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Nature of work and distribution of risk: Evidence from occupational sorting, skills, and tasks[1]

Egor Malkov[2]

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How does the nature of work – teleworkability and contact intensity – shape the distribution of health, labor income, and unemployment risks, created by the COVID-19 pandemic? To answer this question, we consider two contexts. First, we show that the existing spousal nature-of-work-based occupational sorting in the United States matters for the distribution of these risks. In particular, we show that it mitigates the risk of catching COVID-19 through intra-household contagion relative to the case of zero sorting. Furthermore, we show that it creates a larger fraction of couples, who are excessively exposed to labor income and unemployment risks, relative to the case of zero sorting. Second, we document that teleworkable occupations require higher education and experience levels as well as greater cognitive, social, character, and computer skills relative to non-teleworkable occupations. This discrepancy affects labor income and unemployment risks by increasing the likelihood of skill mismatch for newly unemployed workers. Our 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. We discuss the relevant policy implications and associated policy constraints that follow from our findings.

1 The views expressed herein are those of the author and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System. I thank Erin Olson and Brad Holwell for help with getting access to the Gartner TalentNeuron data.

2 Ph.D. Candidate, Department of Economics, University of Minnesota and Federal Reserve Bank of Minneapolis.

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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, see Dingel and Neiman (2020), cannot be performed remotely. Therefore, the nature of work became one of crucial factors behind the distribution of health, labor income, and unemployment risks.

In this paper, we ask the following question. How does the nature of work — teleworkability and contact intensity — shape the distribution of health, labor income, and unemployment risks, created by the COVID-19 pandemic? We consider two contexts. First, we study whether the existing spousal nature-of-work-based occupational sorting in the United States matters for the distribution of these risks. Second, we study how different are the skill requirements and task content in teleworkable versus non-teleworkable and low-contact-intensity versus high-contact-intensity occupations. The answer to the second question may inform about labor income and unemployment risks of workers, who lost their non-teleworkable or high-contact-intensity jobs during the COVID-19 pandemic, in the long run. To address the first question, we use data from the American Community Survey (ACS). To address the second question, we employ data from O*NET and online vacancy postings data from Gartner TalentNeuron.

The main contribution of this paper is threefold. First, we show that the existing spousal occupational sorting in the United States mitigates the risk of catching COVID-19 through intra-household contagion relative to the case of zero sorting. We document that about 67 percent of the U.S. dual-earner couples are exposed to excessive health risk through this transmission channel. Second, we show that the existing spousal occupational sorting creates a larger fraction of couples, who are excessively exposed to labor income and unemployment risks, relative to the case of zero sorting. We document that they constitute about a quarter of all the U.S. dual-earner couples. These are the couples where both spouses work in non-teleworkable occupations. Counterfactual shift from the actual to zero sorting would reduce this fraction down to about 19 percent. Our results imply that nature-of-work-based occupational sorting in couples *matters* for the distribution of health, labor income, and unemployment risks, created by the COVID-19 pandemic. Third, we document a significant differences in skill requirements between teleworkable and non-teleworkable as well as low- and high-contact-intensity occupations. Teleworkable occupations require higher education and experience levels as well as greater cognitive, social, character, and computer skills. This discrepancy increases the likelihood of skill mismatch for workers who lost their 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, we consider the patterns of labor market mobility for occupations of different teleworkability and contact intensity, using data from the Current Population Survey (CPS) and occupational mobility data from Schubert et al. (2020). Overall, our 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 have important policy implications. First, since about 67 percent of the U.S. dual-earner couples are exposed to excessive health risk through intra-household contagion, then targeting individuals who work in occupations that require high contact intensity with testing, vaccination, and providing them with protective equipment would allow to mitigate this transmission channel. Second, a significant fraction of couples where both spouses have non-teleworkable jobs and hence exposed to greater unemployment risk suggests that occupation-specific transfers or transfers based on joint spousal earnings can be potentially desirable. Finally, we stress 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. We 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. the basic computer skills, can be acquired through training, social and character skills are much harder to develop.

This paper contributes to active and growing literature studying the effects of COVID-19 on the labor markets. In what follows we briefly describe the related studies and explain how our paper complements them. Using the data on online job postings provided by Burning Glass Technologies, Kahn et al. (2020a) 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) study 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 experience the largest decline in the likelihood of full-time work. In this paper, we 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.

We 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

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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.

Our work is mostly related to the papers that study the implications of teleworkability and contact intensity of occupations for health and economic outcomes. Mongey et al. (2020) show that workers in low-work-from-home (non-teleworkable) or high-physical-proximity occupations are less educated, have lower income, fewer liquid assets relative to income, and are more likely to be renters. Next, using data from the CPS, they document that workers employed in non-teleworkable occupations experienced greater declines in employment. Using the Real-Time Population Survey, Bick et al. (2020) also document several facts about working from home following the COVID-19 outbreak. In particular, they show that 35.2 percent of the workforce worked entirely from home in May 2020, while in February 2020 this fraction was 8.2 percent. Using the estimates of the potential number of home-based workers from Dingel and Neiman (2020), they conclude that more than 70 percent of the U.S. workers that could work from home did so in May 2020. Using data from the American Time Use Survey (ATUS) in 2017 and 2018, Papanikolaou and Schmidt (2020) measure the industry exposure to the lockdowns using information on the share of the workforce than can work from home. They show that sectors in which a higher fraction of workers is not able to work remotely experienced greater declines in employment, greater reductions in expected revenue growth, worse stock market performance, and higher expected likelihood of default. Furthermore, they document that lower-paid workers, especially female workers with young children, were affected most.

