Nature of Work and Distribution of COVID-19 Risks: Evidence from Occupational Sorting, Skills, and Tasks

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How does the nature of work—teleworkability and contact intensity—shape the distribution of health, earnings, and unemployment risks, created by the COVID-19 pandemic? To answer this question, I consider two contexts. First, I show that the existing patterns of spousal occupational sorting in the United States matter for the distribution of these risks. In particular, I show that sorting into occupations with similar contact intensity in the workplace mitigates the risk of intra-household contagion relative to the situation where spouses match at random in terms of occupations (zero sorting). Furthermore, I show that sorting into occupations with similar teleworkability exacerbates the exposure to earnings and unemployment risks relative to the case of zero sorting. Second, I document that teleworkable occupations more likely require higher education and experience levels as well as greater cognitive, social, character, and computer skills, compared to non-teleworkable occupations. This difference in skill requirements affects earnings and unemployment risks by increasing the likelihood of skill mismatch for the newly unemployed. My results imply that the current economic downturn may have long-run effects on employment prospects and earnings of workers who had non-teleworkable or high-contact-intensity jobs at the onset of the COVID-19 outbreak. I discuss the relevant policy implications and associated policy constraints that follow from my findings.

Keywords: Telecommuting, Couples, Occupational sorting, Skills, Tasks, Labor market mobility, COVID-19.
JEL: I14, J22, J23, J24, J63, J81.

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1 Introduction

Coronavirus disease 2019 (COVID-19) pandemic created substantial challenges for health systems and economies all over the world. To reduce the spread of disease, many countries imposed various mitigation measures, such as lockdowns and stay-at-home orders. These policies forced many workers to work from home. However, a sizeable fraction of jobs, e.g. in the United States it is equal to 63 percent (Dingel and Neiman, 2020), cannot be performed remotely. Therefore, the nature of work has become a crucial factor behind the distribution of health, earnings, and unemployment risks.

In this paper, I ask the following question. How does the nature of work—teleworkability and contact intensity—shape the distribution of health, earnings, and unemployment risks, created by the COVID-19 pandemic? To address it, I consider two contexts. First, I study whether the existing spousal occupational sorting, i.e. how individuals match with each other in terms of occupations, in the United States matters for the distribution of these risks. Using data from the American Community Survey (ACS), I obtain the actual distribution of spouses in the U.S. couples, and compare it against counterfactual distributions that are characterized by different levels of occupational sorting. Second, I study the differences in skill requirements and task content between teleworkable and non-teleworkable as well as low- and high-contact-intensity occupations. These differences may inform about long-run labor market risks of the newly unemployed, who lost their jobs during the COVID-19 pandemic. I use the online vacancy postings data from Gartner TalentNeuron to compare the education, experience, and various skill requirements posted by firms in a pre-pandemic period. I also complement these results by using O*NET data.

The main contribution of this paper is threefold. First, I show that the existing occupational sorting in the U.S. couples creates a lower fraction of individuals who are exposed to intra-household contagion risk, compared to the situation where spouses match at random in terms of occupations (zero sorting). I document that 64.3 percent of the U.S. dual-earner couples are exposed to COVID-19 health risk through the intra-household contagion because there is at least one spouse whose job requires high contact intensity at the workplace. Under zero sorting, this fraction goes up to 66.5 percent. Second, I show that the existing occupational sorting in the U.S. couples creates a larger fraction of individuals who are exposed to greater earnings risk, compared to the case of zero sorting. I document that 21.2 percent of the U.S. dual-earner couples are exposed to greater earnings risk because both spouses have non-teleworkable occupations. Under zero sorting, this fraction goes down to 15.9 percent. Third, I document a significant differences in skill requirements between teleworkable and non-teleworkable as well as low- and high-contact-intensity occupations. Teleworkable occupations more likely require higher education and experience levels as well as greater cognitive, social, character, and computer skills. This difference in skill requirements increases the likelihood of skill mismatch for the newly unemployed who lost their non-teleworkable jobs during the economic downturn following the COVID-19 outbreak. This, in turn, may leave a scarring effect that reduces their wages in future occupations. To complement the discussion, I consider the patterns of labor market mobility for occupations of different teleworkability and contact intensity using data from the Current Population Survey (CPS). Overall, my results imply that the current economic downturn may have *long-run* effects on employment prospects and earnings of workers who had non-teleworkable or high-contact-intensity jobs at the onset of the COVID-19 outbreak.

The results of this paper suggest several policy implications and highlight the importance of targeted policies. First, about two-thirds of the U.S. dual-earner couples are exposed to COVID-19 health risk through intra-household contagion. Targeting individuals who work in occupations that require high contact intensity with testing and vaccination, and providing them with protective equipment, would allow for the mitigation of this transmission channel. Second, a significant fraction of couples where both spouses have non-teleworkable jobs (and are hence exposed to greater unemployment risk) suggests that occupation-specific transfers or transfers based on joint spousal earnings, could potentially be desirable. Finally, I emphasize that while the unemployment benefits or stimulus payments for COVID-19 relief can insure the workers against short-run losses, they fall short of insuring long-run losses originated from skill mismatch. I also emphasize that existing differences in skill requirements may create constraints on policies that propose training programs for the unemployed. While some hard skills (e.g. basic computer skills) can be acquired through training, social and character skills are much harder to adjust.

This paper contributes to active and growing literature studying the effects of COVID-19 on the labor markets. In what follows I briefly describe the related studies and explain how my paper complements them. Using the data on online job postings provided by Burning Glass Technologies, Forsythe et al. (2020) document a significant drop in vacancies in the second half of March 2020. The U.S. labor market collapsed across occupations and states regardless of the initial virus spread intensity or timing of mitigation measures. They also show that unemployment insurance claims demonstrated similar patterns. Next, Coibion et al. (2020) use a repeated large-scale survey of households in the Nielsen Homescan panel and document a sharp decline in the employment-to-population ratio along with a much smaller increase in the unemployment rate. The reason is that many of the newly non-employed report that they do not actively look for work and hence they are not counted as part of the unemployed. Using February-April 2020 data from the CPS, Cowan (2020) studies transitions of workers between the labor-market states—out of the labor force, employed, absent from work, and unemployed—and between full-time and part-time status. He documents that racial and ethnic minorities, individuals born outside the United States, women with children, the least educated, and disabled workers experienced the largest decline in the likelihood of full-time work. In this paper, I study the distribution of labor market transitions across jobs of different teleworkability and contact intensity. This may have a crucial importance for the future prospects of individuals who lost their jobs as a result of the COVID-19 pandemic.

I also complement the literature that study alternative work arrangements and, given the concerns created by the COVID-19 pandemic, jobs that differ in teleworkability and contact intensity at the workplace. Mas and Pallais (2020) provide an excellent literature review on the topic of alternative work arrangements. Using O*NET data, Dingel and Neiman (2020) classify the occupations into those that can and cannot be performed from home. Leibovici et al. (2020) characterize the U.S. occupations in terms of their contact intensity. Since the same occupations may have different task content across countries, some papers study teleworkability by employing data from various countries. Using data from the Skills Toward Employability and Productivity survey, Saltiel (2020) examines the feasibility of working from home in ten developing countries. Delaporte and Peña (2020) analyze the potential to work from home across occupations, industries, regions, and socioeconomic characteristics of workers in 23 Latin American and Caribbean countries. Hatayama et al. (2020) use skills surveys from 53 countries to estimate the feasibility of working from home. They show that the more developed is the country, as measured by the GDP per capita PPP, the greater is the amenability of jobs to working from home. This finding is consistent with the results by Gottlieb et al. (2020) who show that the share of employment that can work from home is around 20 percent in poor countries compared to about 40 percent in rich countries.

My work is closely related to the papers that study the implications of teleworkability and contact intensity of occupations for health and economic outcomes. Mongey et al. (2020) document that workers employed in non-teleworkable occupations experienced greater declines in employment. Papanikolaou and Schmidt (2020) show that lower-paid workers, especially female workers with young children, were affected most. Bick et al. (2020) estimate that more than 70 percent of the U.S. workers that could work from home did so in May 2020. Teleworkability and contact intensity at the workplace are also tightly connected to the household structure and division of labor. First, the presence of the other family members raises the concerns of intra-household COVID-19 contagion. Almagro and Orane-Hutchinson (2020) show the importance of exposure to human interactions across occupations in explaining the disparities in COVID-19 incidence across New York City neighborhoods. Second, the presence of another employed family member serves as partial insurance against earnings and unemployment shocks. Lekfuangfu et al. (2020) show that low-income married couples are much more likely to sort into occupations that are less adaptable to work from home. Peluffo and Viollaz (2020) study the relationship between ability to work from home and access to formal and informal insurance mechanisms for consumption smoothing. Third, because of school and day care closures, the presence of children becomes a crucial factor behind employment prospects for many individuals, especially women. Kahn et al. (2020) discuss how childcare and the presence of COVID-19-high-risk household members can limit the ability to return to work. Adams-Prassl et al. (2020), Alon et al. (2020a) and Alon et al. (2020b) study the implications of the COVID-19 pandemic for gender inequality. I contribute to this literature by studying the occupational sorting of spouses in married couples in the United States and its implications for the distribution of health and unemployment risks.

Furthermore, my paper bridges the literature on alternative work arrangements to the other strands of the literature that study multidimensional skill requirements of occupations (Guvenen et al., 2020; Lise and Postel-Vinay, 2020), apply the "task approach" to labor markets and study labor market polarization (Autor et al., 2003; Acemoglu and Autor, 2011; Foote and Ryan, 2015), and study the patterns of labor market mobility (Moscarini and Thomsson, 2007; Kambourov and

Manovskii, 2008, 2009; Schubert et al., 2020). To construct the measures of skill requirements, I use the online vacancy postings data. Therefore my work is also related to the growing literature that use the vacancy ads data to study the labor markets (Deming and Kahn, 2018; Hershbein and Kahn, 2018; Hazell and Taska, 2019; Schubert et al., 2020). My characterization of occupations that differ in teleworkability and contact intensity in terms of multiple skill requirements may be informative about the prospects of labor market mobility following the pandemic recession. Next, characterization of occupations of different teleworkability and contact intensity in terms of task routineness can guide the modeling choice for studying the changing nature of work following the COVID-19 outbreak.

