. We further validate the measures using realized work-from-home rates from the CPS supplement questions introduced during the pandemic. Section 3 integrates the CPS and PSID data and gives our main results, which are summarized in Figure 4. Section 4 shows how individuals employed in occupations characterized by their work-from-home and physical-proximity measures fared in over the implementation of social-distancing. Section 5 concludes.

## 2 Low work-from-home and high physical-proximity jobs

We now describe the construction of our work-from-home and personal-proximity measures, discuss how the measures compare across occupations, and validate both measures against ATUS data and realized work-from-home behavior during the pandemic. A key data contribution is our simple, portable procedure for aggregating O*NET data and Dingel and Neiman (2020)'s telework measure from the SOC occupational classification to the OCC occupation classification system used by the Census Bureau. More details regarding the data construction are relegated to Appendix A.

### 2.1 Construction of pandemic exposure measures

We use O*NET data on work activities to construct two measures of an occupation's exposure to social distancing. We sign these measures in terms of the expected negative economic impacts of the pandemic: (i) *low work-from-home* ($\overline{LWFH}_j$), and (ii) *high physical-proximity* ($\overline{HPP}_j$).

Our measure $\overline{HPP}_j$ is simply the O*NET variable which measures the physical-proximity required by an occupation on a scale of $1-5$. Occupations which require workers to be in very close physical proximity to others receive scores of 5.[9] We define the binary variable $HPP^*_j$ to take a value of 1 for occupation $j$ if $\overline{HPP}_j$ is above the employment-weighted median across OCC occupations of physical proximity ($= 3.6$) and a value of zero if it is below. For certain figures, we aggregate $\overline{HPP}_j$ to the 2 digit OCC level and rescale so that $\overline{HPP}_j \in [0,1]$.

Our measure of work-from-home, a modification of the telework measure developed by Dingel and Neiman (2020), captures an occupation's ability to be performed remotely. We ask whether

[9] The exact question and the possible answers can be found here: https://www.onetonline.org/find/descriptor/result/4.C.2.a.3.

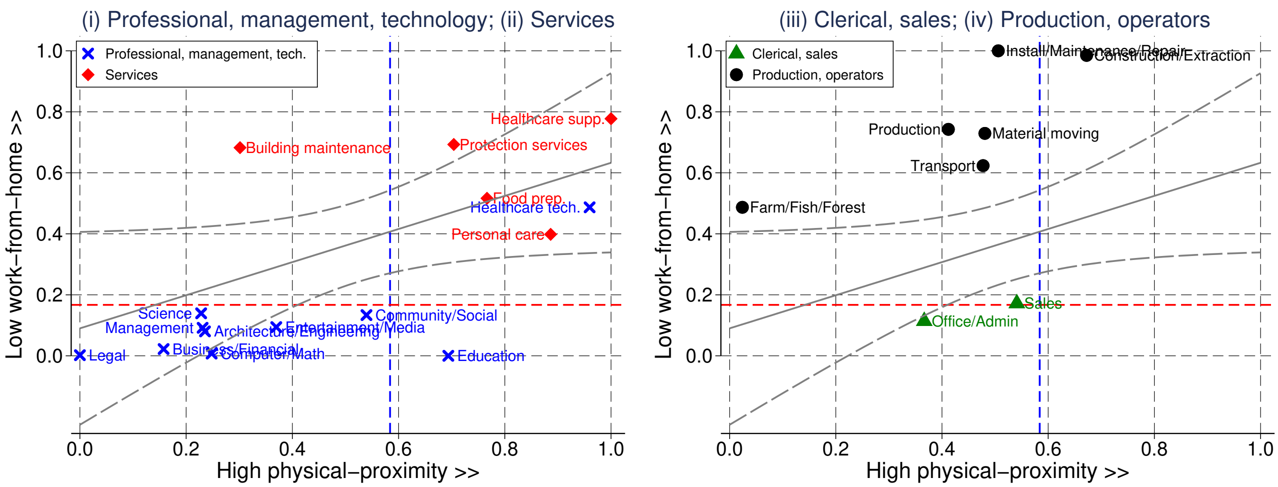



Figure 1: Occupations by Work-from-home and Physical-proximity (2 digit, Census OCC)

Notes: This figure compares groups of 2 digit OCC code occupations. We split the data into panels A and B only for readability, so that occupation titles can be included. To construct this figure, we employment-weight using the OES to aggregate $\overline{LWFH}_j$ and $\overline{HPP}_j$ to the 2 digit level. The gray line plot fitted values and 95% confidence intervals from an employment-weighted linear regression across 2 digit occupations. Occupations *above* the red-dashed line have $LWFH^*_j = 1$, and account for half of employment. Occupations *to the right* of the blue-dashed line have $HPP^*_j = 1$, and account for half of employment.

each occupation is intensive in 17 O*NET work activities.[10] Our continuous measure $\overline{LWFH}_j$ is a tally $\in [0, 17]$ of the number of in-person activities required by the occupation. An occupation which requires workers to perform many in-person activities (i.e. $\overline{LWFH}_j$ is large) is less able to be done at home. Our binary variable $LWFH^*_j$ takes a value of 1 if $\overline{LWFH}_j$ is above the employment weighted median (= 2) and a value of 0 otherwise. For certain figures, we aggregate $\overline{LWFH}_j$ to the 2 digit OCC level and rescale so that $\overline{LWFH}_j \in [0, 1]$.

In our discussion, we will use occasionally use $HPP$ and 'high PP' to refer to $HPP^*_j = 1$ occupations and $LPP$ and 'low PP' to refer to $HPP^*_j = 0$ occupations. Similarly, $LWFH$ and 'low WFH' refer to $LWFH^*_j = 1$ occupations while $HWFH$ and 'high WFH' represent $LWFH^*_j = 0$ occupations.

## 2.2 Which jobs are low work-from-home and high physical-proximity?

Figure 1 shows how occupations - aggregated to the 2-digit OCC level - vary across these two metrics, and where our cut-offs lie for the binary measures.[11] Unsurprisingly, there is a strong positive correlation between low work-from-home and high physical-proximity occupations.[12] Typical office

[10] Examples include: (i) Working outdoors and (ii) Repairing and maintaining mechanical equipment. The full list can be found in Appendix A.

[11] For readability of this figure, we employment-weight using the OES to aggregate $\overline{LWFH}_j$ and $\overline{HPP}_j$ to the 2 digit level. We then linearly transform each measure $\overline{X}_j$ using its minimum and maximum: $(\overline{X}_j - \overline{X}^{Min}_j)/(\overline{X}^{Max}_j - \overline{X}^{Min}_j)$.

[12] In Appendix Table A4, we provide a full list of 2-digit Occupations, their rankings across these measures, and their employment shares.

jobs in financial services or the legal profession have few of the features that make it unamenable to being done from home. There is also little work done within arm's length in these jobs. On the other hand, construction, material moving, and healthcare jobs are low work-from-home and high physical proximity.

A number of occupations stand out as deviations from this pattern. Education jobs require close physical-proximity, but little of the features that would prevent the job being conducted at home. Under broad social-distancing, workers in these jobs can successfully stay employed while operating from home, which has indeed occurred through virtual teaching. Agricultural jobs (Farm/Fish/Forest), meanwhile, may pose lower contagion risk due to low physical-proximity, but are difficult to be done from home. Such jobs may be punished somewhat unduly by indiscriminate social-distancing.

Note that while Figure 1 shows occupations at the aggregated 2 digit OCC level, many more narrow 3 digit OCC occupations differ from their group. Consider for example the 2 digit OCC Entertainment/Media. The broad occupation is $HPP^* = 0$ even while a 3 digit OCC Dancer is $LPP^* = 1$. Figure B1 plots all 3 digit occupations.

Figure 1 and Table A4 rank 2 digit OCC occupations along $\overline{LWFH}_j$ and $\overline{HPP}_j$. The continuous measures can be downloaded at both the 3 digit and 2 digit OCC levels online.[13]

### 2.3 Validation I - Comparison to ATUS

We validate our occupation-level pandemic-exposure measures using the behavior of workers in those occupations in the 2018 American Time Use Survey (ATUS). The ATUS reports where and with whom individuals do various activities. To validate our measure of whether an occupation can be performed from home, we compare the measure to the share of an occupation's work hours that are spent at home. We validate our physical-proximity measure against an imperfect proxy, the share of an occupation's work hours that are spent alone.[14]

Both O*NET measures are negatively correlated with their ATUS counterpart, validating the measures. At the 2 digit level, the ATUS share of work hours at home and $\overline{LWFH}_j$ have a correlation of $-0.80$. The physical proximity measure is less tightly linked, with a correlation of $-0.56$. The looser fit is to be expected given that the ATUS measures whether one is working with co-workers while the O*NET measure uses information on how physically close workers are to others, including customers.

Figure 2 depicts these correlations graphically. It also provides preliminary evidence on the distributional effects of social distancing. Workers in professional services jobs (blue markers)

[13]Download our measures here: https://github.com/simonmongey/Mongey_Pilossoph_Weinberg/tree/master/files

[14]We use the question in the ATUS "who" file which asks - for each activity the respondent recorded - "Who was in the room with you/Who accompanied you?" for the measure of hours working spent alone. We use the question from the interview file which asks "where were you during this activity?" for the measure of hours spend working at home.