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. Furthermore, they provide suggestive evidence that the stay-at-home order is helpful at mitigating contagion at work or in public spaces but can raise the likelihood of intra-household contagion. Second, the presence of

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another employed family member serves as partial insurance against labor income and unemployment shocks. Lekfuangfu et al. (2020) construct indices that capture the extent to which jobs can be adaptable to work from home and the degree of infection risk at workplace. Using the data from Thailand, they show that low-income married couples are much more likely to sort into occupations that are less adaptable to work from home. As a result, these couples tend to face a significantly higher income risk resulted from lockdown measures. 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. (2020b) discuss how childcare and the presence of COVID-19-high-risk household members can limit the ability to return to work. They document that about a quarter of the workforce may be constrained from full-time work because they have young children. Next, roughly one-fifth of the workforce is either in a high-risk group or live with someone who is more likely to suffer from COVID-19. Alon et al. (2020) study the implications of the COVID-19 pandemic for gender inequality. First, they provide supporting evidence that the current recession will have disproportionately negative effect on women and their employment opportunities while the "regular" recessions, such as the Great Recession, affect men's employment more severely. Second, they discuss the potential forces that may ultimately reduce gender inequality in the labor market. These include the increasing adoption of flexible work arrangements that may persist over time and changes in social norms about the division of labor in housework and child care within a household. We 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, our paper bridges the studies of alternative work arrangements to several other strands of the literature. First, it is related to the literature that study multidimensional skill requirements of occupations. Using the 1979 National Longitudinal Survey of Youth (NLSY79) and O*NET data, Guvenen et al. (2020) construct the empirical measure of skill mismatch and show that it is informative about current and future wages and occupational switching. Lise and Postel-Vinay (2020) extend a standard job-search model allowing for multidimensional skills — cognitive, manual, and interpersonal — and on-the-job learning. In their model, cognitive, manual, and interpersonal skills have different returns and speed of adjustment. Abstracting from this multidimensionality and assuming that a worker's skills are described by a single scalar index leads to overestimation of the importance of unobserved heterogeneity and underestimation of the contribution of career shocks relative to observed initial skills. Our 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 COVID-19 outbreak.

To construct the measures of skill requirements, we use online job ads data. Therefore our work is also related to the growing literature that use the vacancy ads data for studying the labor markets, see Deming and Kahn (2018), Hershbein and Kahn (2018), Hazell and Taska (2019), Marinescu and Wolthoff (2020), and Schubert et al. (2020) among many others.

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Furthermore, our work bridges the papers on alternative work arrangements with studies that use the "task approach" to labor markets and the literature on labor market polarization, see Autor et al. (2003), Acemoglu and Autor (2011), and Foote and Ryan (2015). First, our 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. Second, it can be informative about the groups of tasks that are mostly affected in the current economic downturn. 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. Next, Hershbein and Kahn (2018) show that the Great Recession accelerated the process of restructuring of production toward routine-biased technologies and the more-skilled workers that complement them.

Finally, this paper is also related to the literature studying the patterns of labor market mobility, see Moscarini and Thomsson (2007), Kambourov and Manovskii (2008), Kambourov and Manovskii (2009), and Schubert et al. (2020). Our finding that teleworkable occupations feature significantly higher skill requirements — cognitive, social, character, and computer — than non-teleworkable occupations have direct implications for the employment prospects of individuals who lost their jobs during the COVID-19 pandemic. We emphasize the constraints imposed by the differences in skill requirements: 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. See Kambourov et al. (2020) for the discussion of relationship between occupational switching and the returns to training.

The rest of the paper is organized as follows. In Section 2, we describe the datasets and construction of the variables. In Section 3, we provide the empirical results. Section 4 concludes.

2 Data

To study how teleworkability and contact intensity of occupations affect the distribution of health and unemployment risks, created by the COVID-19 pandemic, we employ several data sets. First, we use the classifications of occupations by teleworkability and contact intensity from Dingel and Neiman (2020), Leibovici et al. (2020), and Mongey et al. (2020). These classifications are based on O*NET data. We also construct the continuous measures of teleworkability and contact intensity using the similar inputs as in the papers mentioned above. Second, we use O*NET data to measure the task content of occupations. Third, to measure the skill requirements, we use the proprietary online vacancy posting data from Gartner TalentNeuron with access provided by RealTime Talent. Next, to show the patterns of occupational sorting of spouses in married couples we use the ACS data. Finally, to study the labor market mobility associated with occupations of different teleworkability and contact intensity we employ two sources: Annual Social and Economic Supplement of the CPS (CPS ASEC) and the Burning Glass Technologies occupational mobility data constructed by Schubert et al. (2020). In what follows, we 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, we use the 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, we provide the list of job attributes that they employ.