The rest of the paper is organized as follows. In Section 2, I describe the data and construction of the variables. In Section 3, I provide the empirical results and discuss the relevant policy implications. Section 4 concludes.

2 Data

To obtain the empirical results, I use several data sets. First, I use the classifications of occupations by teleworkability and contact intensity from Dingel and Neiman (2020), Leibovici et al. (2020), and Mongey et al. (2020). Using O*NET data, I construct the continuous measures of teleworkability and contact intensity and also measure the task content of occupations. Next, to measure the skill requirements, I use the proprietary online vacancy posting data from Gartner TalentNeuron with access provided by RealTime Talent. To show the patterns of occupational sorting of spouses in couples I use the ACS data. Finally, to study the patterns in labor market mobility I employ the Annual Social and Economic Supplement of the CPS (CPS ASEC). In what follows, I describe these datasets and construction the variables of interest in more detail.

2.1 Teleworkability and Contact Intensity Classification

To classify the occupations in terms of teleworkability, I use the binary classifications developed by Dingel and Neiman (2020) and Mongey et al. (2020). These papers use similar inputs from O*NET survey responses but follow different methodologies to construct the resulting indices. In Appendix, I provide the list of job attributes that they employ. The classification from Dingel and Neiman (2020) is done at the O*NET SOC level. Totally, there are 968 classified occupations. In turn, Mongey et al. (2020) exploit a different approach and classify the occupations at the 3-digit Census OCC level that is less finer than the O*NET SOC level. I complement their classification by manually adding 22 occupations that they do not characterize. Totally, there are 533 classified occupations. To avoid confusion, I always clearly specify which binary measure of teleworkability, either from Dingel and Neiman (2020) or Mongey et al. (2020) I use. I define an occupation to be *WFH* ("work from home") if it is classified as teleworkable and *NWFH* ("not work from home") if it is classified as non-teleworkable. I also construct a continuous measure of teleworkability at the O*NET SOC level. For each job attribute listed in Appendix, I standardize the score to have mean zero and standard deviation one.[1] Next, I sum the standardized scores and standardize the sum to have mean zero and standard deviation one.[2] Higher values of this measure—I call it the *WFH Index*—correspond to greater feasibility of working from home.

In my analysis, I also use the measures of contact intensity (or physical proximity) constructed by Leibovici et al. (2020), and Mongey et al. (2020). Using "Physical Proximity" from O*NET Work Context module as an input, Leibovici et al. (2020) classify the occupations at the O*NET SOC level. Mongey et al. (2020) construct the measures of physical proximity at the 3-digit Census OCC level. I define an occupation to be *low PP* ("low physical proximity") if it is classified by Mongey et al. (2020) as not requiring high contact intensity and *high PP* ("high physical proximity") if it requires high contact intensity at the workplace. Finally, I construct a continuous measure of contact intensity. To do this, I standardize the reversed score for "Physical Proximity" from O*NET Work Context module to have mean zero and standard deviation one. Higher values of this measure—I call it the *CI Index*—correspond to lower contact intensity at the workplace.

2.2 Occupational Sorting of Spouses in Couples

To document the patterns of occupational sorting in married couples, I use data from the ACS in 2018, the most recent available release.[3] In Online Appendix I also show the results for earlier years, 2010-2018. ACS defines the occupations using the Census OCC codes, and I merge it with the teleworkability and contact-intensity classification from Mongey et al. (2020). I keep the different-sex married couples where both spouses aged 20 to 65. Since my primary interest is in occupational sorting, I keep only those couples where both spouses are employed, i.e. dual-earner couples. Furthermore, I also separately consider dual-earner couples with children, with children under the age of 5, and without children.

2.3 Task Content

To study the task content of occupations that differ in teleworkability and contact intensity, I use O*NET 24.2 data. I construct the composite measures proposed by Acemoglu and Autor (2011) and additionally consider a measure of computer usage at the workplace. In Appendix, I provide the list of job attributes that are used for constructing these indices. For each attribute, I standardize the score to have mean zero and standard deviation one. Next, I sum the standardized scores within each composite task measure (e.g. routine cognitive). Finally, I restandardize the sum to have mean zero and standard deviation one. To compare the task content between occupations

[1] I take the reverse of all the attributes except "Electronic Mail".

[2] When I sum the scores, I assign weight 0.5 to "Repairing and Maintaining Mechanical Equipment", "Repairing and Maintaining Electronic Equipment", "Outdoors, Exposed to Weather", "Outdoors, Under Cover", "Wear Common Protective or Safety Equipment such as Safety Shoes, Glasses, Gloves, Hearing Protection, Hard Hats, or Life Jackets", and "Wear Specialized Protective or Safety Equipment such as Breathing Apparatus, Safety Harness, Full Protection Suits, or Radiation Protection", and weight 1 to all the other attributes.

[3] The data is extracted from IPUMS at https://usa.ipums.org/usa/.

of different teleworkability and contact intensity, I merge these measures with the classifications from Dingel and Neiman (2020) and Leibovici et al. (2020).

2.4 Skill Requirements

To compare the skill requirements between occupations of different teleworkability and contact intensity, I use the online vacancy posting data from Gartner TalentNeuron. It collects the data from more than 65000 global sources and continuously retests it for quality, accuracy, and consistency. I have the data for five states—Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin—that covers the period between September 2014 and September 2018. Gartner TalentNeuron uses algorithms to extract the data on a job title, occupation at the O*NET SOC level, industry, location, posted wage, and also education, experience, and skill requirements from the description of the job posting. In Malkov (2020), I show that the distribution of this Gartner TalentNeuron data by occupations and industries closely matches the Burning Glass Technologies data used by Deming and Kahn (2018). Overall the dataset contains over 14 million non-duplicated online job ads. I use this data to construct the indices of character, cognitive, and social skill requirements. I proceed in the following way. First, I use the keywords and phrases to determine whether each listed skill requirement falls into *cognitive*, *social*, or *character* category. The list of these keywords and phrases is given in Table A.1. Each vacancy may have from zero to many posted skill requirements. Second, I code a vacancy as falling into a skill category if at least one posted skill requirement falls into this category. The skills are mutually exclusive but not collectively exhaustive, i.e. there are ads that fall neither in cognitive, nor social, nor character category. Next, for each occupation defined at the O*NET SOC level, I calculate the share of ads containing each skill category. Finally, I standardize the index for each skill category to have mean zero and standard deviation one using the number of ads as weights. To get additional validation of my results, I also construct the O*NET-based measure of social-skill intensity of occupations proposed by Deming (2017).

2.5 Labor Market Mobility

To document the distribution of labor market mobility for occupations of different teleworkability and contact intensity, I use CPS ASEC data in 2019.[4] In Online Appendix I also show the results for earlier years, 2011-2019. I consider labor market mobility over the year preceding the survey by taking advantage of the questions that ask the respondent's current occupation and their occupation in the previous year. CPS defines the occupations using the Census OCC codes, and I merge it with the classification from Mongey et al. (2020). I keep the individuals aged 25 to 60. I also consider the distribution of labor market transitions separately for men and women.

[4] The data is extracted from IPUMS at https://cps.ipums.org/cps/.

3 Empirical Results

3.1 Occupational Sorting of Spouses in Couples

One of the features associated with the COVID-19 outbreak and subsequent economic downturn is the interaction between unemployment risk and health risk. The extent of exposure to these risks greatly depends on the type of an occupation. Workers who have teleworkable jobs face lower unemployment risk than those who have non-teleworkable jobs. Workers whose occupations do not require high contact intensity at the workplace face lower risk of being infected, compared to those who work in high physical proximity to the other individuals.[5] Note that I discuss the feasibility of working from home or in low contact intensity at the workplace rather than actual behavior of individuals. However, as Bick et al. (2020) show, most of the U.S. workers that can work from home actually do so in May 2020.

Married couples constitute a significant fraction of the U.S. population. According to the U.S. Bureau of the Census, in 2019 there were almost 62 million married couples. This accounts for about 48 percent of all the U.S. households. The sign and extent of occupational sorting in couples plays an important role during the COVID-19 pandemic because it can either exacerbate or mitigate health and earnings risks. In what follows I briefly describe the mechanisms. First, the presence of the other family members creates the risk of intra-household contagion. Under positive sorting (i.e. when it is more likely that both spouses have either high-contact-intensity or low-contact-intensity jobs), this risk is heavily concentrated in high-contact-intensity couples. Under negative sorting, the risk of intra-household contagion is more evenly distributed across the couples. In general, more negative occupational sorting, based on contact intensity, is associated with greater fraction of individuals who are exposed to COVID-19 health risk. Second, the presence of an employed spouse serves as insurance against earnings shocks. Under positive sorting (i.e. when it is more likely that both spouses have either teleworkable or non-teleworkable jobs), earnings risk is heavily concentrated in non-teleworkable couples. Given the evidence from Mongey et al. (2020), these households also have lower income. Under negative sorting, earnings risk is distributed across the couples more evenly (and is easier to insure). In general, more positive occupational sorting, based on teleworkability, is associated with greater fraction of individuals who are heavily exposed to earnings risk. Third, because of school and day care closures, the presence of children becomes a crucial factor behind employment prospects for many individuals, especially women. In the families, where at least one spouse has a teleworkable job, the impact of children on employment and earnings is likely to be mitigated. Overall, the patterns of occupational sorting in couples have crucial importance for the distribution of health and earnings risks and, as a consequence, may have different policy implications.