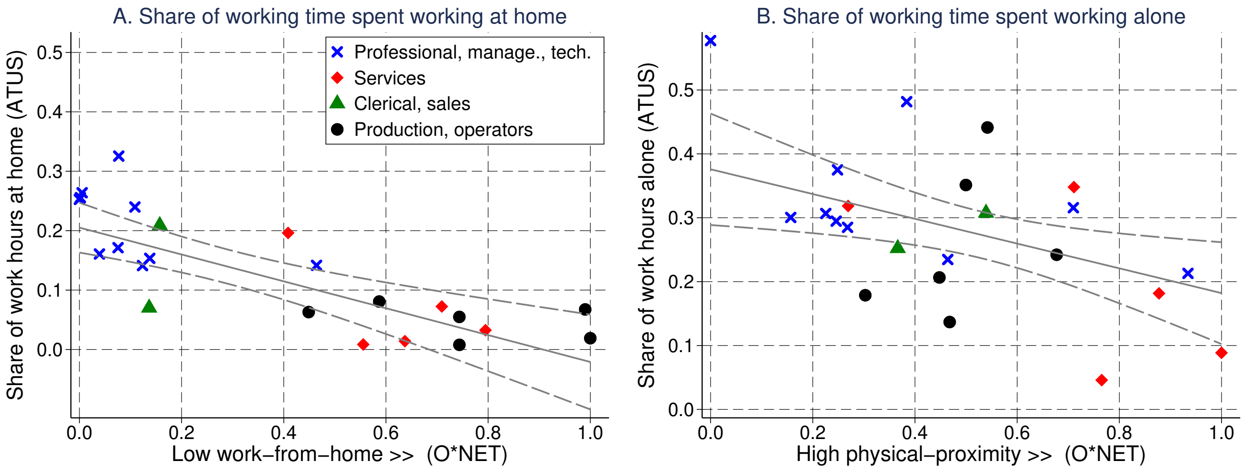



Figure 2: Comparing work-from-home and physical-proximity measures to ATUS

Notes: **Panel A** compares the fraction of individuals reporting that they can work from home in the ATUS against the O*NET WFH measure. **Panel B** compares the physical proximity measures constructed from the two datasets. The share of adjusted work hours accounts for the fact that respondents can answer that they are with multiple individuals while performing a particular activity. Fitted values are from employment-weighted linear regressions, and display 95 percent confidence intervals for the conditional expectation of the dependent variable.

already spend a significant fraction of time working from home and more time working alone. These types of workers—usually higher income and college educated—will be less likely impacted by social distancing. We study this in detail using individual-level data in Section 3.

## 2.4 Validation II - Measures from the CPS Covid-19 Supplement

As a second validation that the pandemic exposure measures are useful, we compare them with realized work-from-home behavior during the pandemic. Starting in May 2020, a series of supplemental questions were added to the CPS to understand the labor market and health impacts of the pandemic. In this Covid Module, the CPS asked respondents *"At any time in the last 4 weeks, did you telework or work at home for pay because of the coronavirus pandemic?"* As shown in Table B5, during the five month period for which data is currently available (May - November, 2020) individuals employed in $HWFH^*$ occupations were 35 percentage points more likely to report teleworking than those employed in $LWFH^*$ occupations. During the same period, individuals employed in $LPP^*$ occupations were 18 percentage points more likely to work-from-home than those employed in $HPP^*$ occupations.

Figure 3 validates our measures against this novel data graphically. Panel A (Panel B) of Figure 3 shows the relationship between our $\overline{LWFH}$ ($\overline{HPP}$) measures and the share of respondents that reported teleworking in the May survey. Our work-from-home measure is the stronger predictor of whether or not workers teleworked during the Covid-19 pandemic. Our regression in Table B5 of an indicator of teleworking on $LWFH^*$ yields an $R^2 = 0.16$ while a similar regression on $HPP^*$ yields $R^2 = 0.04$. Table B4 shows the percent of workers in each occupation type that reported

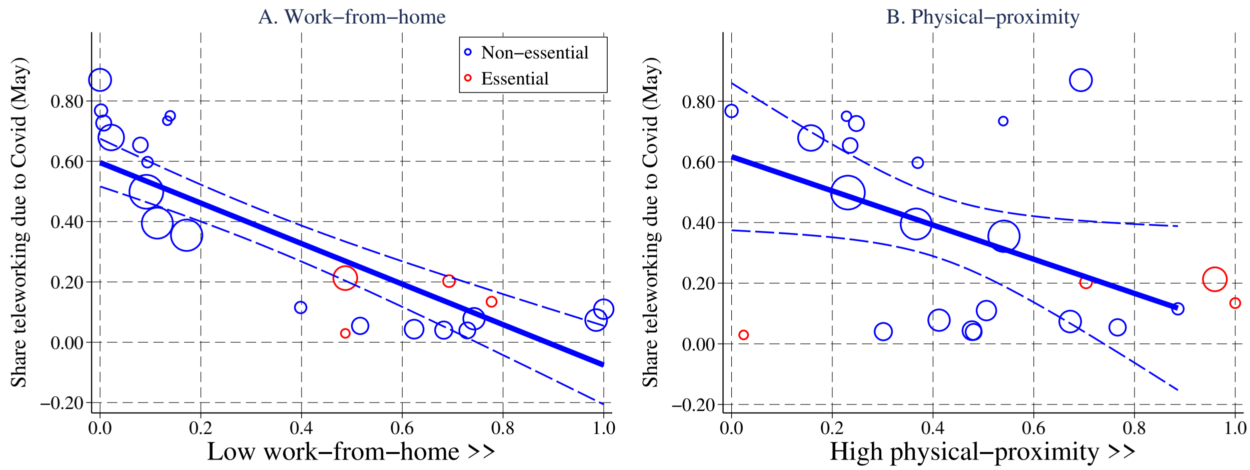



Figure 3: Comparing work-from-home and physical-proximity measures to CPS Covid Module

Notes Data is aggregated to the 2 digit occupation level. Circle sizes reflect employment in each occupation. **Panel A** compares the fraction of individuals in May 2020 reporting that they teleworked due to the Covid-19 pandemic against the O*NET WFH measure. **Panel B** compares the physical-proximity measure with the share of workers who report that they teleworked. Fitted values are from employment-weighted linear regressions of occupations marked as non-essential.

working-from-home each month.

# 3 Characteristics of workers in exposed jobs

We now compare the characteristics of workers employed in low work-from-home $LWFH_j^* = 1$ and high physical-proximity $HPP_j^* = 1$ occupations with workers in $LWFH_j^* = 0$ and $HPP_j^* = 0$ occupations respectively.

We merge our validated measures with worker-level data in the March CPS and PSID. We construct our PSID sample following Kaplan et al. (2014) and our CPS sample following Heathcote et al. (2010).[15] The key finding is that workers employed in social-distancing exposed occupations are disproportionately low income, low education, and economically vulnerable more generally.

## 3.1 Approach

Our approach is simple and designed to be easily interpretable. Let $y_{ij}$ be a binary characteristic of a worker $i$ employed in occupation $j$ last year. For simplicity, we work work with binary variables. As an example, we construct the binary variable 'below median income' from the continuous variable 'wage'. We regress each worker characteristic $y_{ij}$ on both pandemic-exposure measures. Using

[15] We follow Heathcote et al. (2010)'s sample selection criteria for their Sample C which is as follows. We construct wages by dividing total wage and salary income by annual hours worked. Annual hours are the product of weeks worked last year and usual weekly hours. We restrict our sample to individuals aged 25-65 who work at least 260 hours (equivalent to working a month of 8 hour days)paid wages at least half of the Federal minimum wage.

$LWFH_j^*$ as an example, we estimate:

$$y_{ij} = \alpha_y + \beta_y LWFH_j^* + \varepsilon_{ij}. \tag{1}$$

This gives the sample moment:

$$\widehat{\beta}_y = \mathbb{E}\left[y_{ij} \middle| LWFH_j^* = 1\right] - \mathbb{E}\left[y_{ij} \middle| LWFH_j^* = 0\right]$$

where $\mathbb{E}$ is the sample mean. Since $y_{ij}$ is binary, $\widehat{\beta}_y$ is simply the fraction of workers for which $y_{ij} = 1$ in *low* work-from-home occupations, relative to the fraction of workers for which $y_{ij} = 1$ in *high* work-from-home occupations. Our estimate $\widehat{\beta}_y$ is a measure of how *disproportionately* $y_{ij} = 1$ workers in low work-from-home occupations are.

We estimate (1) for the individual characteristics listed below. In each case we assign $y_{ij} = 1$ to the individuals with the characteristic most related to being in a low work-from-home occupation.

- **Demographics.** (i) Non-white, (ii) No college degree, (iii) Age below 50, (iv) Male, (v) Single, (vi) Born outside USA, (vii) Non-US citizen, (viii) Rent their home
- **Work.** (i) No healthcare provided by employer,[16] (ii) Employed at a small firm ($<$ 500 employees), (iii) Part-time employed
- **Income.** (i) Below median wage (ii) Experienced a spell of unemployment in the last year. (iii) Hand-to-mouth (iv) Poor hand-to-mouth[17]

### 3.2 Results

Our main results consist of plotting $\widehat{\beta}_y$ in Figure 4.[18] Clearly $\widehat{\beta}_y \in [-1, 1]$ and takes the maximum value of 1 when $y_{ij} = 1$ for all individuals for which $LWFH_j^* = 1$, and $y_{ij} = 0$ for all individuals for which $LWFH_j^* = 0$. Comparing estimates across measures $y$ and $y'$, a higher value of $\widehat{\beta}_y > \widehat{\beta}_{y'}$ can be interpreted as

> *"Workers in occupations for which $LWFH_j^* = 1$ are relatively more different from workers in occupations for which $LWFH_j^* = 0$ along dimension $y$ than along dimension $y'$".*

In Figure 4A, we plot the estimates for each of these characteristics for the low work-from-home regression, ordering these attributes from the highest to the lowest point estimate. Figure 4B repeats the exercise for the high personal-proximity regression. For most of the individual characteristics, the results for high work-from-home occupations and low physical-proximity occupations are the same in terms of their sign, as is evident from the fact that most of the dots are to the right of

[16]We set the indicator for employer provided healthcare to 1 if the employer pays for any part of the individual's health insurance premiums.

[17]Households are hand-to-mouth when they are liquidity-constrained. See Kaplan et al. (2014) for details on construction using the PSID.