Dingel and Neiman (2020) classify an occupation as one that can or cannot be performed at home based on the conditions defined over the listed inputs (e.g., if, in a given occupation, an average respondent says they are exposed to diseases or infection at least once a week, then this occupation is classified as non-teleworkable). As a result, their classification is done at the O*NET SOC level. Totally, there are 968 classified occupations. We use this classification to study the differences in task content, skill requirements, and labor market mobility for teleworkable and non-teleworkable occupations.

In turn, Mongey et al. (2020) exploit a different approach to construct the measure of teleworkability. They classify the occupations at the 3-digit Census OCC level that is less finer than O*NET SOC level. To do this, they aggregate 6-digit SOC level O*NET scores using employment from the Occupational Employment Statistics (OES) as weights. As a result, they get a continuous measure of teleworkability at the 3-digit Census OCC level. Next, using this measure, they construct a binary variable that divides occupations into high work-from-home (more likely to be able to work remotely, i.e. teleworkable) and low work-from-home (less likely to be able to work remotely, i.e. non-teleworkable) such that each of both groups is comprised of half of employment. Totally, there are 511 classified occupations. See Mongey et al. (2020) for more details. We use their binary classification to study the occupational sorting of spouses in couples and labor market mobility because ACS and CPS define occupations at the 3-digit Census OCC level. To avoid confusion, we always clearly specify which binary measure of teleworkability, either from Dingel and Neiman (2020) or Mongey et al. (2020) we use. We define an occupation to be *WFH* (work-from-home) if it is classified as teleworkable. We define an occupation to be *NWFH* (not-work-from-home) if it is classified as non-teleworkable.

We also construct a continuous measure of teleworkability at the O*NET SOC level. For each job attribute listed in Appendix, we standardize the score to have mean zero and standard deviation one.[1] Next, we sum the standardized scores and standardize the sum to have mean zero and standard deviation one.[2] Since we are interested in the distribution of teleworkability across occupations, not workers, we do not use the employment weights when constructing the indices. The higher values of this measure — we define it as *WFH Index* — correspond to greater feasibility

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

[2] When we sum the scores, we 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.

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of working from home.

In addition to teleworkability, we also employ 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. They divide the occupations into three groups: (i) low contact-intensity (*low CI*) if O*NET score is between 0 and 49, (ii) medium contact-intensity (*medium CI*) if O*NET score is between 50 and 74, and (iii) high contact-intensity (*high CI*) if O*NET score is between 75 and 100. We use this classification to study the differences in task content, skill requirements, and labor market mobility for more and less contact-intensive occupations.

Next, Mongey et al. (2020) construct the measures of physical proximity in a way similar to teleworkability measures. We use their binary classification, defined at the 3-digit Census OCC level, to study the occupational sorting in couples and labor market mobility. To avoid confusion with the contact-intensity categories from Leibovici et al. (2020), we define an occupation to be *low PP* (low physical proximity) if it is classified by Mongey et al. (2020) as requiring lower physical proximity at the workplace. We define an occupation to be *high PP* (high physical proximity) if it is classified as requiring higher physical proximity at the workplace.

Finally, we also construct a continuous measure of contact intensity. To do this, we standardize the reversed score for "Physical Proximity" from O*NET Work Context module to have mean zero and standard deviation one. As with the WFH Index, we do not use the employment weights when constructing this index. Higher values of this measure — we define it as *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, we use data from the ACS in 2018, the most recent available release.[3] In Online Appendix we also show the results for the earlier years, namely, 2010-2018. ACS defines the occupations using the Census OCC codes, and we merge it with the teleworkability and contact-intensity classification from Mongey et al. (2020). We keep the different-sex married couples where both spouses aged 20 to 65. Since our primary interest is in occupational sorting, we keep only those couples where both spouses are employed. Furthermore, we also separately consider the couples with children, couples with children under the age of 5, and couples without children.

2.3 Task Content

To study the task content of occupations that differ in teleworkability and contact intensity, we use O*NET 24.2 data. We construct the composite measures proposed by Acemoglu and Autor

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

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(2011) and additionally consider a measure of computer usage at the workplace. In Appendix, we provide the list of job attributes that are used for constructing these indices.

For each attribute, we standardize the score to have mean zero and standard deviation one. Next, we sum the standardized scores within each composite task measure (e.g. routine cognitive). Finally, we restandardize the sum to have mean zero and standard deviation one. All the measures are constructed at the O*NET SOC level. Since we are interested in the distribution of routineness/offshorability/computer usage across occupations, not workers, we do not use the employment weights when constructing the indices. To compare the task content between occupations of different teleworkability and contact intensity, we 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, we use the online vacancy posting data from Gartner TalentNeuron. Gartner TalentNeuron collects the data from more than 65000 global sources and continuously retests it for quality, accuracy, and consistency. We 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), we show that the distribution of our 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. We use this data to construct the indices of character, cognitive, and social skill requirements across the occupations defined in O*NET. We proceed in the following way. First, we 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. To create it, we use the categorization from Atalay et al. (2020), Deming and Kahn (2018), and Hershbein and Kahn (2018), and add several more keywords by ourselves. In our dataset, we have 9924 unique skill requirements. Each vacancy may have from zero to many posted skill requirements. Second, we 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, we calculate the share of ads containing each skill category. Finally, we standardize the index for each skill category to have mean zero and standard deviation one using the number of ads as weights. We merge our constructed indices with the teleworkability and contact intensity classifications from Dingel and Neiman (2020) and Leibovici et al. (2020).