[5] I consider contact intensity at the workplace, rather than both contact intensity *and* teleworkability, as the factor that drives contagion risk. A non-teleworkable occupation that does not require high contact intensity (e.g., operation of a machine) is not associated with higher risk of contagion at the workplace. It is possible to catch COVID-19 during commuting to work but this channel is beyond the scope of my paper.

Table 1 shows the distribution of spouses in dual-earner married couples in the United States in 2018 by the groups of occupations based on teleworkability and contact intensity.[6] I also separately consider the couples with children, couples with children under the age of 5, and couples without children. Figure 1 compares the actual occupational distributional of spouses against two counterfactual distributions: zero sorting (or random matching) and "ideal" sorting. For teleworkability-based distribution, I define ideal sorting to be the distribution where the fraction of couples with both spouses in non-teleworkable jobs is minimized. The actual sorting creates 21.2 percent of couples where both spouses have non-teleworkable occupations and are hence exposed to greater earnings risk. Under zero sorting, this fraction goes down to 15.9 percent. Under ideal sorting, it further reduces to zero. Therefore, the existing occupational sorting in the U.S. couples creates a greater fraction of individuals who are exposed to greater earnings risk, compared to the case of zero sorting. For contact-intensity-based distribution, I define ideal sorting to the distribution wherethe fraction of "mixed" couples is minimised (i.e. the risk of intra-household contagion is minimized). The actual sorting creates 64.3 percent of couples with at least one spouse whose job requires high contact intensity at the workplace. These couples are exposed to greater intra-household contagion risk. Under zero sorting, this fraction goes up to 66.5 percent. Under ideal sorting, it falls down to 48.5 percent. Therefore, the existing occupational sorting in the U.S. couples creates a lower fraction of individuals who are exposed to greater intra-household contagion risk, compared to the case of zero sorting.

Another observation from Table 1 emphasizes the differences in job characteristics by gender. Women more likely work in teleworkable than non-teleworkable occupations. In turn, men more likely work in low- rather than high-contact-intensity occupations. They more likely work in occupations that cannot be performed at home but at the same time do not require close contact intensity at the workplace (e.g. postal service mail carriers or aircraft mechanics and service technicians).

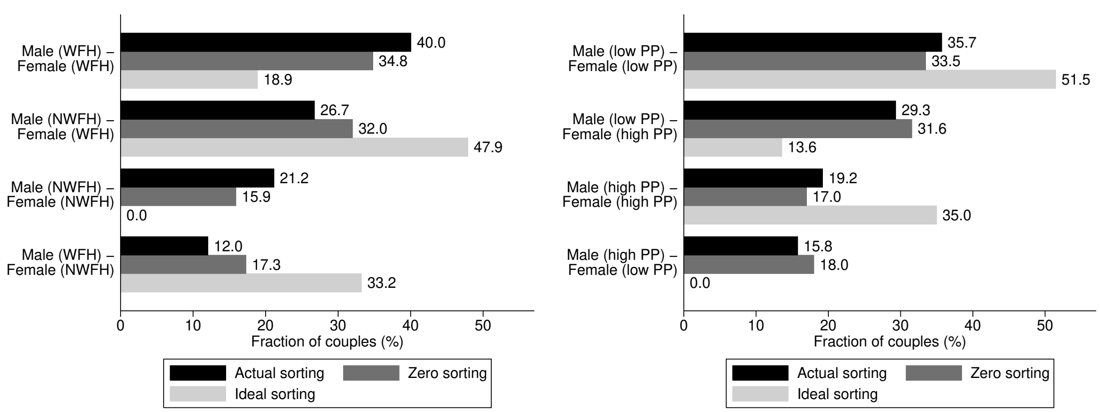
My findings suggest several policy implications and highlight the importance of targeted policies. First, about two-thirds of the U.S. dual-earner couples are exposed to COVID-19 health risk through intra-household contagion. Targeting individuals who work in occupations that require high contact intensity with testing and vaccination, and providing them with protective equipment, would allow for the mitigation of this transmission channel. Second, a significant fraction of couples where both spouses have non-teleworkable jobs (and are hence exposed to greater unemployment risk) suggests that occupation-specific transfers, or transfers based on joint spousal earnings, could potentially be desirable. Formal study of these policy proposals is an important avenue for future research.

[6] When I use 2019 ASEC CPS data, I get very close results. Furthermore, I get qualitatively similar results for sorting by teleworkability when restrict the sample to couples where both spouses work in non-essential industries. These results are available upon request. In Online Appendix, I show that the patterns documented in Table 1 were stable over the last decade, see Figures OA.1-OA.5.

Table 1: Occupational distribution of spouses in dual-earner couples, by family type (with/without children) (%).

	All	With children	With children under 5	Without children
Male (WFH) – Female (WFH)	40.0	39.5	41.3	41.1
Male (NWFH) – Female (WFH)	26.7	26.2	24.1	27.7
Male (NWFH) – Female (NWFH)	21.2	22.2	21.4	19.3
Male (WFH) – Female (NWFH)	12.0	12.1	13.2	11.9
Spouses have similar WFH-type jobs	61.2	61.7	62.7	60.4
At least one spouse cannot work from home	60.0	60.5	58.7	58.9
Male (low PP) – Female (low PP)	35.7	34.2	32.4	38.5
Male (low PP) – Female (high PP)	29.3	30.2	30.8	27.8
Male (high PP) – Female (high PP)	19.2	20.2	22.2	17.5
Male (high PP) – Female (low PP)	15.8	15.5	14.5	16.3
Spouses have similar PP-type jobs	54.9	54.4	54.6	56.0
At least one spouse should work in high phys. proximity	64.3	65.8	67.6	61.5

NOTES: I use 2018 American Community Survey data with the household weights to produce this table. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020). WFH ("work from home") stands for teleworkable occupations. NWFH ("not work from home") stands for non-teleworkable occupations. Low PP ("low physical proximity") stands for occupations that do not require high contact intensity at the workplace. High PP ("high physical proximity") stands for occupations that require high contact intensity at the workplace.



(a) Teleworkability-based classification.

(b) Contact-intensity-based classification.

Figure 1: Occupational distribution of spouses in dual-earner couples: actual, zero, and ideal sorting (%).

NOTES: Actual sorting correspond to the first column of Table 1. Zero sorting corresponds to the case of random matching of spouses in terms of occupations. Ideal sorting for the teleworkability-based classification is defined to be the distribution where the fraction of couples with both spouses in non-teleworkable jobs is minimised. Ideal sorting for the contact-intensity-based classification is defined to be the distribution where the fraction of couples with one spouse in a low PP job and another spouse in a high PP job is minimised.

3.2 Skills and Tasks

Having discussed the patterns in spousal occupational sorting, I turn to the characteristics of occupations per se. How different are the task content and skill requirements for jobs that can or cannot be performed at home and require high or low contact intensity at the workplace? The answers to this question have direct implications for employment prospects and future earnings of workers who had non-teleworkable or high-contact-intensity jobs at the onset of the COVID-19 outbreak.

The differences in task content of jobs, considered through the lens of routine and non-routine occupations, may matter for the discussion about the U.S. labor market polarization. Foote and Ryan (2015) document that job losses during the Great Recession were concentrated among middle-skill workers, those who worked in routine cognitive occupations. How different is the pandemic recession? To study this question, I estimate two regressions for a set of outcomes y that include the measures of non-routine cognitive (analytical and interpersonal), routine cognitive, routine manual, and non-routine manual physical content of occupations defined at the O*NET SOC level. In addition, I also estimate regressions for the measures of offshorability and computer usage. All outcome variables y are standardized to have mean zero and standard deviation one.

For teleworkability-based classification I estimate

$$y_i = \alpha_0 + \alpha_1 WFH_i + \varepsilon_i \tag{1}$$

where $WFH_i = 1$ if occupation i is teleworkable and $WFH_i = 0$ otherwise.

Next, for contact-intensity-based classification I estimate

$$y_i = \beta_0 + \beta_1 LCI_i + \beta_2 MCI_i + \upsilon_i \tag{2}$$

where $LCI_i = 1$ if occupation i is low-contact-intensity and $LCI_i = 0$ otherwise, $MCI_i = 1$ if occupation i is medium-contact-intensity and $MCI_i = 0$ otherwise.

I plot the values for estimates $\hat{\alpha}_1$ in the left panel, and the values for estimates $\hat{\beta}_1$ and $\hat{\beta}_2$ in the right panel of Figure 2. The left panel demonstrates that teleworkable occupations, on average, have a higher score of non-routine cognitive tasks, both analytical (+0.88 standard deviation) and interpersonal (+0.41 standard deviation), but lower scores along non-routine manual physical (-1.33 standard deviation) and routine manual (-1.16 standard deviation) dimensions, compared to non-teleworkable occupations. The right panel shows that low-contact-intensity occupations, on average, have a lower score of non-routine cognitive (interpersonal), routine cognitive, routine manual, and non-routine manual physical tasks, compared to high-contact-intensity occupations. Furthermore, teleworkable occupations and occupations of lower contact intensity are more likely to be offshorable and require greater computer usage. The latter argument, coupled with the observation about excessive job loss for workers in non-teleworkable occupations, may lead to large and persistent decline in earnings for these workers, see Braxton and Taska (2020).