[18]Table B1 and Table B2 further decompose these results; providing the moments $\mathbb{E}\left[y_{ij} \middle| LWFH_j^* = 0\right]$ and $\mathbb{E}\left[y_{ij} \middle| LWFH_j^* = 1\right]$, and similarly for $HPP$.

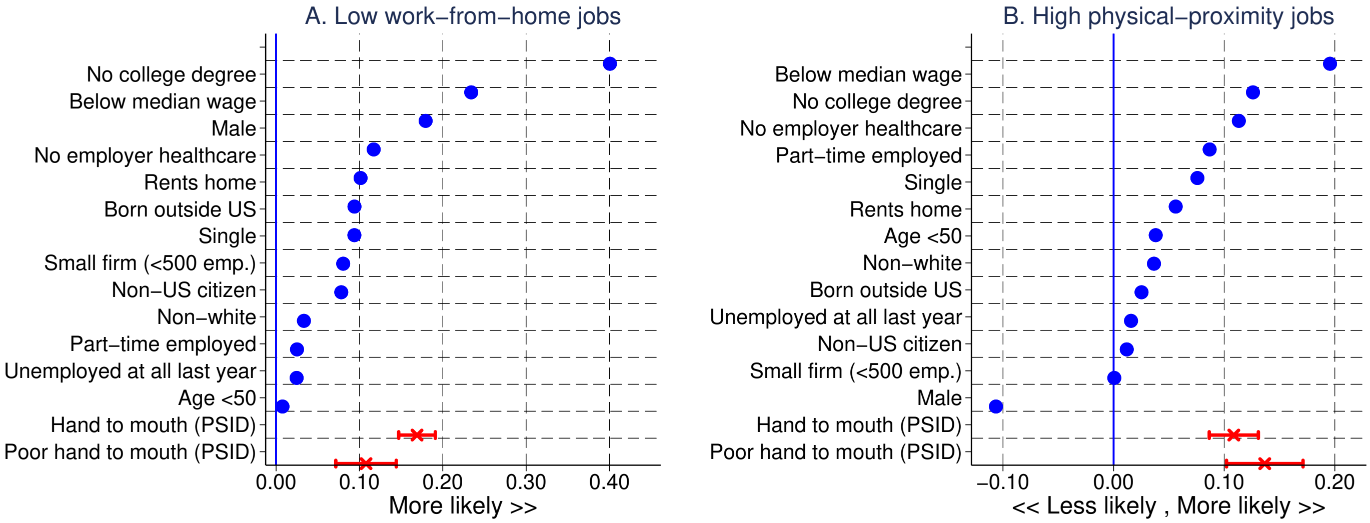



Figure 4: Characteristics of workers in *Low Work-from-home* and *High physical-proximity* jobs

Notes This figure plots estimates of $\widehat{\beta}_y$ for 10 characteristics $y$ from regressions in which $LWFH^*_j \in \{0,1\}$ is the independent variable (Panel A), and in which $HPP_j \in \{0,1\}$ is the independent variable (Panel B). If $x$% of workers in *high work-from-home* occupations have, for example, *no college degree*, then Panel A shows that $(x+38)$% of workers in *low work-from-home* occupations have *no college degree*. A high value of $\widehat{\beta}_y$ therefore means that workers in *low work-from-home occupations* are more likely than workers in *high work-from-home occupations* to be in the category listed on the vertical axis. Point estimates are given by the circle markers, and 95 percent confidence intervals are given by the lines through each marker. All blue results are derived from the CPS, red results are derived from the PSID.

zero. For example, workers in both high physical-proximity occupations and low work-from-home occupations are less likely to have a college degree than workers in low physical-proximity and high work-from-home occupations, respectively. The results are less stark for the high physical proximity occupations, as the magnitudes of the coefficients are usually smaller.

Occupations which cannot be performed from home or that have high physical proximity requirements feature workers that, by all measures, are economically more vulnerable. Workers in low WFH (high PP) occupations are 40 (12) percentage points less likely to have a college degree and 23 (19) ppt more likely to be below median income. They are more likely to rent rather than own their homes and so are less likely to be in positions to take advantage of interest rate cuts, and have fewer collateralizable assets to borrow against to compensate for earnings losses. Additionally, those in low WFH occupations are more likely to work in smaller firms (though this is not the case for workers in high physical proximity occupations), which are on average less financially robust and so more likely to suffer from the financial effects of the crisis (Chodorow-Reich, 2014).

Workers in low WFH and high PP jobs are also less likely to have access to *informal insurance channels* that may help them weather the crisis. They are less likely to be married, which can diversify household income against individual income risk. They are less likely to be US citizens or born in the US, which may lead to less family support, as well as restricting access to emergency government programs. Finally, they are more likely to have unstable employment; they are less likely to be employed full-time and more likely to have recently experienced unemployment.

Availability of healthcare is obviously a key insurance mechanism in a pandemic. Workers in low work from home occupations and high physical proximity occupations are less likely to have any employer-subsidized healthcare. However, we find that the age of workers across these high- and low- work-from-home occupations does not systematically differ. Given that the mortality rate for those with COVID-19 is significantly higher for older individuals,[19] this means that workers across the different types of jobs have the same fundamental health risks as they relate to age, but those in low WFH or high PP jobs are less likely to have the health insurance to provide for them in the case of infection.

We expect that low access to liquid savings will compound the economic consequences of job loss or reduction in hours, and the health consequences of infection. To understand whether workers in low work-from-home jobs have disproportionately lower levels of liquid savings we add data from the PSID and construct measures of whether a household is hand-to-mouth following Kaplan and Violante (2014).[20] Hand-to-mouth households are households with liquid assets that are less than half of one month's income.

The results are depicted in red in Figure 4. We find that households in which the highest earner is employed in a low work-from-home or high physical-proximity job are disproportionately hand-to-mouth. Conditional on being hand-to-mouth, households may be poor-hand-to-mouth or wealthy-hand-to-mouth depending on whether they have positive or negative net-assets, respectively. Conditional on being hand-to-mouth, workers in jobs most likely affected by social distancing policy are disproportionately poor-hand-to-mouth.

The magnitudes of the point estimates are economically significant. Hand-to-mouth low work-from-home households are 10 ppt more likely to be poor hand-to-mouth than hand-to-mouth high work-from-home households. To put this in perspective we could compare this to how, as households age, the composition of hand-to-mouth households shifts from poor- to wealthy-. Starting at age 30, one would need to move all the way up to age 50—a period of high income growth—in order to obtain a 10 percent decline in the fraction of hand-to-mouth households that are poor hand-to-mouth (Kaplan et al., 2014, Figure 6). Despite not being significantly younger, low work-from-home households have finances as if they are twenty years further back in their lifecycle.

The results differ across these two occupation exposure measures most sharply for sex. Individuals in occupations that score highly in terms of work-from-home are more likely to be male, while individuals in occupations that have high physical-proximity are more likely to be female. This relates to the earlier example of Education jobs from Figure 1, which are female-dominated. Taking these results at face value, female workers may be relatively less affected by universal social distancing measures, but could be relatively more affected if restrictions or behavior responds around

[19] See `https://www.cdc.gov/nchs/nvss/vsrr/covid19/index.htm`

[20] We use the code made publicly available from Kaplan et al. (2014).

occupations with higher personal-proximity.

Finally, a policy maker may not be interested in programs targeted below and above the median of the indexes we create since they rule in too many individuals. We therefore verify that if we make more extreme comparisons using the tails of our measures, then we get more extreme results. Figure B3 in Appendix B compares the lower quartile to the upper quartile (dropping the middle quartile, in red), and the second quartile to the third quartile (dropping the upper and lower quartile, in green). When we compare workers in *very low* work-from-home occupations to workers in *very high* work-from-home occupations (in red), the coefficients are uniformly larger in magnitude. For example, workers in the lowest quartile of work-from-home occupations are nearly 50 ppt more likely to not have a college degree than workers in the highest quartile. Targeting policies into the lower tail of the distribution is thus both cheaper (lower incomes to replace) and more effective (lower resources initially available).

Taken together, the evidence shows that those in low work from home occupations and high physical proximity occupations are less prepared to weather the economic and hardship induced by the Covid pandemic. Moreover, the correlation between low work-from-home and high physical-proximity jobs discussed in Section 2 creates a double-edged sword. It induces a correlation in *economic risks* due to policy and *health risks* due to transmission of Coronavirus. More vulnerable workers are therefore relatively more exposed to both.

**Joint examination of work-from-home and physical proximity.** Since $\overline{LWFH}_j$ and $\overline{HPP}_j$ are correlated, perhaps our results are best explained by one measure and not the other. We repeat our analysis in Figure B2 and B3 jointly examining HPP and LWFH. For example, the left panel of Figure B2 depicts the coefficient $\widehat{\beta}_y$ from the same WFH regression (1), but conditioning on the HPP status of the job. The blue dots therefore represent how much more likely workers are to have attribute $y$ if they are in low WFH jobs, *conditional on working in a high PP job.* Similarly, the red crosses represent how much more likely workers are to have attribute $y$ if they are in low WFH jobs, *conditional on working in a low PP job.*

Conditional on working in a high physical proximity occupation, the characteristics of workers in low and high work from home jobs are similar, with a couple of notable exceptions. First, regardless of physical proximity, workers in low work from home jobs are disproportionately male. Second, conditional on being in a HPP occupation, low work from home workers disproportionately do not have a college degree (panel A). As expected, this implies that if instead we first condition on low or high work from home, then compare workers in low and high physical proximity jobs, the composition of workers is relatively similar (panel B).

# 4 Employment during the epidemic

We now use the data available since the start of the epidemic to demonstrate that pandemic-exposed occupations experienced larger employment losses. Our main results in Figure 4 suggest that workers associated with low work-from-home jobs should expect to see larger employment losses. Indeed, these workers experienced larger declines in employment during the early months of the outbreak.