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Furthermore, to get additional validation of our results, we also construct the measure of social-skill intensity of occupations considered by Deming (2017). In particular, we use the following four attributes from O*NET: "Coordination" (adjusting actions in relation to others' actions), "Negotiation" (bringing others together and trying to reconcile differences), "Persuasion" (persuading others to change their minds or behavior), and "Social Perceptiveness" (being aware of others' reactions and understanding why they react as they do). For each attribute, the score is standardized to have mean zero and standard deviation one. Next, we sum the standardized scores and restandardize the sum to have mean zero and standard deviation one.

2.5 Labor Market Mobility

To document the distribution of labor market mobility for occupations of different teleworkability and contact intensity, we use CPS ASEC data in 2019.[4] In Online Appendix we also show the results for the earlier years, namely, 2011-2019. We 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.[5] CPS defines the occupations using the Census OCC codes, and we merge it with the classification from Mongey et al. (2020). We keep the individuals aged 25 to 60. We also consider the distribution of labor market transitions separately for men and women.

To complement our analysis, we also employ the Burning Glass Technologies occupational mobility data from Schubert et al. (2020). To construct this dataset, the authors use 16 million unique resumes with more than 80 million job observations over 2002-2018, with the majority of observations in the later years. The advantage of this data is that it defines the occupations at the 6-digit SOC level. This level of granularity is not available in such datasets as CPS where the transitions within broader occupation categories cannot be observed. See Schubert et al. (2020) for more details. We merge this dataset with the teleworkability and contact intensity classifications from Dingel and Neiman (2020) and Leibovici et al. (2020).

3 Empirical Results

This section contains our empirical findings. We begin by documenting the patterns of occupational sorting of spouses in married couples in the United States. We proceed with the task content and skill requirements of occupations that differ in teleworkability and contact intensity. Finally, we document the patterns of labor market mobility for these groups of occupations.

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

[5] We intentionally do not define it as annual mobility because, as discussed by Kambourov and Manovskii (2013), CPS ASEC data most likely measure mobility over a much shorter period.

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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 occupation that an individual has. Workers who have teleworkable jobs face lower unemployment risk than those who have non-teleworkable jobs. Workers whose occupations require less contact intensity at the workplace face lower risk of being infected than those who work in high physical proximity to the other individuals. Note that we discuss the feasibility of working from home or in low physical proximity 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. Several studies document that low-income individuals are, in general, more vulnerable to both types of risk. For example, Mongey et al. (2020) show that in the United States workers in less teleworkable or high-contact-intensity jobs are less educated, have lower income, and fewer liquid assets relative to income.

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 48 percent of all the U.S. households. The sign and extent of actual occupational sorting in couples plays an important role during the COVID-19 pandemic because it can either exacerbate or mitigate health and labor income risks relative to the case of zero sorting. In what follows we briefly discuss this idea. First, the presence of the other family members raises the concerns of intra-household COVID-19 contagion. Under perfect positive contact-intensity-based sorting, i.e. when both spouses have either high-contact-intensity or low-contact-intensity jobs, the risk of intra-household contagion is heavily concentrated in high-contact-intensity couples. Under perfect negative contact-intensity-based sorting, i.e. when in each couple there is a spouse in a high-contact-intensity-based job and a spouse in a low-contact-intensity-based job, the risk of intra-household contagion is evenly distributed across the couples. In general, more negative contact-intensity-based occupational sorting is associated with greater fraction of individuals who are exposed to health risk. Second, the presence of another employed family member serves as insurance against labor income shocks. Under perfect positive teleworkability-based sorting, i.e. when both spouses have either teleworkable or non-teleworkable jobs, labor income risks are heavily concentrated in non-teleworkable couples. Given the results of Mongey et al. (2020), these individuals also have lower income. Under perfect negative teleworkability-based sorting, i.e. when in each couple there is a spouse in a teleworkable job and a spouse in a non-teleworkable job, labor income risks are distributed across the couples more evenly and are easier to insure. In general, more positive teleworkability-based occupational sorting is associated with greater fraction of individuals who are heavily exposed to labor income 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. Couples face higher unemployment risk because at least one spouse has to be responsible for childcare. In the families, where at least one spouse has a teleworkable job, the impact of children on employment and labor income is likely to be mitigated.

Overall, the patterns of occupational sorting in couples have crucial importance for the distribution of health and labor income risks over the population and, as a consequence, may have different policy implications. What are the sign and level of occupational sorting is an empirical question that we address in this section.