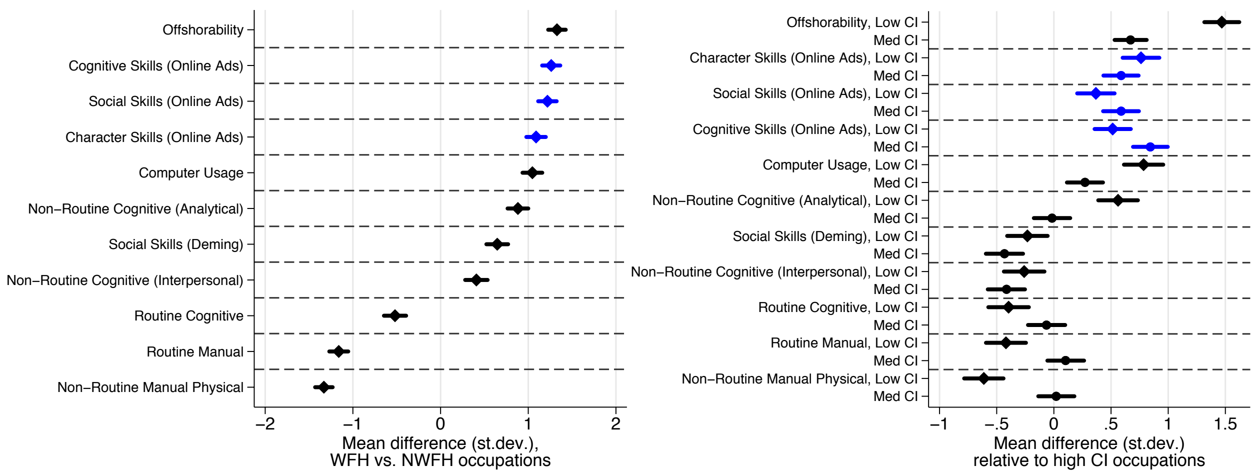


Figure 2: Left panel: Mean difference between characteristics of teleworkable (WFH) and non-teleworkable (NWFH) occupations. Right panel: Mean difference between characteristics of low-contact-intensity (low CI)/medium-contact-intensity (medium CI) occupations and high-contact-intensity (high CI) occupations.

Notes: The left panel illustrates the results of estimated $\hat{\alpha}_1$ from regression (1). The right panel illustrates the results of estimated $\hat{\beta}_1$ and $\hat{\beta}_2$ from regression (2). The classification of occupations in terms of teleworkability (WFH/NWFH) is from Dingel and Neiman (2020). WFH ("work from home") stands for teleworkable occupations. NWFH ("not work from home") stands for non-teleworkable occupations. The classification of occupations in terms of contact intensity (low CI/medium CI/high CI) is from Leibovici et al. (2020). The outcome variables are standardized to have mean zero and standard deviation one. Point estimates are given by the markers, and 95 percent confidence intervals are given by the lines through each marker. I use black color for results obtained from O*NET data and blue color for results obtained from Gartner TalentNeuron online vacancy posting data. The occupations are defined at the O*NET SOC level.

In comparison with the results of Foote and Ryan (2015) for the Great Recession, job losses during the COVID-19 economic downturn are not concentrated in routine occupations only. Both non-teleworkable and high-contact-intensity occupations, that suffer most, are also heavily represented in non-routine manual occupations. My characterization of occupations of different teleworkability and contact intensity in terms of task routineness can guide the modeling choice for studying the changing nature of work following the COVID-19 outbreak.

I turn to the differences in skill requirements. Those individuals who lose their jobs during the current economic downturn will probably want to find a job that can be performed at home. Skill mismatch, or discrepancy between the portfolio of skills required by an occupation and the portfolio of worker's skills, constitutes one of the factors that affect the likelihood of finding a new job (Restrepo, 2015). The greater are the differences in skill requirements between teleworkable and non-teleworkable (or high- and low-contact-intensity occupations), the less likely a displaced worker can switch an occupation. Moreover, if these differences exist, it is also important what are the skill dimensions where the gaps are greater. While some hard skills, e.g. basic computer skills, can be acquired through the training courses, the social or character skills are significantly more difficult to adjust (Lise and Postel-Vinay, 2020).

Table 2: Descriptive statistics of online job ads data.

	WFH Jobs		NWFH Jobs		Low CI Jobs		Medium CI Jobs		High CI Jobs	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Full-time job (%)	94.2	23.4	88.2	32.3	95.9	19.9	89.5	30.7	84.5	36.2
Wage is posted (%)	13.1	33.8	17.7	38.2	17.7	38.1	16.5	37.1	12.9	33.5
Posted full-time wage, 2012 USD	57641	34983	51953	40847	63105	39417	44282	28189	56041	53523
Education is posted (%)	52.4	49.9	29.5	45.6	36.2	48.1	41.9	49.3	33.8	47.3
GED/High School	19.1	39.3	48.5	50.0	16.4	37.0	43.4	49.6	37.5	48.4
Associate Level	9.0	28.6	13.7	34.4	7.8	26.8	12.5	33.1	13.9	34.6
Bachelor's Degree	67.2	47.0	30.5	46.0	71.4	45.2	40.9	49.2	34.5	47.5
Master's Degree	3.1	17.3	2.8	16.6	2.8	16.6	2.1	14.4	5.0	21.7
Doctoral Degree	1.7	12.8	4.4	20.6	1.6	12.5	1.1	10.5	9.2	28.9
Experience is posted (%)	78.8	40.8	65.1	47.7	75.4	43.1	71.4	45.2	61.1	48.8
0-2 years	38.6	48.7	58.8	49.2	43.3	49.6	51.3	50.0	60.3	48.9
3-7 years	37.8	48.5	31.1	46.3	37.2	48.3	32.7	46.9	30.8	46.2
8+ years	23.6	42.5	10.1	30.1	19.5	39.6	16.0	36.6	8.9	28.4
Social Skills (%)	42.1	49.4	21.1	40.8	28.9	45.3	32.6	46.9	22.5	41.8
Cognitive Skills (%)	37.4	48.4	12.5	33.1	26.9	44.3	23.4	42.4	11.8	32.3
Character Skills (%)	44.3	49.7	25.9	43.8	32.5	46.8	38.1	48.6	23.8	42.6
Number of observations	4744107		7998162		4303069		5340712		3098488	

NOTES: I use Gartner TalentNeuron data on online vacancy ads in Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin for September 2014-September 2018 to produce this table. Occupations are defined at the O*NET SOC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Dingel and Neiman (2020). WFH ("work from home) stands for teleworkable occupations. NWFH ("not work from home") stands for non-teleworkable occupations. The classification of occupations in terms of contact intensity (low CI/medium CI/high CI) is from Leibovici et al. (2020). Posted full-time annual wages are adjusted for inflation to 2012 dollars using the personal consumption expenditures (PCE) price index.

To address this question, I use Gartner TalentNeuron data on online vacancy ads. Table 2 shows the descriptive statistics. I divide the sample in two ways. First, I compare teleworkable and non-teleworkable occupations. Vacancies in teleworkable occupations are more likely to be full-time jobs, are more likely to request education and experience requirements, but are less likely to post a wage. Conditional on posting an education requirement, they more likely require a college degree. Conditional on posting an experience requirement, they more likely require longer prior experience. Finally, teleworkable jobs more likely require social, cognitive, and character skills.

Second, I compare the occupations of different contact intensity. Vacancy postings in low-contact-intensity occupations more likely advertise full-time jobs, post a wage, and state an experience requirement. Conditional on posting an experience requirement, they more likely require longer prior experience. Conditional on posting an education requirement, these occupations more likely require a college degree. Finally, comparing low- and high-contact-intensity occupations, we see that the former group more likely require social, cognitive, and character skills.

When comparing posted full-time annual wages, I observe several patterns. First, teleworkable occupations are, on average, offer higher wages than non-teleworkable occupations. Second, low-contact-intensity occupations are, on average, offer higher wages than high-contact-intensity occupations. As Hazell and Taska (2019) show, wages posted in online ads is a good proxy for the wages for new hires. However, from the distributions, shown in Figure A.1, we see that non-teleworkable and high-contact-intensity occupations are characterized by higher posted wages at the top. This result is mostly driven by occupation group "Health Diagnosing and Treating Practitioners" (29-1000 SOC code).

To get additional evidence, I also consider the O*NET-based measure of social skill intensity proposed by Deming (2017). I show the relation between measures constructed from the online ads and O*NET data at the O*NET-SOC-occupation level in Figure OA.6 in Online Appendix. Correlation between the online-ads-based measure and the measure from Deming (2017) is 0.42.

Figure 2 shows the results of estimated regressions (1) and (2) for four skill measures — cognitive, character, social from the online ads data, and social from Deming (2017). Teleworkable occupations, on average, have higher requirements of cognitive, social, and character skills, compared to non-teleworkable occupations. Despite the fact that the work can be performed remotely, workers in teleworkable occupations still need to demonstrate the ability to communicate, cooperate, and negotiate. This observation is consistent with the idea of complementarity between cognitive and social skills (Weinberger, 2014). The right panel of Figure 2 shows that low-contact-intensity occupations, on average, have higher requirements of cognitive and character skills, compared to high-contact-intensity occupations.

To summarize, I demonstrate that the skill requirements significantly differ between teleworkable and non-teleworkable or low- and high-contact-intensity occupations. Teleworkable occupations have higher requirements in terms of education and experience. Furthermore, they more likely require cognitive, social, and character skills. This difference may matter a lot for the labor market prospects of unemployed individuals. While the cognitive skills can be acquired through training, social and character skills are much harder to develop. The skill requirements may respond to the crisis as well. For example, Hershbein and Kahn (2018) show that routine cognitive occupations featured increase in skill requirements during the Great Recession.

3.3 Labor Market Mobility

If an unemployed individual finds a new job, how likely is this new occupation teleworkable? If an individual switches from a non-teleworkable occupation to another occupation, how likely is this new occupation teleworkable? Having discussed the differences in skill requirements, I document several patterns in labor market transitions before the COVID-19 outbreak.

I use CPS ASEC data to document the distribution of labor market transitions between 2018 and 2019. First, consider the teleworkability-based classification of occupations. The upper panel of Table 3 shows that occupational mobility mostly occurs within teleworkable and non-teleworkable groups of occupations. Between-group mobility accounts for about a quarter of all switches. The fraction of switches from non-teleworkable to teleworkable occupations accounts for 11.4 percent of the total occupational mobility. The distributions for males and females follow a similar pattern. Turning to the unemployment-to-employment transitions, we see that about 60 percent of newly-hired individuals work in non-teleworkable occupations. This result is to a large extent driven by male workers.