## 4.1 Employment losses by occupation

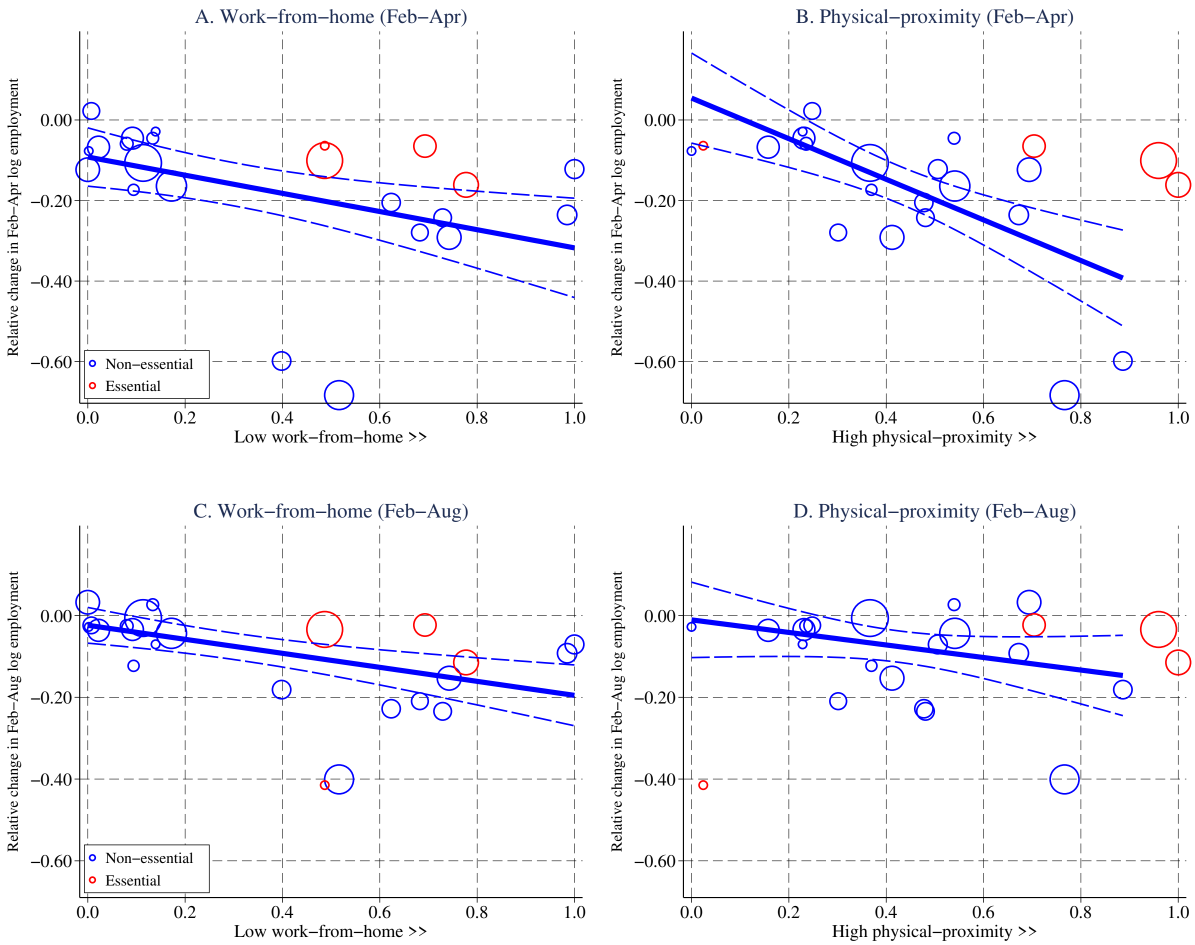
Excess employment losses from February to April of 2020 show a clear pattern: occupations with low work-from-home and high physical-proximity scores had relatively larger declines in employment compared to occupations with high WFH scores and low PP scores, respectively. Jobs that are more easily done at home and involve lower physical proximity were more likely to remain intact. We show that this is the case using CPS occupational employment data.[21] To account for seasonal factors and long run trends in occupation employment changes, we construct excess employment losses by taking the log change in employment from February to April 2020 and subtracting the average February to April log change in employment from 2010-2019. Figure 5 compares the relationship between this excess decline in employment against $\overline{LWFH}_j$ (Panel A) and $\overline{HPP}_j$ (Panel B), showing that low work-from-home jobs and high physical proximity jobs experienced larger excess employment losses.

Comparing Figure 5 panels A and B of reveals that physical-proximity is the stronger predictor of employment losses during the initial period of the pandemic from February-April. This may be because high physical-proximity jobs such as food service or personal care are associated with infection exposure for the consumer in addition to the worker. By August, however, the relationship between physical-proximity and employment losses flattened as social distancing mandates expired and some individuals chose to return to purchasing in-person services such as restaurant meals. Employment losses remained larger in low work from home occupations which are less sensitive to demand-side concerns.

**Essential workers.** An important exception to this relationship, as expected, are those jobs deemed essential by public policy. These essential occupations are unlikely to have employment losses that correlate with the ability to telework, or with whether the job entails high physical proximity with others. For example, front line medical workers have very low work-from-home measures (healthcare supplemental workers have a $\overline{LWFH}_j$ index of around 0.8) and high physical-proximity measures (healthcare supplemental workers have an $\overline{HPP}_j$ index of 1.0). Because healthcare is considered essential, workers in these occupations have not experienced the dramatic employment losses implied by their physical-proximity and work-from-home scores. We use industry data cre-

[21] Summary statistics are reported in Table A1

Figure 5: Employment declines by occupations and worker characteristics

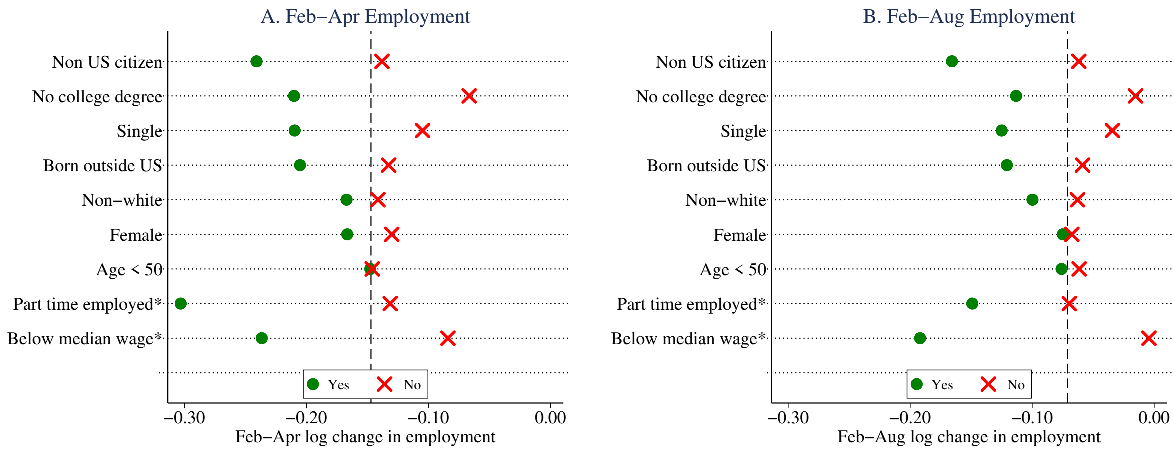



Notes These figures plots employment changes by 2-digit OCC occupation against $\overline{LWFH}_j$ (**Panel A**) and $\overline{HPP}_j$ (**Panel B**). Employment change is the Feb-April log change in employment in 2020 of each occupation, relative to the average Feb-April log change in employment over 2010-2019 for the occupation. **Panel C** and **Panel D** are similarly plotted for Feb-August log changes in employment. Occupations marked with red diamonds are defined as "essential" using the grouping from Tomer and Kane (2020). Fitted values are from an employment-weighted linear regression estimated on non-essential occupations, and gives 90 percent confidence intervals for the conditional expectation of the dependent variable. Data is from the CPS.

ated by Tomer and Kane (2020), that categorizes certain 4-digit NAICS industries as "essential".[22] For each 2 digit occupation we use the 2018 OES to calculate the share of employment in essential industries, and categorize an occupation as essential if more than 75 percent of employment work in an essential industry. Occupations that meet this criterion are depicted in red in Figure 5. Among these occupations there is no significant relationship between the WFH measure and employment

[22]Tomer and Kane (2020) use job descriptions from the government statement which announced guidelines for categorizing essential jobs. The text for this document can be found at https://www.cisa.gov/publication/guidance-essential-critical-infrastructure-workforce.

Figure 6: Employment declines by worker characteristics




Notes These figures plot employment changes by type of worker. **Panel A** plots employment changes from February to April of 2020, adjusted by subtracting the average February-April change in employment for that group over 2010 to 2019. The variables on the $y$-axis are used to split workers into two groups: those in the group given by the label ('**Yes**', marked with a green circle), and those outside that group ('**No**', marked with a red cross). For the whole sample, we obtain a total decline in employment of $-14.7$ log points (black dashed line). **Panel B** is similarly constructed for employment changes February-August 2020. For the whole sample, we obtain a total decline in employment of $-7.1$ log points (black dashed line) ($*$) For the last two cases the sample is restricted to the Outgoing Rotation Group, a subsample of the monthly CPS reporting hours—in the case of *Part time employed*—and hours+earnings—in the case of *Below median wage*.

growth.[23]

## 4.2 Employment losses by worker characteristics

As a final exercise, we study how excess employment losses vary across the worker characteristics considered in Section 3. For each group of workers we compute two objects: the total employment change over February-April 2020, and the total employment change over February-August 2020. We subtract off from each of these the mean total employment change across their respective months for 2010-2019. We focus on employment rather than unemployment due to issues associated with the labeling of workers as unemployed versus out of the labor force. Figure 6 shows the results.[24]

Once again, a clear pattern emerges: Figure 6A shows that those groups of individuals who have a higher employment share in low WFH occupations (as identified using the methodology of Section

[23]The metric we use to categorize occupations as essential is able to pick up certain obvious 2-digit occupations such as healthcare technicians and healthcare support. However, some occupations are left out despite having numerous mentions in the aforementioned government text. For example, the word *construction* is mentioned thirty three times; the word legal is mentioned only once.