We show the distribution of occupations in terms of teleworkability and contact intensity for dual-earner married couples in the United States in 2018 in Table 1.[6] In addition, we separately consider the couples with children, couples with children under the age of 5, and couples without children. To study the patterns of occupational sorting, we also refer to Table 2 that contains the actual distribution of spouses across occupations from Table 1 and compares them with two counterfactual benchmark distributions. The first benchmark is the distribution under zero sorting. The second benchmark is the distribution under "ideal" sorting. For teleworkability-based distribution, we define "ideal" sorting as the situation when the fraction of couples where both spouses have non-teleworkable jobs is minimized. For contact-intensity-based distribution, we define "ideal" sorting as the situation when the fraction of couples where one spouse has a high-contact-intensity job and another one has a low-contact-intensity job is minimized, i.e. the risk of intra-household contagion is minimized.

We begin with teleworkability-based distribution. In the data, there is positive sorting: in about 60 percent of couples both spouses work in either teleworkable or non-teleworkable occupations. Almost a quarter of couples have spouses that both work in non-teleworkable occupations, and hence are exposed to greater unemployment risk. Under zero sorting, this fraction goes down to 18.7 percent. Under "ideal" sorting, it further reduces to zero as more males and females form mixed (one has a teleworkable job and another one has a non-teleworkable job) couples. Therefore, the actual teleworkability-based occupational sorting in the U.S. couples creates a greater fraction of individuals who are excessively vulnerable to labor income and unemployment risks relative to the case of zero sorting.

Next, we turn to contact-intensity-based distribution. In the data, there is weak positive sorting: in about 54 percent of couples both spouses have either high-physical-proximity or low-physical-proximity jobs. Around 67 percent of couples include a spouse whose job requires a high contact intensity at the workplace, and hence are exposed to greater intra-household contagion risk. Under zero sorting, this fraction goes up to 69.5 percent. Under "ideal" sorting, it falls to 52.1 percent because more males and females form couples where both spouses have low-physical-proximity jobs. Therefore, the actual contact-intensity-based occupational sorting in the U.S. couples creates a lower fraction of individuals who are excessively exposed to intra-household contagion risk relative to the case of zero sorting.

[6] Table 1 uses 2018 ACS data. When we use 2019 ASEC CPS data, we get very close results. They are available upon request.

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Table 1: Occupational distribution of couples, by family type (with/without children) (%)

	All	With children	With children under 5	Without children
Male (WFH) – Female (WFH)	36.0	35.4	36.7	36.9
Male (NWFH) – Female (WFH)	27.9	27.4	25.4	28.9
Male (NWFH) – Female (NWFH)	23.9	24.9	24.4	22.1
Male (WFH) – Female (NWFH)	12.2	12.3	13.6	12.1
Spouses have similar WFH-type jobs	59.9	60.3	61.1	59.0
At least one spouse cannot work from home	64.0	64.6	63.3	63.1
Male (low PP) – Female (low PP)	32.7	31.3	28.9	35.4
Male (low PP) – Female (high PP)	30.9	31.6	32.4	29.6
Male (high PP) – Female (high PP)	21.2	22.2	25.2	19.5
Male (high PP) – Female (low PP)	15.1	14.9	13.5	15.5
Spouses have similar PP-type jobs	54.0	53.5	54.1	54.8
At least one spouse should work in high phys. proximity	67.3	68.7	71.1	64.6

Note: We use 2018 American Community Survey data 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 require low contact intensity at the workplace. High PP (high-physical-proximity) stands for occupations that require high contact intensity at the workplace. To obtain the results, we use household weights provided by IPUMS. Percentages may not add up to 100% due to rounding.

Table 2: Distribution of males and females in dual-earner couples : actual occupational sorting / zero occupational sorting / "ideal" occupational sorting (%)

	Teleworkable and non-teleworkable jobs		
	Female (WFH)	Female (NWFH)	Total
Male (WFH)	36.0 / 30.8 / 12.1	12.2 / 17.4 / 36.1	48.2
Male (NWFH)	27.9 / 33.1 / 51.8	23.9 / 18.7 / 0.0	51.8
Total	63.9	36.1	100.0

	Low- and high-physical-proximity jobs		
	Female (low PP)	Female (high PP)	Total
Male (low PP)	32.7 / 30.4 / 47.8	30.9 / 33.2 / 15.8	63.6
Male (high PP)	15.1 / 17.4 / 0.0	21.2 / 18.9 / 36.3	36.3
Total	47.8	52.1	100.0

Note: We use 2018 American Community Survey data to produce this table. Numbers correspond to the first column of Table 1. The classification of occupations in terms of teleworkability (WFH/NWFH) and physical proximity (low PP/high PP) is from Mongey et al. (2020). To obtain the results, we use household weights provided by IPUMS.