Table 3: Distribution of labor market transitions in the United States, (%).

	All	Males	Females
From WFH to WFH occupation	38.8	32.6	45.6
From NWFH to NWFH occupation	37.7	45.6	29.0
From WFH to NWFH occupation	12.1	11.7	12.4
From NWFH to WFH occupation	11.4	10.1	12.9
From unemployment to WFH occupation	39.5	31.7	46.1
From unemployment to NWFH occupation	60.5	68.3	53.9
From low PP to low PP occupation	37.9	40.8	34.8
From high PP to high PP occupation	27.2	21.1	33.9
From high PP to low PP occupation	18.4	20.3	16.3
From low PP to high PP occupation	16.5	17.8	15.0
From unemployment to low PP occupation	46.1	50.9	42.0
From unemployment to high PP occupation	53.9	49.1	58.0

NOTES: I use 2019 Annual Social and Economic Supplement of the Current Population Survey data with the individual weights to produce this table. Occupations are defined at the 3-digit Census OCC level. Occupational switching is defined as change of occupation over the year preceding the survey. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020).

Next, I turn to the physical-proximity-based classification of occupations. The lower panel of Table 3 shows that 34.9 percent of switches occur between low- and high-physical-proximity groups. Women demonstrate smaller between-group mobility than men, 31.3 percent against 38.1 percent. The fraction of switches from high- to low-physical-proximity occupations accounts for 18.4 percent of the total occupational mobility. Among the unemployment-to-employment transitions, about 54 percent of new hires are in high-physical-proximity occupations. Females, who move from unemployment to employment, more likely start working in high-physical-proximity occupations. In Online Appendix, I show that the patterns documented in Table 3 were stable over the last decade, see Figure OA.7.

To draw a line under my empirical findings, I also consider pairwise correlations between continuous measures of teleworkability (WFH Index) and contact intensity (CI Index) and the other characteristics of occupations. Table A.2 shows the results. Teleworkability is positively correlated with the measures of computer usage, social, cognitive, and character skills. Furthermore, conditional on occupational switching, the extent of teleworkability of a current occupation is positively correlated with the probability of moving to another teleworkable occupation. Occupations characterized by lower contact intensity (higher values of CI Index) demonstrate similar patterns.

I conclude this section by emphasizing that teleworkable and non-teleworkable (as well as low- and high-contact-intensity) occupations significantly differ along skill requirements and task content. This implies that workers in non-teleworkable and high-contact-intensity occupations, who bear higher risk of losing a job during the economic downturn that follows the COVID-19 outbreak, may incur not only short-run but also *long-run* losses (scarring effects) originated from skill mismatch. My findings suggest several policy implications. While the unemployment benefits or stimulus payments for COVID-19 relief can insure these workers against short-run losses, they fall short of insuring long-run losses. The observation that scarring effects are typically larger for low-earnings workers (Guvenen et al., 2017) strengthens my arguments even further. Study of optimal policies that can provide insurance against short-run and long-run losses is an important avenue for future research (Mitman and Rabinovich, 2020). I also emphasize that existing differences in skill requirements may create constraints on policies that propose training programs for the unemployed. While some hard skills (e.g. basic computer skills) can be acquired through training, social and character skills are much harder to develop.

4 Conclusion

In this paper, I study how the nature of work—teleworkability and contact intensity—shapes the distribution of health, earnings, and unemployment risks, created by the COVID-19 pandemic. First, I show that the existing patterns of spousal occupational sorting in the United States matter for the distribution of these risks. In particular, sorting into occupations with similar contact intensity in the workplace, observed in the data, mitigates the risk of intra-household COVID-19 contagion relative to the situation where spouses match at random in terms of occupations (zero sorting). Next, sorting into occupations with similar teleworkability, observed in the data, exacerbates the exposure to earnings and unemployment risks relative to the case of zero sorting. Second, I document that teleworkable occupations more likely require higher education and experience levels as well as greater cognitive, social, character, and computer skills, compared to non-teleworkable occupations. These patterns in skill requirements increase the likelihood of skill mismatch for the newly unemployed. This, in turn, may leave a scarring effect that will reduce their wages in future occupations. My results imply that the current economic downturn may have *long-run* effects on labor market outcomes of workers who had non-teleworkable or high-contact-intensity jobs at the onset of the COVID-19 outbreak. These observations have direct policy implications whilst highlighting potential constraints on their effectiveness.

While I briefly discuss several policy implications that follow from my analysis, more careful and formal study of optimal policies is necessary. Baqaee et al. (2020) is an example of a quantitative paper that studies the economic reopening using the data on teleworkability and contact intensity by sector. Current evidence suggests that firms rapidly adopt flexible work arrangements and highly likely this tendency will persist in the future. An important question that needs a careful study is how working from home affects productivity (Bloom et al., 2015). Using data from a field experiment with national scope, Mas and Pallais (2017) show that the average worker is willing to give up 20 percent of wages to avoid a schedule set by an employer, and 8 percent for the option to work from home. Has COVID-19 shifted the preferences for work from home? Answers to these questions are fruitful avenues for future research.

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Appendix

O*NET Job Attributes used by Dingel and Neiman (2020) and Mongey et al. (2020)

- **Work Activities:** 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; Repairing and Maintaining Mechanical Equipment; Repairing and Maintaining Electronic Equipment; Inspecting Equipment, Structures, or Materials.

- **Work Context:** Electronic Mail; Outdoors, Exposed to Weather; Outdoors, Under Cover; Deal With Physically Aggressive People; Wear Common Protective or Safety Equipment such as Safety Shoes, Glasses, Gloves, Hearing Protection, Hard Hats, or Life Jackets; Wear Specialized 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.

O*NET Job Attributes used by Acemoglu and Autor (2011)

- **Non-Routine Cognitive (Analytical):** Analyzing Data or Information; Thinking Creatively; Interpreting the Meaning of Information for Others.

- **Non-Routine Cognitive (Interpersonal):** Establishing and Maintaining Interpersonal Relationships; Guiding, Directing, and Motivating Subordinates; Coaching and Developing Others.

- **Routine Cognitive:** Importance of Repeating Same Tasks; Importance of Being Exact or Accurate; Structured versus Unstructured Work (reverse).

- **Routine Manual:** Pace Determined by Speed of Equipment; Controlling Machines and Processes; Spend Time Making Repetitive Motions.

- **Non-Routine Manual Physical:** Operating Vehicles, Mechanized Devices, or Equipment; Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls; Manual Dexterity; Spatial Orientation.

- **Offshorability:** Face-to-Face Discussions (reverse); Assisting and Caring for Others (reverse); Performing for or Working Directly with the Public (reverse); Inspecting Equipment, Structures, or Material (reverse); Handling and Moving Objects (reverse); $0.5\times$Repairing and Maintaining Mechanical Equipment (reverse); $0.5\times$Repairing and Maintaining Electronic Equipment (reverse).

- **Computer Usage:** Interacting with Computers. *Not used by Acemoglu and Autor (2011).*

Table A.1: Keywords and phrases for skill category classification.

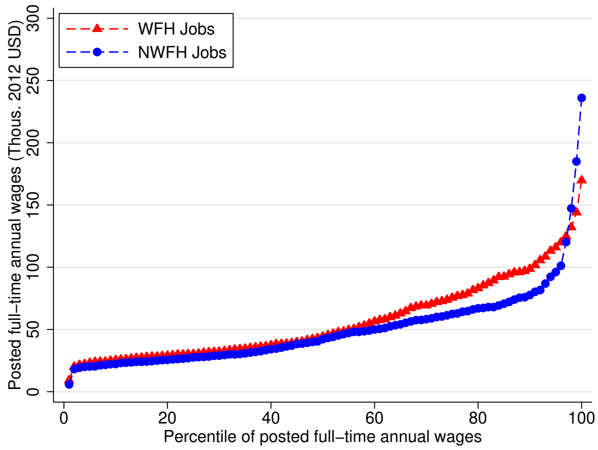
Skill Category	Keywords and Phrases
Cognitive	Analy, Arithmetic, Assess, Brainstorming, Cognitive, Critical, Decision, Economics, Estimating, Financial, Forecasting, Intelligence, Learn, Math, Modelling, Numer, Problem, Quantitative, Research, Solving, Science, Statistics, Thinking
Social	Collaboration, Communication, Conjunction, Cooperation, Interpersonal, Listening, Negotiation, Partnership, People skills, Presentation, Public speaking, Relationship building, Social, Teamwork
Character	Administrative, Ambitious, Assertive, Autonomy, Bright, Career-minded, Character, Charismatic, Detail-oriented, Dynamic, Energetic, Enterprising, Enthusiastic, Hardworking, Initiative, Inquisitive, Intellectual Curiosity, Leadership, Meeting deadlines, Minded, Motivated, Multi-tasking, Organizational skills, Organized, Responsibility, Time management

NOTES: This table contains the list of keywords and phrases that I use to determine whether a skill requirement from the Gartner TalentNeuron online vacancy postings data falls into one of categories: cognitive, social, or character. To create this list, I use the categorization from Atalay et al. (2020), Deming and Kahn (2018), and Hershbein and Kahn (2018), and add several more keywords by myself.