[24]We check that the total employment losses February-April 2002 that we construct using survey weights lines up with total employment losses reported by the BLS. We obtain a value of -14.7 percent for February-April. Because our sample selection drops workers tenuously tied to the workforce, our estimate differs from the official value from the BLS, -17.4 percent, which we compute as $\log(\frac{133{,}403{,}000}{158{,}759{,}000})$ from Summary Table A of the following: BLS 'Employment Situation' report - April, 2020.

2) experienced, on average, more severe employment outcomes in April 2020 relative to those in occupations with high work-from-home capability.

For example, non-college workers (associated with in-person occupations) experienced a 21 percent excess decline in employment from February to April 2020, while college educated workers (associated with teleworkable occupations) saw only a 7 percent decline.

The characteristics with the largest differential in employment outcomes between groups are income, work status, nativity, marital status, and education. Figure 6B depicts cumulative excess employment losses from February through August. The data continue to show the same pattern as in April, but the magnitudes of the differences in employment outcomes across groups decreased as some in-person work returned.

### 4.3 Comparing employment losses to previous recessions

Our main results from Section 3 showed that economically more vulnerable workers were more likely to be employed in highly exposed jobs as measured by our HPP and LWFH measures. However, since these workers are generally more economically vulnerable, it may be the case that the employment losses they suffered are independent from their exposure to the pandemic through their occupation, and reflect standard employment dynamics in a recession.

To see whether individuals with the characteristics we have identified as being more exposed suffered larger employment losses than would typically be expected, we conduct a simple difference-in-difference exercise.

Table 1 compares peak to trough employment changes in LPP and HPP occupations during both the Great recession and the Covid recession. We find that during the covid recession, high PP occupations saw much larger employment losses relative to low PP occupations ($-11.91$ percentage points). During the Great recession, High PP actually saw smaller decreases in employment relative to low PP occuations (3.33 percentage points). This shows that high physical-proximity occupations were uniquely exposed to the economic downturn induced by the novel Coronavirus and do not see disproportionate employment losses during all recessions.

The outcome is similar but smaller in magnitude for our work-from-home classification. It is true that in the Great Recession, workers in low work-from-home occupations saw 3.67 percentage point larger employment losses than workers in high work-from-home occupations. However, in the Covid recession, employment losses for workers in low work from home occupations were 9.14 percentage points larger than workers in high work-from-home occupations. This exercise confirms that workers that cannot work-from-home or were in high physical proximity jobs were uniquely exposed to the pandemic-induced recession.

Table 1: Employment losses by work-from-home and physical-proximity during two recessions

| | A. Work-from-home | | | | B. Physical proximity | | | |
|---|---|---|---|---|---|---|---|---|
| | Great Recession | | Covid Recession | | Great Recession | | Covid Recession | |
| | High WFH | Low WFH | High WFH | Low WFH | Low PP | High PP | Low PP | High PP |
| **A. Employment** | | | | | | | | |
| Peak employment (level) | 68.40 | 52.70 | 74.39 | 55.22 | 73.12 | 47.98 | 77.14 | 52.48 |
| Trough employment (level) | 66.27 | 49.12 | 67.64 | 45.16 | 68.70 | 46.69 | 70.85 | 41.95 |
| **B. Relative job losses** | | | | | | | | |
| Percent change | -3.12 | -6.79 | -9.08 | -18.23 | -6.04 | -2.71 | -8.16 | -20.06 |
| 2nd difference | | -3.67 | | -9.14 | | 3.33 | | -11.91 |
| 3rd difference | | | | -5.47 | | | | -15.24 |

Notes This table compares employment changes by LWFH and HPP during the Great Recession with the Covid Recession. **Panel A** reports employment in millions at the peak and trough of both downturns. The peaks for the Great and Covid recessions are January 2008 and February 2020. The troughs are January 2010 and April 2020. **Panel B** reports percent decreases in employment for each occupation group from peak to trough. Second difference compares percent decrease in employment between HWFH and LWFH and between LPP and HPP within a given recession. Third difference compares relative employment losses between the Covid and Great Recession. LWFH occupations saw 5.47 percentage point larger decrease in employment relative to HWFH occupations during the Covid Recession than they did during the Great Recession. Similarly, HPP occupations saw a $-15.24$ percentage point larger decrease in employment relative to LPP occupations during the Covid recession relative to the Great Recession. LWFH and HPP occupations are not recession-exposed, rather there is a unique element of the Covid recession which explains they larger drop in employment.

# 5 Conclusion

We show that workers systematically differ across the types of occupations that were most likely to be hit by social distancing involved in both the public policy and behavioral responses to the Coronavirus pandemic. Workers in occupations that are *most likely* to be affected—those with a low score in the O*NET work-from-home measure, or a high score in the O*NET measure of personal-proximity—are predominantly characterized by traits associated with the more economically vulnerable in the US economy. These workers are disproportionately less educated, have limited healthcare, are toward the bottom of the income distribution, and have low levels of liquid assets. We showed that this was a useful way of understanding job losses following the start of the pandemic in 2020.

Given the occupation-level indicators we have constructed and made available with this paper, our measures can be used to capture geographic or group level exposure to social distancing policies. Moreover, our simple approach can be extended to individual economic indicators in any microdata that records occupation, including, but not limited to, the Survey of Consumer Finances, the Survey of Income and Program and Participation, and the Survey of Consumer Expectations.

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# Appendix

## A Data

In this appendix, we describe the construction of our work-from-home and personal-proximity measures in detail. We begin with an overview of the various datasets before detailing the construction of our pandemic-exposure measures.

### A.1 Overview of data sources

**O*NET.** The Occupational Information Network (O*NET) is a database sponsored by the U.S. Department of Labor; it contains standardized measures on occupation skills, abilities, knowledge requirements, work activities, and work contexts. Workers in more than 900 occupations rate their job from 1 to 5 along many work activities and work contexts.[25] The data is published using the granular O*NET-SOC occupation classification system. O*NET-SOC is a refinement of the Standard Occupational Classification (SOC) system developed by the Office of Management and Budget (OMB).[26] In this paper we use O*NET database 24 which makes use of the 2010 taxonomy of the O*NET-SOC occupation codes. We aggregate the variables to the SOC level by taking means weighted by the number of survey respondents in each O*NET-SOC code.

**OES.** The Occupational Employment Statistics (OES) provides wage and employment data by occupation and industry. We use the 2018 snapshot which makes use of the 2010 taxonomy of the SOC codes (SOC 2010). We use this data to employment-weight when aggregating O*NET data from the SOC classification to the coarser OCC occupational classification system used by the CPS.

We use industry-occupation employment counts to develop our classification of essential occupations. If at least 75% of an occupation's employment is in industries deemed essential according to the Department of Homeland Security, then we call that occupation 'essential'.[27]

**CPS.** The Current Population Survey (CPS) is the official source of many U.S. government statistics. We use this monthly survey to examine employment outcomes by occupation. Starting in May 2020, the CPS appended a series of questions related to the coronavirus pandemic to the monthly questionaire. We use this module to examine teleworking behavior in Figure 3 and Table B4. Table A1 contains summary statistics from selected months of the CPS.

[25] Survey questions available here: https://www.onetcenter.org/dl_files/MS_Word/Work_Context.pdf. Human resource experts rank occupation skills and abilities using both their own expertise and the survey responses.

[26] For example, O*NET-SOC codes '33-2011.01' Municipal Firefighters and '33-2011.02' Forest Firefighters both map to the SOC code '33-2011' Firefighters.

[27] Our essential industry data comes from Tomer and Kane (2020).

Table A1: Monthly CPS - Summary statistics

| | February | | April | | August | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD |
| **I. Continuous variables** | | | | | | |
| Age | 43.55 | 11.26 | 43.57 | 11.26 | 43.54 | 11.28 |
| Hourly wage* | 26.30 | 21.12 | 26.25 | 19.53 | 26.48 | 18.83 |
| Usual weekly hours* | 39.92 | 10.04 | 40.01 | 10.03 | 40.22 | 9.91 |
| Years of education | 13.99 | 2.72 | 13.98 | 2.73 | 13.99 | 2.73 |
| **II. Binary variables** | | | | | | |
| College degree | 0.38 | | 0.38 | | 0.38 | |
| Male | 0.53 | | 0.53 | | 0.53 | |
| Born in US | 0.80 | | 0.80 | | 0.80 | |
| Married | 0.59 | | 0.59 | | 0.59 | |
| US citizen | 0.91 | | 0.91 | | 0.91 | |
| White | 0.79 | | 0.79 | | 0.79 | |
| Full-time employed | 0.91 | | 0.91 | | 0.92 | |
| Age 50+ | 0.34 | | 0.34 | | 0.34 | |
| N | 585737 | | 577490 | | 571602 | |

Notes This table reports summary statistics from the monthly CPS in the months of February, April, and August. **Panel A** reports the mean and standard deviation of continuous variables. **Panel B** reports the share of workers with the listed characteristic. Variables marked with an asterisk come from the Outgoing Rotation Group, a subsample of the monthly CPS which asks questions about wages and hours.

The March 2019 Annual Social and Economics Supplement (ASEC) asks detailed questions on work and income. We use this March supplement to examine worker characteristics by occupation in Figure 4, Figure B2, Figure B3, and Figure B4. Table A2 displays summary statistics.

**PSID.** The Panel Study of Income Dynamics (PSID) is a longitudinal survey of more than 18,000 individuals. We make use of the detailed data on income, expenditures, and wealth to study household liquidity patterns by occupation. We follow the definition of hand-to-mouth used Kaplan and Violante (2014). Summary statistics from the 2017 wave are shown in Table A3.

