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

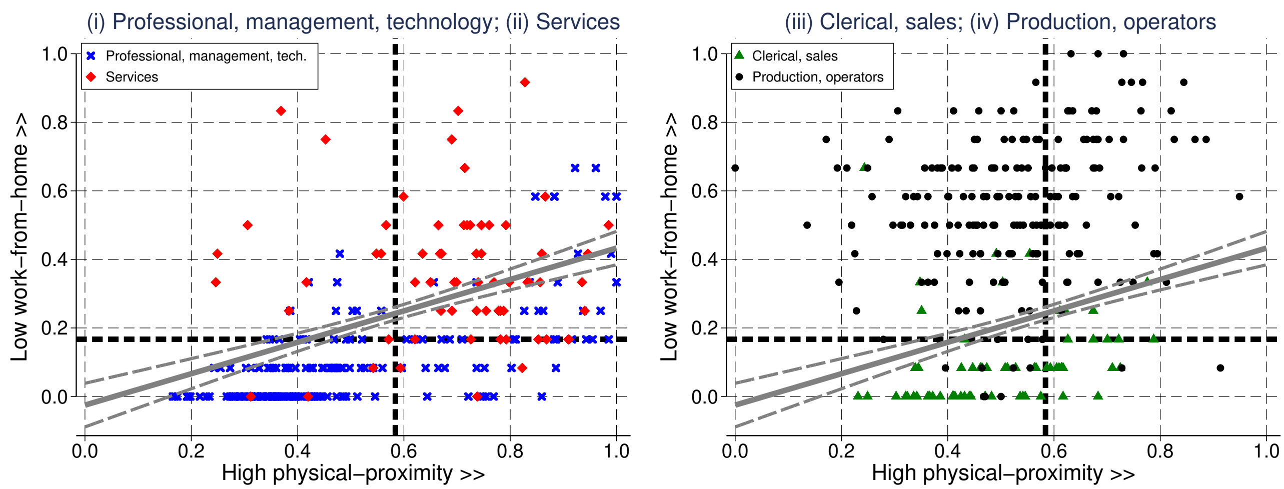

Figure B1: Occupations by Work-from-home and Physical-proximity (3 digit, Census OCC)

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). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

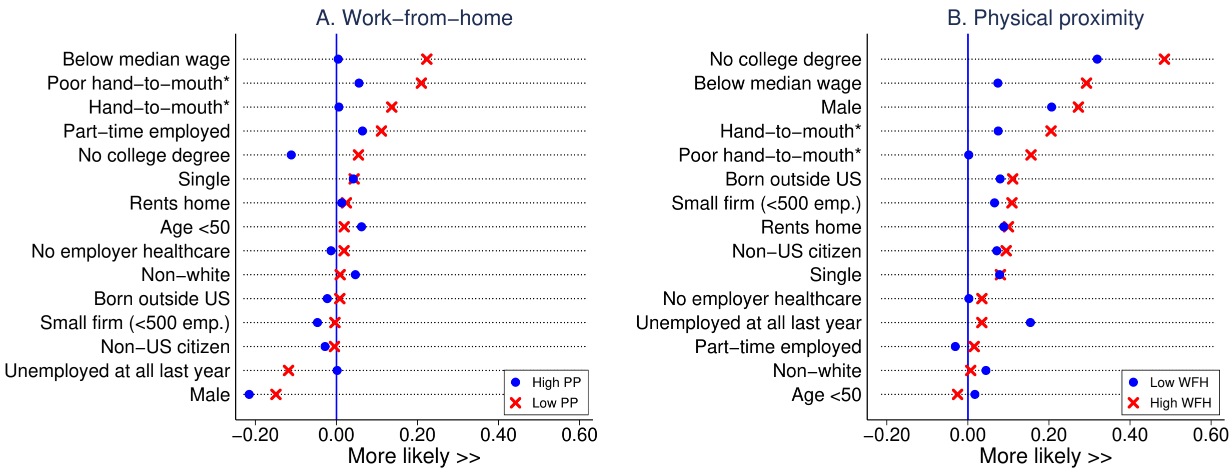

Figure B2: Worker characteristics jointly examining physical-proximity and work-from-home

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 β^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.