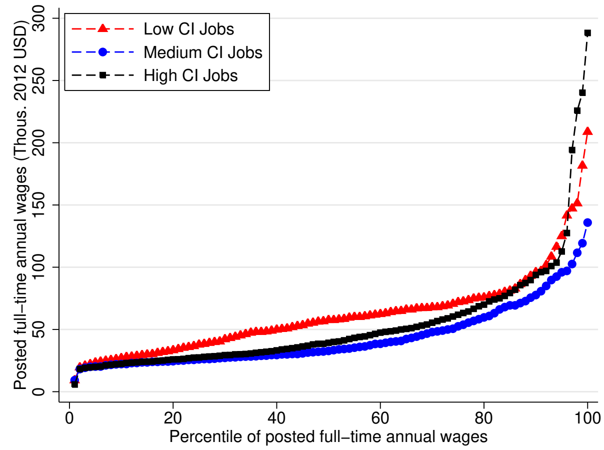
Table A.2: Correlations for continuous measures of teleworkability and contact intensity.

	WFH Index	CI Index
WFH Index		0.42
CI Index	0.42	
Non-Routine Cognitive (Analytical)	0.48	0.20
Non-Routine Cognitive (Interpersonal)	0.16	-0.11
Routine Cognitive	-0.19	-0.16
Non-Routine Manual Physical	-0.88	-0.22
Offshorability	0.81	0.57
Computer Usage	0.62	0.27
Social Skills (Deming, 2017)	0.34	-0.10
Social Skills (Online Ads)	0.72	0.15
Cognitive Skills (Online Ads)	0.74	0.34
Character Skills (Online Ads)	0.66	0.22

NOTES: Construction of WFH ("work from home") Index and CI ("contact intensity") Index is described in Section 2.1. Higher values of WFH Index correspond to greater teleworkability of occupation. Higher values of CI Index correspond to lower requirements of contact intensity at the workplace. Construction of measures from lines 3-8 is described in Section 2.3. Construction of measures from lines 9-12 is described in Section 2.4. Correlations are calculated using occupations at the O*NET SOC level. Correlations in lines 10-12 are weighted by the number of posted ads in each O*NET SOC occupation.



(a) Teleworkability classification.

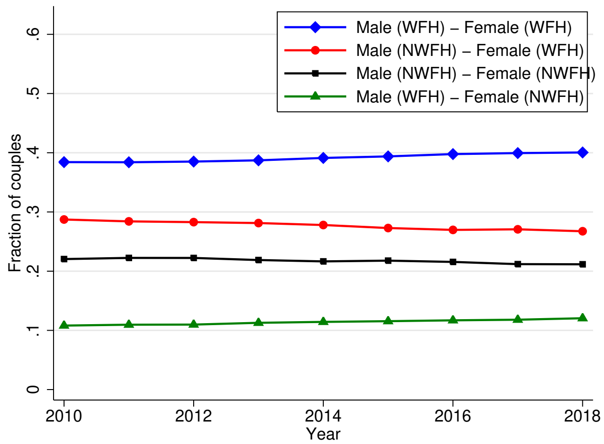


(b) Contact intensity classification.

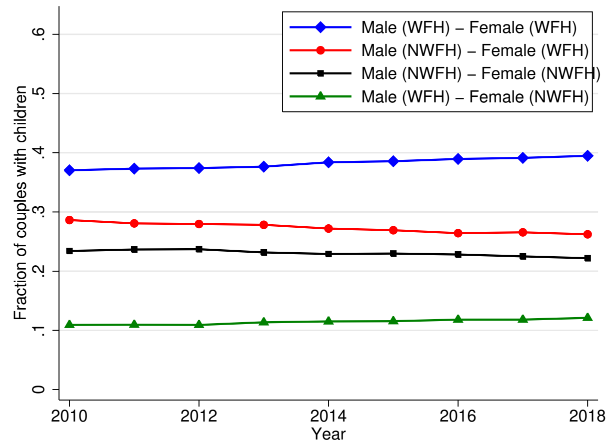
Figure A.1: Cumulative distribution of posted full-time annual wages.

NOTES: I use Gartner TalentNeuron data on online vacancy ads in Iowa, Minnesota, North Dakota, South Dakota, and Wisconsin for September 2014-September 2018 to produce these figures. Occupations are defined at the O*NET SOC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Dingel and Neiman (2020). WFH ("work from home") stands for teleworkable occupations. NWFH ("not work from home") stands for non-teleworkable occupations. The classification of occupations in terms of contact intensity is from Leibovici et al. (2020). Low CI stands for low contact intensity. Medium CI stands for medium contact intensity. High CI stands for high contact intensity. For each percentile, statistics are based on the minimum full-time posted wage in that percentile. Posted wages are adjusted for inflation to 2012 dollars using the PCE price index.

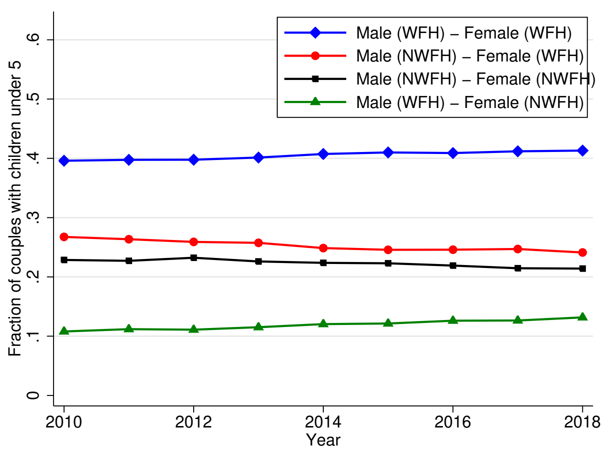
Online Appendix



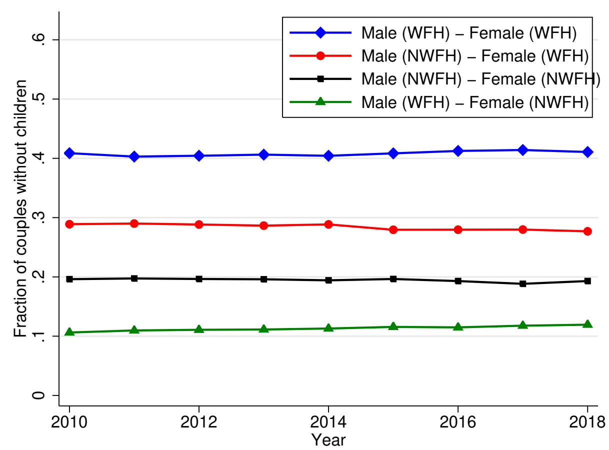
(a) All couples.



(b) Couples with children.



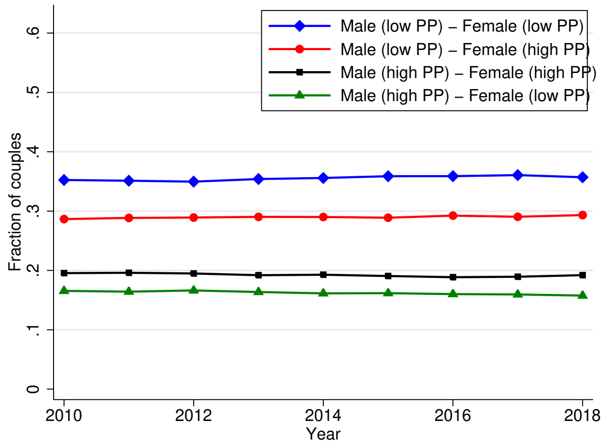
(c) Couples with children under 5.



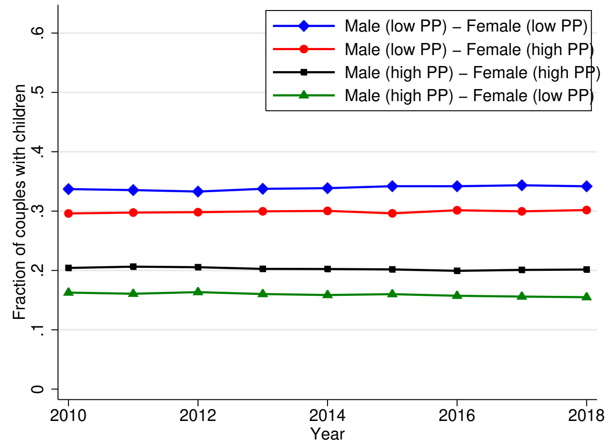
(d) Couples without children.

Figure OA.1: Distribution of spouses in the U.S. dual-earner married couples by occupations of different teleworkability.

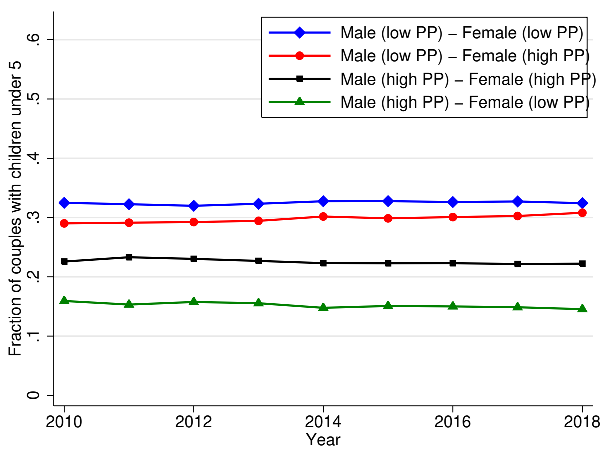
Notes: I use 2010-2018 American Community Survey data with the household weights to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Mongey et al. (2020). WFH ("work from home") stands for teleworkable occupations. NWFH ("not work from home") stands for non-teleworkable occupations.



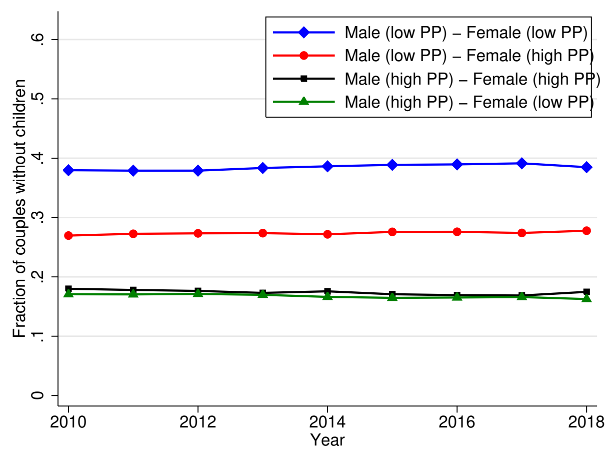
(a) All couples.