## A.2 Construction of pandemic exposure measures

We construct two measures that measure an occupation's exposure to social distancing during a pandemic. We sign these measures in terms of expected negative economic impacts of the crisis: (i) *low work-from-home* ($LWFH$), and (ii) *high physical-proximity* ($HPP$). To create our measures, we combine the SOC-level O*NET data on work activities with employment counts from the OES. Merging these two data sources allows us to aggregate the work activities data to the coarser OCC classification system used by the datasets which contain data on individual workers (ATUS, CPS, and PSID).

We first detail the construction of $HPP$ and then describe the construction of $LWFH$ which follows many of the same steps. Our procedure delivers two continuous variables $\overline{LWFH}_j$ and

Table A2: CPS - ASEC 2019 March Supplement Summary Statistics

| | Mean | Median | SD |
|---|---|---|---|
| **I. Continuous variables** | | | |
| Age | 43.12 | 42.00 | 11.03 |
| Hourly wage | 29.90 | 22.50 | 33.40 |
| Log annual hours | 7.57 | 7.64 | 0.37 |
| Years of education | 14.14 | 14.00 | 2.77 |
| **II. Binary variables** | | | |
| College degree | 0.41 | | |
| Male | 0.52 | | |
| Has employer healthcare | 0.94 | | |
| Owns home | 0.70 | | |
| Born in US | 0.79 | | |
| Married | 0.63 | | |
| Big firm (500+ emp.) | 0.51 | | |
| US citizen | 0.90 | | |
| White | 0.78 | | |
| Full-time employed | 0.89 | | |
| No unemployment last year | 0.67 | | |
| Age 50+ | 0.31 | | |
| N | 66786 | | |

Notes This table reports summary statistics from the Annual Social and Economic Supplement attached to the 2019 March CPS. **Panel A** reports the mean, median, and standard deviation of continuous variables. **Panel B** reports the share of workers with the characteristic. Sample is restricted following the Sample C procedure described in Heathcote et al. (2010).

Table A3: PSID Summary statistics

| | Mean | SD |
|---|---|---|
| **I. Continuous variables** | | |
| Age | 53.14 | 18.05 |
| Family income from wages and salaries | 52,546.74 | 82,730.07 |
| Labor income incl. welfare | 53,156.19 | 82,636.23 |
| Usual weekly hours | 41.81 | 13.56 |
| Net worth | 385,612.95 | 1,282,929.78 |
| **II. Binary variables** | | |
| College degree | 0.39 | |
| Male | 0.68 | |
| Owns home | 0.60 | |
| Born in US | 0.91 | |
| Married | 0.43 | |
| White | 0.78 | |
| Full-time employed | 0.92 | |
| Age 50+ | 0.57 | |
| N | 9155 | |

Notes This table reports summary statistics from the 2017 wave of the Panel Study of Income Dynamics (PSID). **Panel A** reports the mean and standard deviation of continuous variables. **Panel B** reports the share of workers with the characteristic.

$\overline{HPP}_j$ and two binary variables $LWFH_j^*$ and $HPP_j^*$ that can be mapped into the occupational codes contained in the CPS, ATUS, and PSID. Let $j \in \{1, \ldots, J\}$ denote a 3-digit OCC-code occupation, which is the measure available in worker-level data. Let $l \in \{1, \ldots, L\}$ denote the fine SOC-code categorization of occupations in O*NET and OES.

**Construction of physical-proximity measure.** O*NET publishes data on the physical-proximity, $m_l$, at work for over 900 SOC occupations. The physical proximity measure takes on values $m_l \in [1, 5]$.[28]

1. We start with $m_l$, the O*NET measure of physical-proximity at the SOC level.
2. We aggregate $m_l$ to the OCC level, using the OES to compute an employment-weighted mean $\overline{HPP}_j$ for all SOC occupations $l \in j$. To map SOC code occupations into OCC code occupations we start with a cross-walk obtained from US Census, which we then substantially edit and verify.[29]

[28] Workers that respond to the survey administered by O*NET choose one of: 1 = 'I don't work near other people (beyond 100ft)', 2 = 'I work with others but not closely (e.g. private office)', 3 = 'Slightly close (e.g. shared office)', 4 = 'Moderately close (at arm's length)', 5 = 'Very close (near touching)'. Publicly available O*NET data consists of an average of these responses. For additional information regarding this question, see https://www.onetonline.org/find/descriptor/result/4.C.2.a.3

[29] The basic cross-walk from Census is available here: https://www2.census.gov/programs-surveys/demo/guidance/industry-occupation/2010-occ-codes-with-crosswalk-from-2002-2011.xls

$$\overline{HPP}_j = \sum_{l \in j} \omega_l m_l$$
$$\omega_l = \frac{n_l}{\sum_{l' \in j} n_{l'}}$$

3. We assign the dummy $HPP_j^* = 1$ (*high physical-proximity*) if the occupation is *above* the employment-weighted median of $\overline{HPP}_j$ (=3.6).[30]

4. We then re-scale $\overline{HPP}_j$ to the interval $[0, 1]$ by subtracting $\overline{HPP}_j^{Min}$ and dividing by $\left(\overline{HPP}_j^{Max} - \overline{HPP}_j^{Min}\right)$.

**Construction of work-from-home measure.** The procedure to construct $\overline{LWFH}_j$ and $LWFH_j^*$ is similar to the above. We differ from Dingel and Neiman (2020) in how we aggregate skills, but use their set of O*NET job characteristics.

1. We take the following 17 measures of SOC-level occupation attributes in the O*NET data from Dingel and Neiman (2020). We index them by $k = 1, \ldots, K$. In the underlying job characteristic data, each takes on a value $m_{lk} \in [1, 5]$, representing the average response of workers to an underlying survey in which the options are $\{1, \ldots, 5\}$:

   - **Work Activities module**: Performing General Physical Activities; Handling and Moving Objects; Controlling Machines and Processes; Operating Vehicles, Mechanized Devices, or Equipment; Performing for or Working Directly with the Public; Inspecting Equipment, Structures, or Material; Repairing and Maintaining Electronic Equipment; Repairing and Maintaining Mechanical Equipment.

   - **Work Contexts module**: Electronic Mail Use;[31] Outdoors, Exposed to Weather; Outdoors, Under Cover; Deal With Physically Aggressive People; Wear Specialized Protective or Safety Equipment such as Breathing Apparatus, Safety Harness, Full Protection Suits, or Radiation Protection; Wear Common Protective or Safety Equipment such as Breathing Apparatus Safety Harness, Full Protection Suits, or Radiation Protection; Spend Time Walking and Running; Exposed to Minor Burns, Cuts, Bites, or Stings; Exposed to Disease or Infections.

   Within each 3-digit OCC occupation $j$, we take the employment-weighted average of $m_{lk}$ across SOC occupations $l \in j$. This gives a measure for each occupation-attribute pair: $\overline{m}_{jk} = \sum_{l \in j} \omega_l m_{lk}$, where $\omega_l = n_l / \sum_{l' \in j} n_{l'}$.

[30] Since the cut-off value of $\overline{HPP}_j$ is 3.6, then $HPP_j^* = 1$ for occupations in which the average response to the survey question is at least 4. Our high physical-proximity occupations therefore represent occupations for which the average respondent said they worked at arm's length or less away from others.

[31] In the case of Electronic Mail Use, we reverse the values such that a *high value* implies that the occupation is less suited to working from home.

2. We convert these into binary variables $m^*_{jk} \in \{0,1\}$ based on whether $\overline{m}_{jk} \geq 3.5$. Since we employment-weighted when computing $\overline{m}_{jk}$ then $m^*_{jk} = 1$ if *"The average respondent to the question in the underlying O*NET survey answered at least 4, where an answer of 4 corresponds to performing the given activity 'once a week or more but not every day'."*[32]

3. We then construct a single measure for each occupation $\overline{LWFH}_j$ by taking the unweighted mean of $m^*_{jk}$: $\overline{LWFH}_j = K^{-1}\sum_{k=1}^{K} m^*_{jk}$. In words, this gives the fraction of the $K$ low work-from-home measures $\overline{m}_{jk}$ for which occupation $j$ has a high score. We rescale this to $[0,1]$ by subtracting the minimum value and dividing by the maximum minus the minimum values.

4. We then assign the binary variable $LWFH^*_j = 1$ (*low work-from-home*) if occupation $j$ is *above* the employment-weighted median value of $\overline{LWFH}_j$ (=2).

To recap, by construction $HPP^*_j$ and $LWFH^*_j$ are binary variables that equal 1 for the occupations that are *most* likely to be effected by the epidemic and ensuing policies. Half of employment is in $HPP^*_j = 1$ jobs and half of employment is in $LWFH^*_j = 1$ jobs.

# B Additional figures and tables

## B.1 Worker characteristic results

Table B1 reports the share of workers in $LWFH^* = 1$ and $LWFH^* = 0$ (i.e. $HWFH^*$) with the worker characteristics of interest. As discussed in Section 2, $\widehat{\beta}_y$ is the difference. Table B2 similarly reports worker characteristics for $HPP^* = 1$ and $HPP^* = 0$ (i.e. $LPP^*$).

To examine the characteristics of workers who are employed in occupations which are *both* LWFH and HPP we report the share of workers which the characteristics of interest in each of the following bins ordered from least pandemic-exposed to most pandemic-exposed: (i) HWFH$^*$ and LPP$^*$ (ii) HWFH$^*$ and HPP$^*$ (iii) LWFH$^*$ and LPP$^*$ (iv) LWFH$^*$ and HPP$^*$. In Table B3 the left-most column reports the share of workers in (i) HWFH$^*$ and LPP$^*$ occupations with the relevant characteristic. The second column reports the difference between the share of workers in (ii) HWFH$^*$ and HPP$^*$ relative to group (i). The third column reports the difference in the share of workers in (iii) LWFH$^*$ and LPP$^*$ occupations with the characteristic relative to column (ii). Column (iv) reports the difference between LWFH$^*$ and HPP$^*$ occupations compared to column (iii).