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Another observation from Table 1 is related to the differences in job characteristics by gender. Consider the classification of occupations in terms of teleworkability. Women more likely work in teleworkable than non-teleworkable occupations. Furthermore, they more likely have teleworkable jobs than males. Men are equally distributed between teleworkable and non-teleworkable jobs. Next, consider the classification of occupations in terms of contact intensity. Men more likely work in low-physical-proximity than high-physical-proximity occupations. This highlights the difference between teleworkability and contact intensity. Men 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. In the classification from Mongey et al. (2020), 147 out of 511 occupations satisfy these criteria.[7] Men also more likely have low-physical-proximity jobs than women. Women are almost equally distributed between low-physical-proximity and high-physical-proximity jobs. In Online Appendix, we show that the patterns documented in Table 1 were stable over the last decade, see Figures O.1-O.5.[8]

Our findings have several policy implications. First, we document that about 67 percent of the U.S. dual-earner couples are exposed to excessive health risk through intra-household contagion. Therefore, targeting individuals who work in occupations that require high contact intensity with testing, vaccination, and providing them with protective equipment would allow to mitigate this transmission channel. However, we also show that the patterns of spousal occupational sorting in the United States reduce the risk of catching COVID-19 through intra-household contagion relative to the case of zero sorting. Second, a significant fraction of couples where both spouses have non-teleworkable jobs and hence exposed to greater unemployment risk suggests that occupation-specific transfers or transfers based on joint spousal earnings can be potentially desirable. Formal study of this policy proposal is an important avenue for future research.

3.2 Skills and Tasks

We turn to the discussion of 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 economic downturn that follows the COVID-19 outbreak?

[7] For example, "Postal service mail carriers" or "Aircraft mechanics and service technicians".

[8] The classification from Mongey et al. (2020), that we use both in Table 1 and Figures O.1-O.5, by construction depends on the distribution of employment by occupations in 2018. We fix it and use for the pre-2018 years as well.

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To study this question, we estimate two regressions for a set of 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, we 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, see details about their construction in Section 2.3.

For teleworkability-based classification we 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 we 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.

We 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 1. The left panel demonstrates that teleworkable occupations are, in average, have higher score of non-routine cognitive tasks, both analytical (+0.88 st.dev.) and interpersonal (+0.41 st.dev.), than non-teleworkable occupations. The greatest differences are observed along non-routine manual physical (teleworkable is 1.33 st.dev. less) and routine manual (teleworkable is 1.16 st.dev. less) dimensions. The right panel shows that low-contact-intensity occupations are less likely to be classified as non-routine cognitive (interpersonal), routine cognitive, routine manual, and non-routine manual physical than high-contact-intensity occupations. Medium-contact-intensity occupations are not significantly different from high-contact-intensity occupations except non-routine cognitive (interpersonal) dimension. Furthermore, Figure 1 demonstrates that teleworkable occupations and occupations of lower contact intensity are more likely to be offshorable and require greater use of the computer. 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).

In comparison with the results of Foote and Ryan (2015) for the Great Recession, job losses during the COVID-19 economic downturn do not seem to be 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.

Our 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.

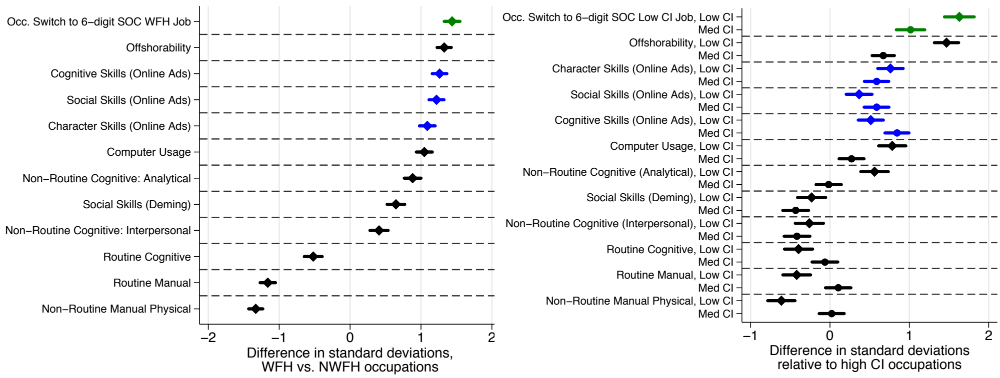

Figure 1: Left panel — Difference between characteristics of teleworkable (WFH) and non-teleworkable (NWFH) occupations. Right panel — Difference between characteristics of low-contact intensity (low CI)/medium-contact-intensity (medium CI) occupations and high-contact-intensity (high CI) occupations

Note: 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. We use black color for results obtained from O*NET data, blue color for results obtained from Gartner TalentNeuron online vacancy posting data, green color for results obtained from Schubert et al. (2020) data. For results in black and blue, the occupations are defined at the O*NET SOC level. For results in green, the occupations are defined at the 6-digit SOC level.

We turn to the differences in skill requirements. A fraction of individuals who lost their non-teleworkable or high-contact-intensity 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. 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, see Lise and Postel-Vinay (2020).

Table 3: 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	

Note: We use 2014-2018 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 wages are adjusted for inflation to 2012 dollars using the personal consumption expenditures (PCE) price index.