(b) Couples with children.



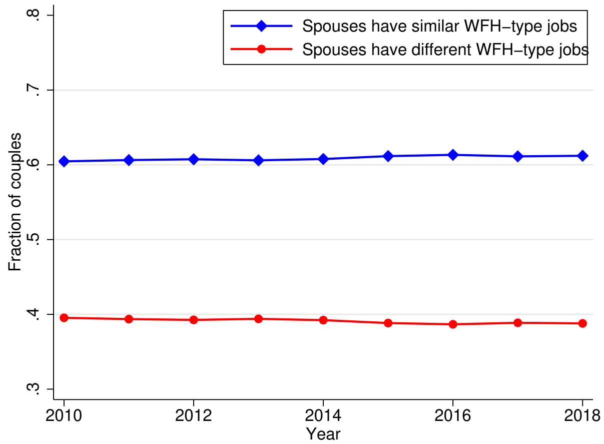
(c) Couples with children under 5.



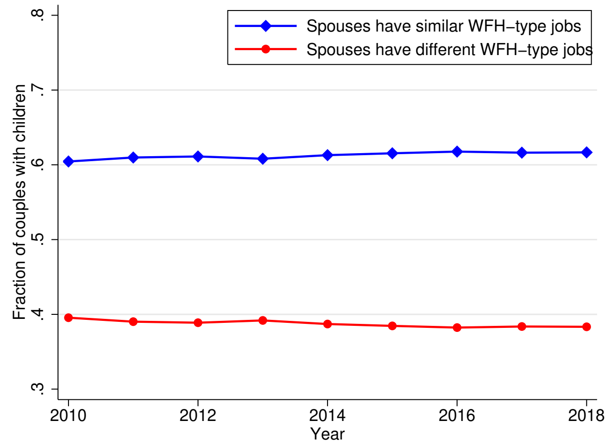
(d) Couples without children.

Figure OA.2: Distribution of spouses in the U.S. dual-earner married couples by occupations of different contact intensity.

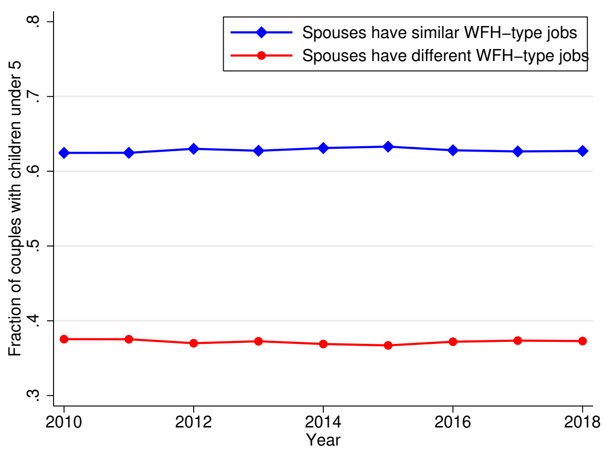
Notes: I use 2010-2018 American Community Survey data with the household weights to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of physical proximity (low PP/high PP) is from Mongey et al. (2020). Low PP ("low physical proximity") stands for occupations that do not require high contact intensity at the workplace. High PP ("high physical proximity") stands for occupations that require high contact intensity at the workplace.



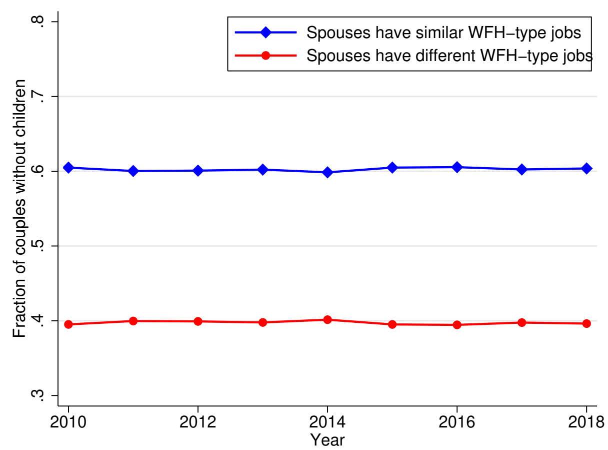
(a) All couples.



(b) Couples with children.



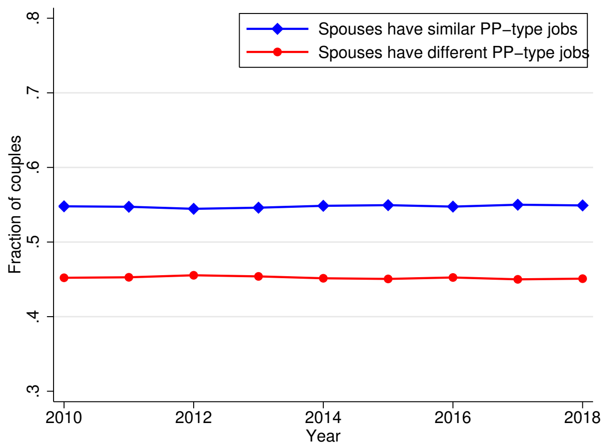
(c) Couples with children under 5.



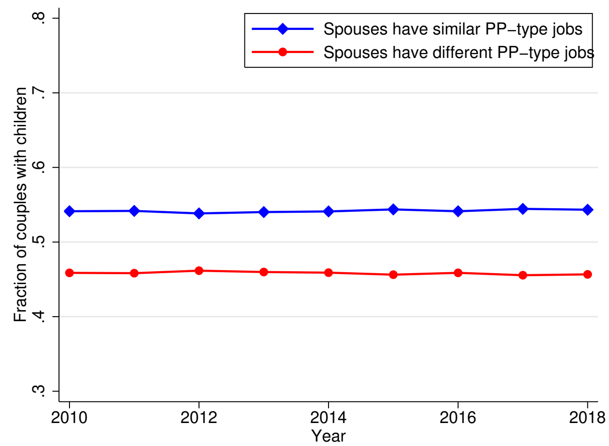
(d) Couples without children.

Figure OA.3: Fraction of dual-earner married couples where spouses have jobs of similar/different teleworkability.

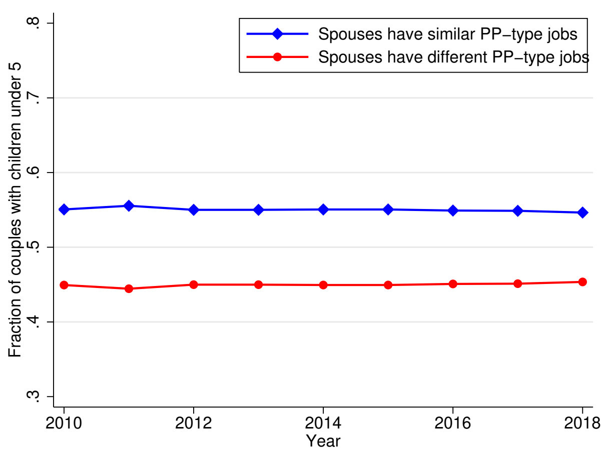
Notes: I use 2010-2018 American Community Survey data with the household weights to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Mongey et al. (2020). WFH ("work from home") stands for teleworkable occupations. NWFH ("not work from home") stands for non-teleworkable occupations. Couples with similar WFH-type jobs are those where both spouses have either WFH or NWFH jobs. Couples with different WFH-type jobs are those where one spouse has WFH job and another spouse has NWFH job.



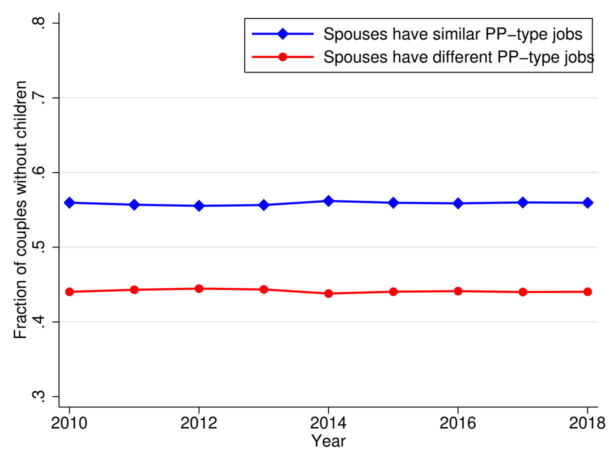
(a) All couples.



(b) Couples with children.



(c) Couples with children under 5.



(d) Couples without children.

Figure OA.4: Fraction of dual-earner married couples where spouses have jobs of similar/different contact intensity.

Notes: I use 2010-2018 American Community Survey data with the household weights to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of physical proximity (low PP/high PP) is from Mongey et al. (2020). Low PP ("low physical proximity") stands for occupations that do not require high contact intensity at the workplace. High PP ("high physical proximity") stands for occupations that require high contact intensity at the workplace. Couples with similar PP-type jobs are those where both spouses have either low PP or high PP jobs. Couples with different PP-type jobs are those where one spouse has low PP job and another spouse has high PP job.