Figure B2 extends the main results plotted in Figure 4 to examine disproportionate-ness conditional on both HPP and LWFH.

Table A4: Occupation Rankings by $LWFH_j$ and $HPP_j$

| Occupation | Employment share | Rank $LWFH_j$ | Rank $HPP_j$ |
|---|---|---|---|
| Install/Maintenance/Repair | 0.04 | 1 | 10 |
| Construction/Extraction | 0.04 | 2 | 7 |
| Healthcare supp. | 0.03 | 3 | 1 |
| Production | 0.06 | 4 | 13 |
| Material moving | 0.03 | 5 | 11 |
| Protection services | 0.02 | 6 | 5 |
| Building maintenance | 0.03 | 7 | 16 |
| Transport | 0.04 | 8 | 12 |
| Food prep. | 0.09 | 9 | 4 |
| Farm/Fish/Forest | 0.003 | 10 | 22 |
| Healthcare tech. | 0.06 | 11 | 2 |
| Personal care | 0.04 | 12 | 3 |
| Sales | 0.10 | 13 | 8 |
| Science | 0.01 | 14 | 20 |
| Community/Social | 0.02 | 15 | 9 |
| Office/Admin | 0.15 | 16 | 15 |
| Entertainment/Media | 0.01 | 17 | 14 |
| Management | 0.05 | 18 | 19 |
| Architecture/Engineering | 0.02 | 19 | 18 |
| Business/Financial | 0.05 | 20 | 21 |
| Computer/Math | 0.03 | 21 | 17 |
| Legal | 0.01 | 22 | 23 |
| Education | 0.06 | 23 | 6 |

Notes This table ranks 2 digit OCC occupations by inability to work-from-home ($LWFH^*$) and physical-proximity ($HPP^*$). Construction of $LWFH^*$ and $HPP^*$ described in Appendix A. Employment data is from OES.

Table B1: Share of workers in LWFH* and HWFH* occupations with the following characteristic

| Worker characteristic | Share of LWFH | Share of HWFH | Difference |
|---|---|---|---|
| No college degree | 0.82 | 0.42 | 0.40 |
| Below median wage | 0.55 | 0.32 | 0.23 |
| Male | 0.63 | 0.45 | 0.18 |
| Rents home | 0.38 | 0.28 | 0.10 |
| Born outside US | 0.26 | 0.17 | 0.09 |
| Single | 0.46 | 0.37 | 0.09 |
| Unemployed at all last year | 0.38 | 0.30 | 0.08 |
| Small firm (<500 emp.) | 0.54 | 0.46 | 0.08 |
| Non-US citizen | 0.14 | 0.06 | 0.08 |
| Non-white | 0.25 | 0.21 | 0.03 |
| Part-time employed | 0.12 | 0.10 | 0.03 |
| No employer healthcare | 0.08 | 0.05 | 0.02 |
| Age <50 | 0.67 | 0.67 | 0.01 |

Notes This table reports the share of workers in $HWFH^*$ and $LWFH^*$ occupations with the characteristics lists in the leftmost column. The data comes from the 2019 March ASEC Supplement to the CPS.

Table B2: Share of workers in HPP* and LPP* occupations with the following characteristic

| Worker characteristic | Share of HPP | Share of LPP | Difference |
|---|---|---|---|
| Below median wage | 0.53 | 0.34 | 0.19 |
| No college degree | 0.65 | 0.53 | 0.12 |
| Part-time employed | 0.16 | 0.07 | 0.09 |
| Single | 0.45 | 0.38 | 0.07 |
| Rents home | 0.35 | 0.30 | 0.05 |
| Age <50 | 0.69 | 0.65 | 0.04 |
| Non-white | 0.25 | 0.21 | 0.03 |
| Born outside US | 0.22 | 0.20 | 0.03 |
| Non-US citizen | 0.11 | 0.09 | 0.01 |
| No employer healthcare | 0.07 | 0.06 | 0.01 |
| Small firm (<500 emp.) | 0.49 | 0.49 | 0.01 |
| Unemployed at all last year | 0.32 | 0.36 | -0.04 |
| Male | 0.47 | 0.57 | -0.10 |

Notes This table reports the share of workers in $HPP^*$ and $LPP^*$ occupations with the characteristics lists in the leftmost column. The data comes from the 2019 March ASEC Supplement to the CPS.

Table B3: Share of workers in occupations with the following characteristic

| Worker characteristic | (i) $HWFH^*$ & $LPP^*$ | (ii) $HWFH^*$ & $HPP^*$ | (iii) $LWFH^*$ & $LPP^*$ | (iv) $LWFH^*$ & $HPP^*$ |
|---|---|---|---|---|
| No college degree | 0.40 | +0.05 | +0.43 | -0.11 |
| Male | 0.49 | -0.15 | +0.42 | -0.22 |
| Age < 50 | 0.66 | +0.02 | -0.04 | +0.06 |
| Small firm (< 500 emp.) | 0.46 | +0.00 | +0.11 | -0.05 |
| Below median wage | 0.26 | +0.22 | +0.07 | +0.00 |
| Single | 0.36 | +0.04 | +0.04 | +0.04 |
| Unemployed at all last year | 0.35 | -0.12 | +0.15 | +0.00 |
| Rents home | 0.27 | +0.02 | +0.08 | +0.01 |
| Born outside US | 0.17 | +0.01 | +0.10 | -0.02 |
| Non-white | 0.21 | +0.01 | +0.00 | +0.05 |
| Non-US citizen | 0.07 | +0.00 | +0.10 | -0.03 |
| No employer healthcare | 0.05 | +0.02 | +0.02 | -0.01 |
| Part-time employed | 0.07 | +0.11 | -0.10 | +0.06 |

Notes Data is from the March 2019 ASEC supplement to the CPS. The column labeled (i) reports the share of workers employed in $HWFH^*$ & $LPP^*$ occupations with the individual characteristics listed on the left-most column. The columns labeled (ii) $HWFH^*$ & $HPP^*$, (ii) $LWFH^*$ & $LPP^*$, (iii) $LWFH^*$ & $HPP^*$ report the *difference* in the share of workers with the worker characteristic *relative to the column immediately to the left.* For example, 40% of workers in (i) $HWFH^*$ & $LPP^*$ occupations do not have a college degree. (ii) $HWFH^*$ & $HPP^*$ have $40\% + 5\% = 45\%$ of their workers reporting that they do not have a college degree. Occupations which are (iii) $LWFH^*$ & $LPP^*$ have $40\% + 5\% + 43\% = 88\%$ of their workers reporting that they do not have a college degree.

Table B4: Share teleworking due to Covid

| Month | All | $HWFH^*$ | $LWFH^*$ | Difference |
|---|---|---|---|---|
| May | 0.36 | 0.55 | 0.09 | 0.46 |
| June | 0.32 | 0.49 | 0.08 | 0.41 |
| July | 0.26 | 0.41 | 0.06 | 0.35 |
| August | 0.24 | 0.39 | 0.05 | 0.34 |
| September | 0.23 | 0.36 | 0.05 | 0.31 |
| October | 0.21 | 0.35 | 0.04 | 0.30 |
| November | 0.22 | 0.35 | 0.05 | 0.30 |

Notes This table reports the share of all workers and the share of workers in HWFH* and LWFH* occupations who worked-from-home due to the coronavirus pandemic. Difference is the share of workers in HWFH* minus the share of workers in LWFH* occupations who teleworked. Construction of $HWFH^*$ and $LWFH^*$ measures is described in Appendix A. Survey responses come from the Covid module appended to the CPS beginning in May 2020.

## B.2 Telework behavior during the Pandemic

## B.3 Additional figures

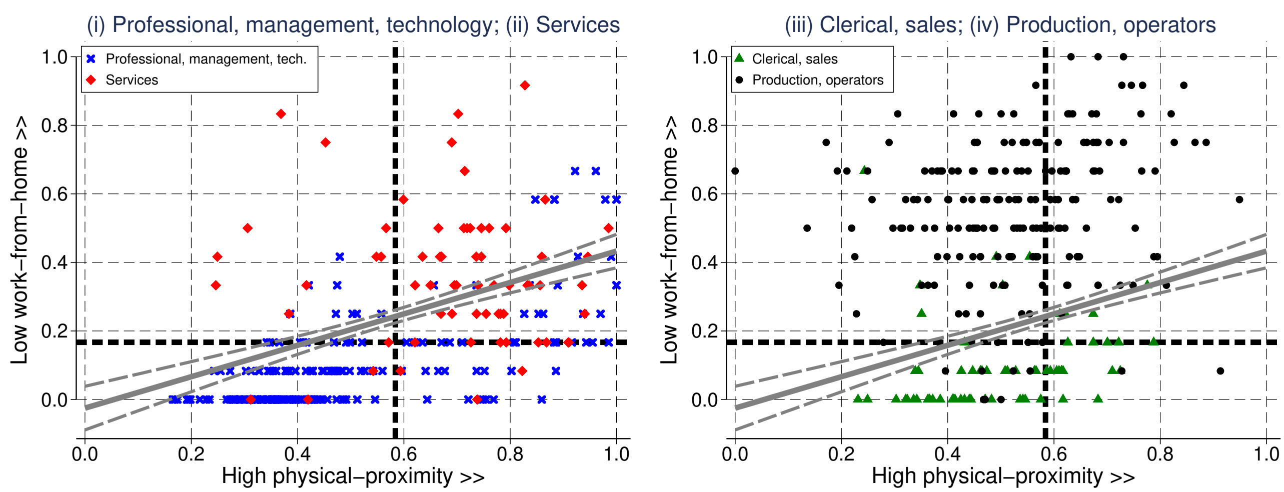


Figure B1: Occupations by Work-from-home and Physical-proximity (3 digit, Census OCC)

Notes: This figure compares groups of 3 digit OCC code occupations. We split the data into panels A and B only for readability, so that occupation titles can be included. The gray line plot fitted values and 95% confidence intervals from an employment-weighted linear regression across all 3 digit occupations. Occupations *above* the red-dashed line have $LWFH_j^* = 1$, and account for half of employment. Occupations *to the right* of the blue-dashed line have $HPP_j^* = 1$, and account for half of employment.