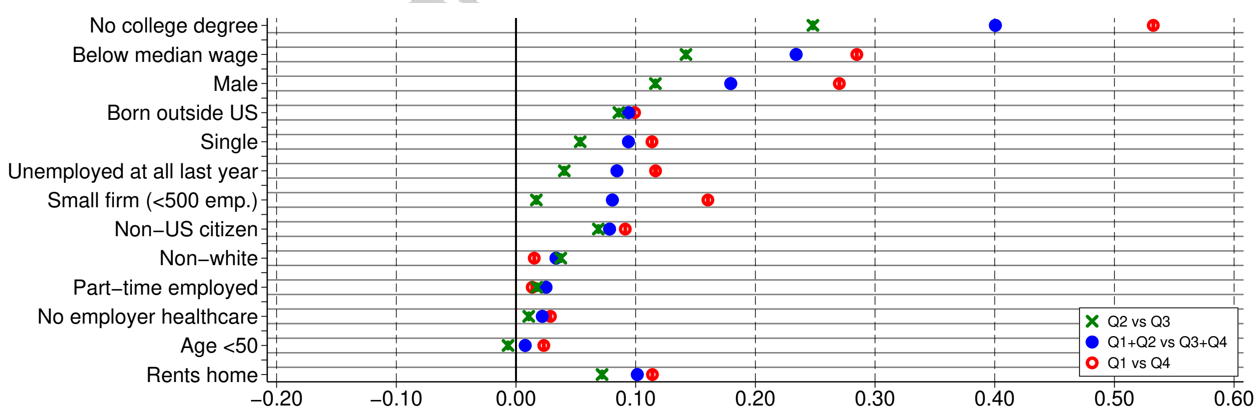

Figure B3: Comparing different groups of occupations on the Work-from-home measure

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 $\bar{z}_j$, and $LWFH_j = 1$ for the third quartile of $\bar{z}_j$. In constructing the estimates plotted in red, we set $LWFH_j = 0$ for the first quartile of $\bar{z}_j$, and $LWFH_j = 1$ for the fourth quartile of $\bar{z}_j$.

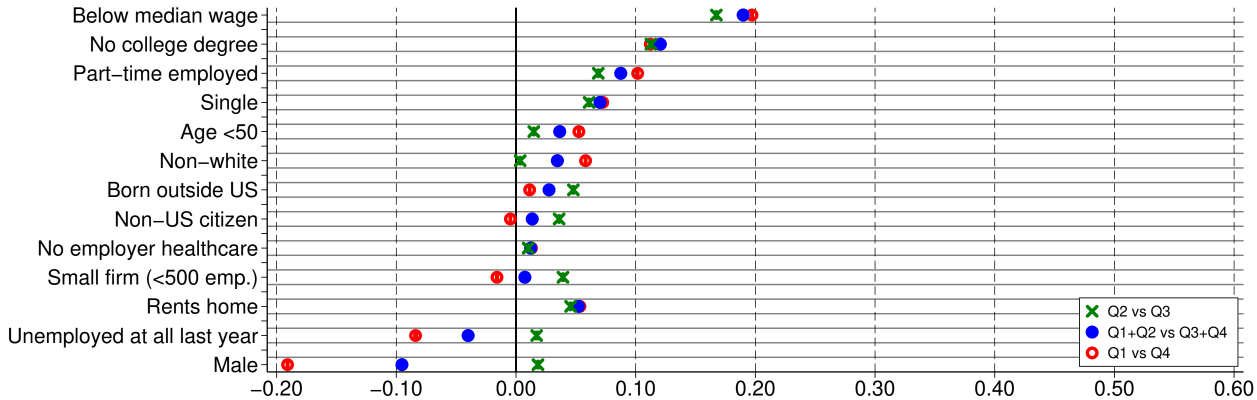

Figure B4: Comparing different groups of occupations on the Physical Proximity measure

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 $\overline{z}_j$.