To address this question, we use Gartner TalentNeuron data on online vacancy ads. Table 3 contains the descriptive statistics. We divide the sample in two ways. First, we compare teleworkable and non-teleworkable occupations. Relative to non-teleworkable occupations, vacancy postings in teleworkable occupations more likely advertise full-time jobs, more likely post education and experience requirements, but less likely post a wage. Conditional on posting an education requirement, teleworkable occupations more likely require college degree. Conditional on posting an experience requirement, teleworkable occupations more likely require longer experience. Finally, teleworkable jobs significantly more likely require social, cognitive, and character skills.

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

When comparing posted full-time annual wages, we observe the following patterns. First, teleworkable occupations are, in average, offer higher wages than non-teleworkable occupations.

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Second, low-contact-intensity occupations are, in 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. When we consider the distribution, shown in Figure A.1, we see that non-teleworkable and high-contact-intensity occupations are characterized with higher posted wages at the top of it. This result is mostly driven by occupation group "Health Diagnosing and Treating Practitioners" (29-1000 SOC code).

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

Figure 1 contains the results of estimated regressions (1) and (2) for four skill measures — cognitive, character, and social from the online ads data and social from Deming (2017). Teleworkable occupations, in average, have higher requirements of cognitive, social, and character skills, than non-teleworkable occupations. Despite 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, see Weinberger (2014). The right panel of Figure 1 shows that low-contact-intensity occupations, in average, have higher requirements of cognitive and character skills, than high-contact-intensity occupations. Two measures of social skill requirements deliver the opposite results.

To summarize, we find evidence that the skill requirements between teleworkable and non-teleworkable or low- and high-contact-intensity occupations are significantly different. Teleworkable occupations have higher requirements in terms of education and experience. Furthermore, they require better cognitive, social, and character skills. This difference may matter a lot for the labor market prospects of newly 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 demonstrated 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, we document patterns in labor market transitions before the COVID-19 outbreak. We consider it at two levels of granularity, 3-digit Census OCC and 6-digit SOC classifications.

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Table 4: Distribution of labor market transitions in the United States, (%)

	All	Males	Females
From WFH to WFH occupation	38.5	32.8	44.8
From NWFH to NWFH occupation	37.6	45.3	29.1
From WFH to NWFH occupation	12.4	12.0	12.9
From NWFH to WFH occupation	11.5	9.9	13.3
From unemployment to WFH occupation	39.7	32.0	46.3
From unemployment to NWFH occupation	60.3	68.0	53.7
From low PP to low PP occupation	37.1	40.2	33.7
From high PP to high PP occupation	27.3	20.9	34.4
From high PP to low PP occupation	18.9	20.9	16.6
From low PP to high PP occupation	16.7	18.0	15.3
From unemployment to low PP occupation	45.8	50.3	41.9
From unemployment to high PP occupation	54.2	49.7	58.1

Note: We use 2019 Annual Social and Economic Supplement of the Current Population Survey data 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). To obtain the results, we use ASEC individual weights.

We use CPS ASEC data to document the distribution of labor market transitions between 2018 and 2019. Consider the teleworkability-based classification of occupations. The upper panel of Table 4 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 11.5 percent of the total occupational mobility. The distributions for males and females follow a similar pattern. Turning to unemployment-to-employment transitions, we see that about 60 percent of newly-hired individuals work in non-teleworkable occupations. This result is mostly driven by male workers. Next, we turn to physical-proximity-based classification of occupations. The lower panel of Table 4 demonstrates that 35.6 percent of switches occur between low-physical-proximity and high-physical-proximity groups. Women demonstrate smaller between-group mobility than men, 31.9 percent against 39.7 percent. The fraction of switches from high-physical-proximity to low-physical-proximity occupations accounts for 18.9 percent of the total occupational mobility. Among the unemployment-to-employment transitions, about 55 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, we show that the patterns documented in Table 4 were stable over the last decade, see Figure O.7.

Next, we use the data on occupation-to-occupation transitions, defined at the finer 6-digit SOC level, from Schubert et al. (2020). We should note that the results for this dataset, shown in Tables A.2 and A.3, are not directly comparable to those from Table 4. The first reason is that Table 4 shows the results for labor market mobility between 2018 and 2019, while the data from Schubert et al. (2020) contains occupation-to-occupation transitions averaged over all observations over starting years 2002-2015. Second, we use different classifications of occupations: in Table 4 we use the classification from Mongey et al. (2020), while in Tables A.2 and A.3 we use the classifications from Dingel and Neiman (2020) and Leibovici et al. (2020). Finally, the finer level of granularity implies that in the data from Schubert et al. (2020) we observe more job-to-job transitions within broader categories (e.g., defined by 3-digit Census OCC) that are not observed in the CPS data. Besides that, it is still instructive to document two observations. First, from Table A.2, about 45 percent of occupational switches occur between teleworkable occupations, while the remaining 55 percent is almost evenly distributed between the other types of transition. Second, from Table A.3, most of occupational switches are concentrated in low- and medium-contact-intensity occupations. Workers more rarely switch from or to the occupations that require high contact intensity at the workplace. Green markers in Figure 1 illustrate that (i) if a worker has a teleworkable occupation, then, conditional on switching, they more likely switch to another teleworkable occupation than if they had a non-teleworkable occupation, and (ii) if a worker has low- or medium-contact-intensity occupation, then, conditional on switching, they more likely switch to a low-contact-intensity occupation than if they had a high-contact-intensity occupation.