As a robustness check, we confirm that our results are monotonic.

[32] We choose a cutoff of for $\overline{m}_{jk}$ of 3.5 exactly because we wanted to be able to make this kind of statement. If we chose a cutoff of 4, then the average respondent would have answered above 4.

Table B5: Share teleworking due to Covid-19 Pandemic

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| LWFH Dummy | -0.354*** | | -0.329*** | -0.327*** | -0.321*** |
| | (0.00197) | | (0.00200) | (0.00198) | (0.00224) |
| HPP Dummy | | -0.184*** | -0.0943*** | -0.0928*** | -0.0916*** |
| | | (0.00222) | (0.00212) | (0.00210) | (0.00209) |
| May | | | | 0 | 0 |
| | | | | (.) | (.) |
| June | | | | -0.0434*** | -0.0434*** |
| | | | | (0.00445) | (0.00445) |
| July | | | | -0.0935*** | -0.0937*** |
| | | | | (0.00433) | (0.00433) |
| August | | | | -0.115*** | -0.116*** |
| | | | | (0.00421) | (0.00421) |
| September | | | | -0.125*** | -0.125*** |
| | | | | (0.00407) | (0.00407) |
| October | | | | -0.138*** | -0.138*** |
| | | | | (0.00399) | (0.00399) |
| November | | | | -0.137*** | -0.137*** |
| | | | | (0.00402) | (0.00402) |
| Essential | | | | | -0.0184*** |
| | | | | | (0.00280) |
| Constant | 0.413*** | 0.337*** | 0.440*** | 0.534*** | 0.543*** |
| | (0.00172) | (0.00163) | (0.00185) | (0.00346) | (0.00378) |
| Observations | 192229 | 192229 | 192229 | 192229 | 192229 |
| $R^2$ | 0.159 | 0.042 | 0.169 | 0.181 | 0.182 |

Notes Standard errors in parentheses. Regressions use data from Covid module appended to the monthly CPS. We regress the binary variable of whether a worker teleworked due to the coronavirus pandemic on our measures of an occupation's pandemic exposure. Occupations are essential if more than 75% of that occupations workers are employed industries marked as essential by Tomer and Kane (2020). $^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

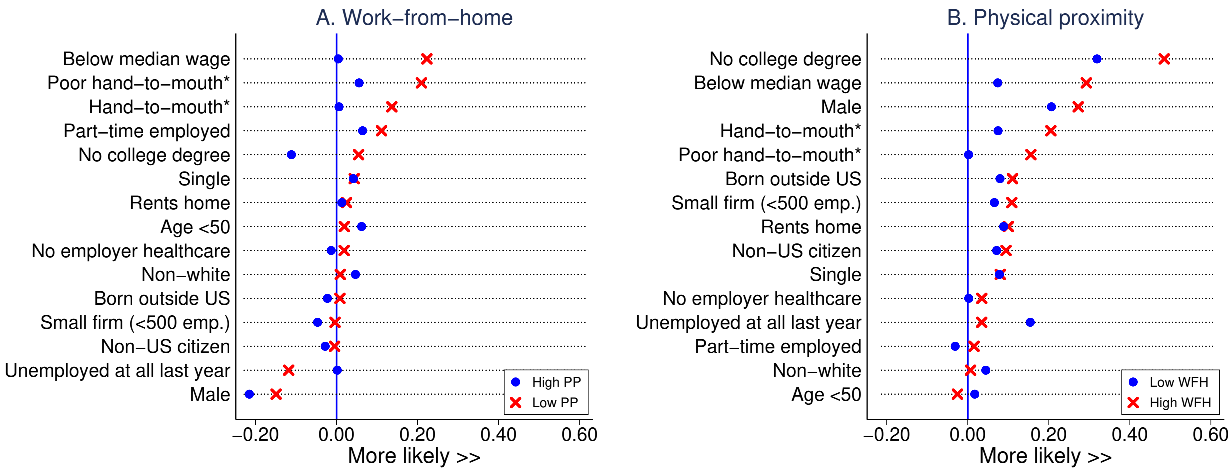


Figure B2: Worker characteristics jointly examining physical-proximity and work-from-home

Notes This figure extends Figure 4 to jointly examine differences in worker characteristics of occupations using both work-from-home and physical-proximity. This figure plots estimates of $\beta^y$ for 10 worker characteristics $y$. In **Panel A**, the independent variable is LWFH$^*$ $\in \{0,1\}$, our measure of inability to work-from-home. We run each regression twice, conditioning on HPP$^*$. Conditional on the occupation requiring low physical-proximity (**red** cross), a point estimate $\beta^y = 0.25$ shows that workers in both low PP and low WFH occupations are 25 ppt more likely to be below median wage than occupations which are both low PP and high WFH. The **blue** dots condition similarly on high PP. In **Panel B**, the independent variable is HPP$^*$ $\in \{0,1\}$, our measure of high physical proximity required to perform the job. We run each regression twice, conditioning on LWFH$^*$. Blue dots compare HPP and LPP occupations which are both low WFH. Red crosses compare HPP and LPP occupations which are both high WFH. We use O$^*$NET to construct our LWFH$^*$ and HPP$^*$ and use worker data from the CPS (non-asterisk) and PSID (asterisk) for the regressions.

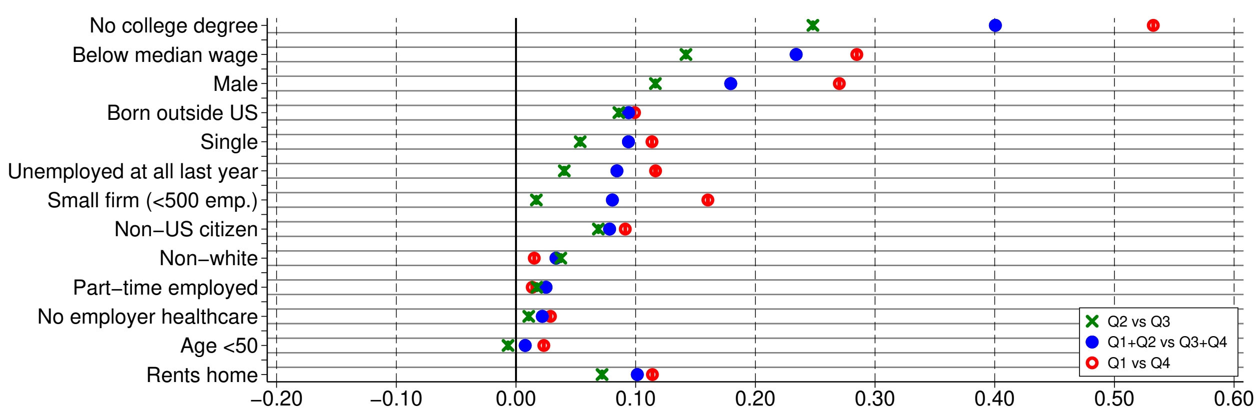


Figure B3: Comparing different groups of occupations on the Work-from-home measure

Notes This figure extends Figure 4. The blue markers replicate Figure 4. In constructing the estimates plotted in green, we set $LWFH_j = 0$ for the second quartile of our continuous measure $\overline{z}_j$, and $LWFH_j = 1$ for the third quartile of $\overline{z}_j$. In constructing the estimates plotted in red, we set $LWFH_j = 0$ for the first quartile of $\overline{z}_j$, and $LWFH_j = 1$ for the fourth quartile of $\overline{z}_j$.

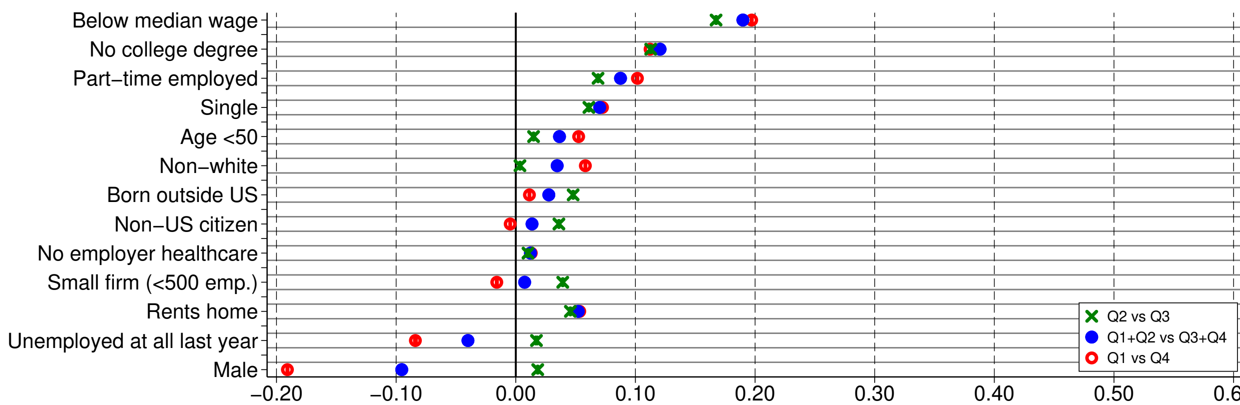


Figure B4: Comparing different groups of occupations on the Physical Proximity measure

Notes This figure extends Figure 4. The blue markers replicate Figure 4. In constructing the estimates plotted in green, we set $HPP_j = 0$ for the second quartile of our continuous measure $\overline{z}_j$, and $HPP_j = 1$ for the third quartile of $\overline{z}_j$. In constructing the estimates plotted in red, we set $HPP_j = 0$ for the first quartile of $\overline{z}_j$, and $HPP_j = 1$ for the fourth quartile of $\overline{z}_j$.