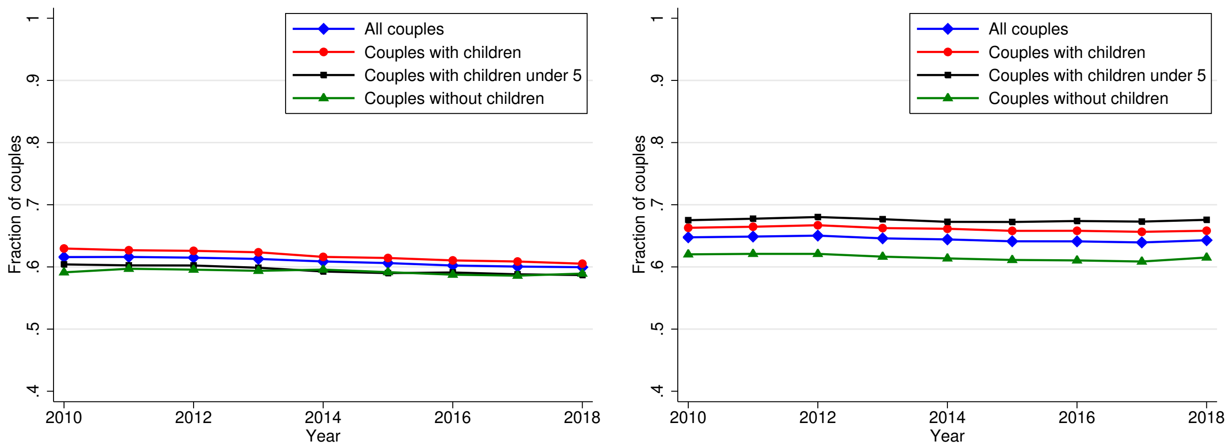
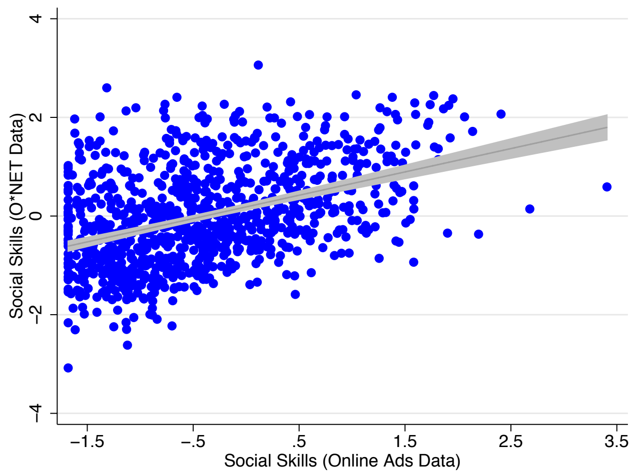
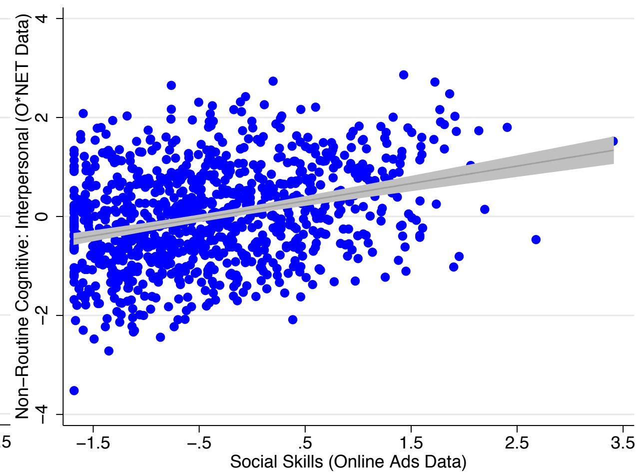


Figure OA.5: Left panel: Fraction of dual-earner married couples where at least one spouse cannot work from home (has NWFH job). Right panel: Fraction of dual-earner married couples where at least one spouse has a job that requires high contact intensity at the workplace (has high PP job).

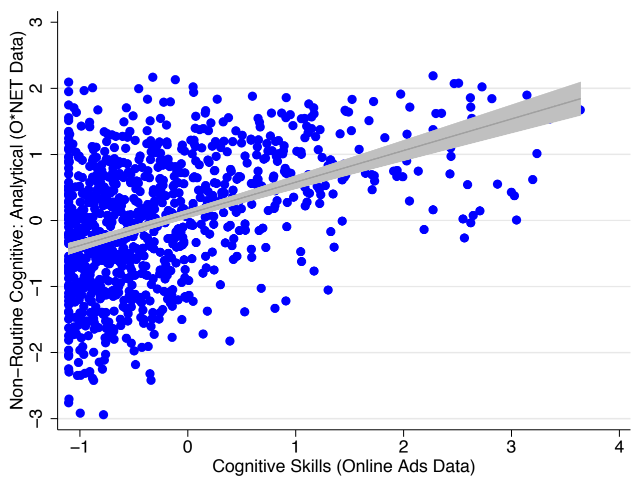
Notes: I use 2010-2018 American Community Survey data with the household weights to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020).



(a) Social skills.



(b) Social skills vs. non-routine cogn. (interpersonal).



(c) Cognitive skills vs. non-routine cogn. (analytical).

Figure OA.6: Association between measures constructed from the online job ads data and measures constructed from O*NET data.

NOTES: Blue dots represent occupations defined at the O*NET SOC level. The grey shaded area represents the 95% confidence interval. In these figures, I show the relationship between the measures of skill requirements, constructed using Gartner TalentNeuron online ads data, and the measures, constructed using O*NET data. Social-skill measure from O*NET data, used in Figure OA.6a, corresponds to the measure constructed by Deming (2017). Non-routine cognitive measures, interpersonal and analytical, from O*NET data, used in Figure OA.6b and Figure OA.6c, correspond to the measures proposed by Acemoglu and Autor (2011).

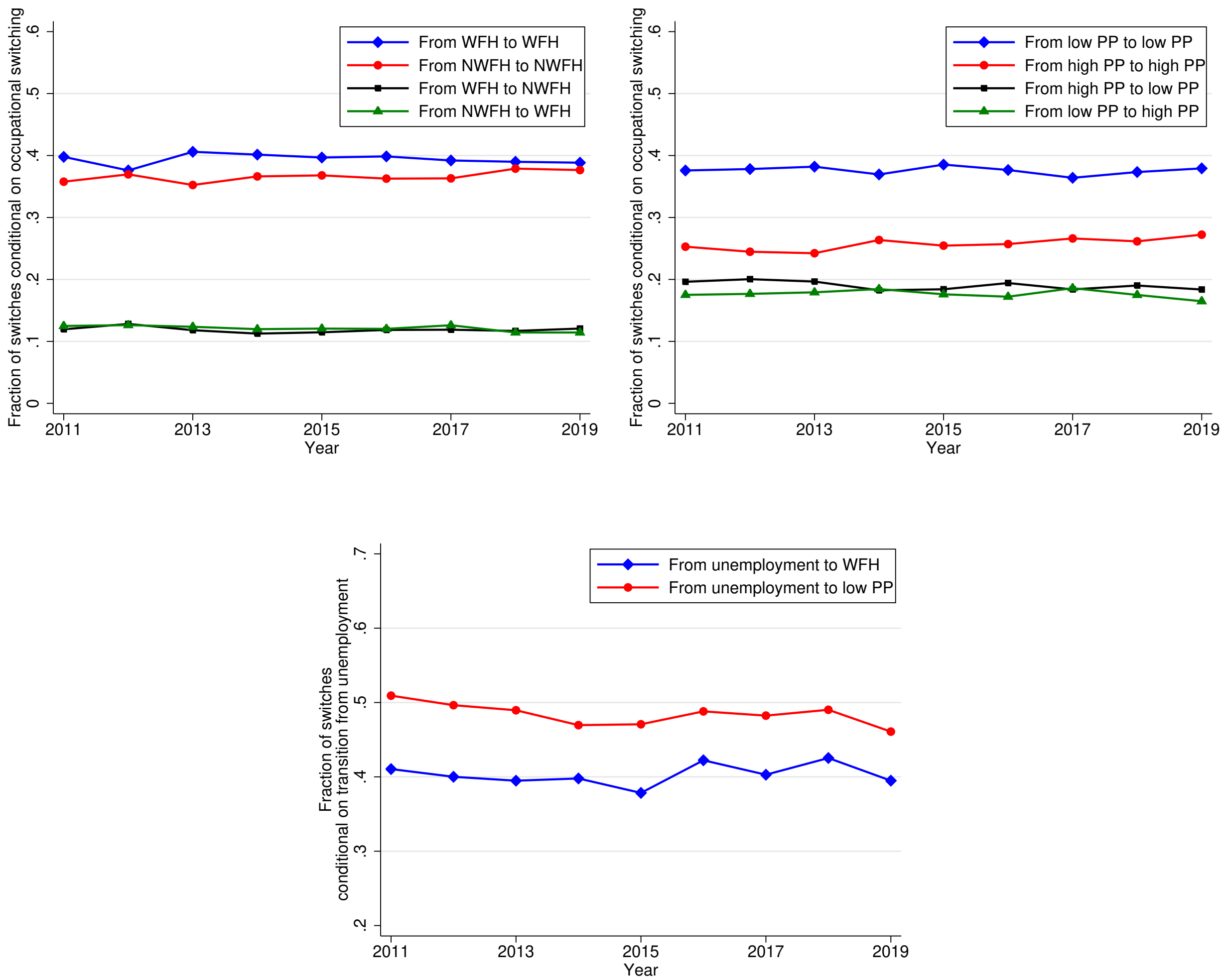


Figure OA.7: Left upper panel: Distribution of occupational switching over teleworkable (WFH) and non-teleworkable (NFWH) occupations. Right upper panel: Distribution of occupational switching over occupations that require (high PP) and do not require (low PP) high contact intensity at the workplace. Bottom panel: Shares of unemployment-to-employment transitions that end in teleworkable (WFH) or low-physical-proximity (low PP) occupations.

Notes: I use 2011-2019 Annual Social and Economic Supplement of the Current Population Survey data with the individual weights to construct these figures. Occupations are defined at the 3-digit Census OCC level. Occupational switching is defined as change of occupation over the year preceding the survey. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020).