To draw a line under our empirical findings, we consider correlations between continuous measures of teleworkability (WFH Index) and contact intensity (CI Index) and the other characteristics of occupations. Table A.4 contains the results. Teleworkability is positively correlated with the measures of computer usage, social, cognitive, and character skills. Furthermore, conditional on occupational switch, the level 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.

We conclude this section by emphasizing that teleworkable and low-contact-intensity occupations significantly differ along multiple characteristics, namely skill requirements and task content, from non-teleworkable and high-contact-intensity occupations respectively. 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. Our findings have important 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, see Guvenen et al. (2017), strengthens our arguments even further. Study of

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optimal policies that can provide insurance against short-run and long-run losses is an important avenue for future research. We 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

We study how the nature of work — teleworkability and contact intensity — shapes the distribution of health, labor income, and unemployment risks, created by the COVID-19 pandemic. To answer this question, we consider two contexts. First, we show that the existing spousal nature-of-work-based occupational sorting in the United States matters for the distribution of these risks. In particular, we show that it mitigates the risk of catching COVID-19 through intra-household contagion relative to the case of zero sorting. Next, we show that it creates a larger fraction of couples, who are excessively exposed to labor income and unemployment risks, relative to the case of zero sorting. Second, we document a significant differences in skill requirements between teleworkable and non-teleworkable as well as low- and high-contact-intensity occupations. Teleworkable occupations require higher education and experience levels as well as greater cognitive, social, character, and computer skills relative to non-teleworkable occupations. This discrepancy increases the likelihood of skill mismatch for workers who lost their 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. Our 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.

While in the text we briefly discuss several policy implications that follow from our 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, see Bloom et al. (2015) for a recent contribution to this topic. 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).*

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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

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

Table A.2: Distribution of occupational switches in the United States: teleworkable and non-teleworkable occupations, (%)

	To WFH	To NWFH	Total
From WFH	45.8	16.4	62.2
From NWFH	20.5	17.2	37.8
Total	66.3	33.7	100

Note: We use the data from Schubert et al. (2020) to construct this table. Occupations are defined at the 6-digit 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.

Table A.3: Distribution of occupational switches in the United States: low-, medium-, and high-contact-intensity occupations, (%)

	To low CI	To medium CI	To high CI	Total
From low CI	16.2	16.2	3.0	35.4
From medium CI	18.9	23.2	6.1	48.2
From high CI	4.7	7.7	4.1	16.5
Total	39.7	47.1	13.2	100

Note: We use the data from Schubert et al. (2020) to construct this table. Occupations are defined at the 6-digit SOC level. The classification of occupations in terms of contact intensity (low/medium/high CI) 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. Percentages may not add up to 100% due to rounding.

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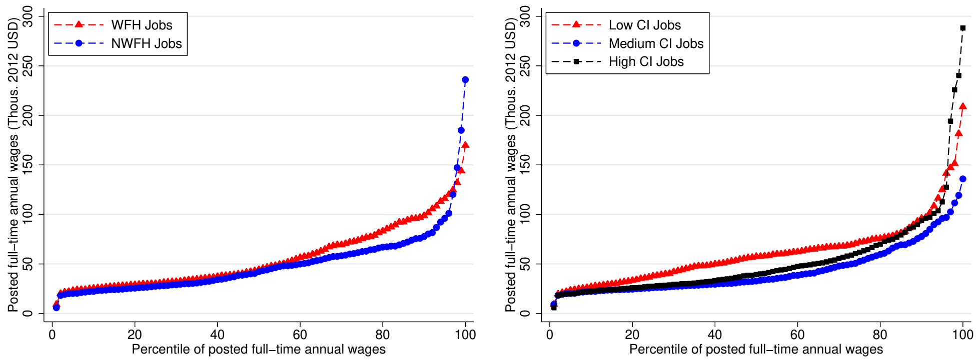
Table A.4: Correlations for continuous measures of teleworkability and contact intensity

	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)	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
Transition to a new WFH job	0.81	0.73
Transition to a new low CI job	0.58	0.66

Note: Construction of WFH Index (WFH stands for "work-from-home") and CI Index (CI stands for "contact intensity") 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 of task content (lines 3-8) is described in Section 2.3. Construction of measures of skill requirements (lines 9-12) is described in Section 2.4. Transition probabilities (lines 13-14) are calculated using the data from Schubert et al. (2020). For lines 1-12, correlations are calculated using occupations at the O*NET SOC level. For lines 13-14, correlations are calculated using occupations at the 6-digit SOC level, and we use WFH Index and CI Index for the starting occupations. Correlations in lines 10-12 are calculated using the number of posted ads for each O*NET SOC occupation as weights.



(a) Teleworkability classification

(b) Contact intensity classification

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

Note: We use 2014-2018 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 (low/medium/high CI) 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.

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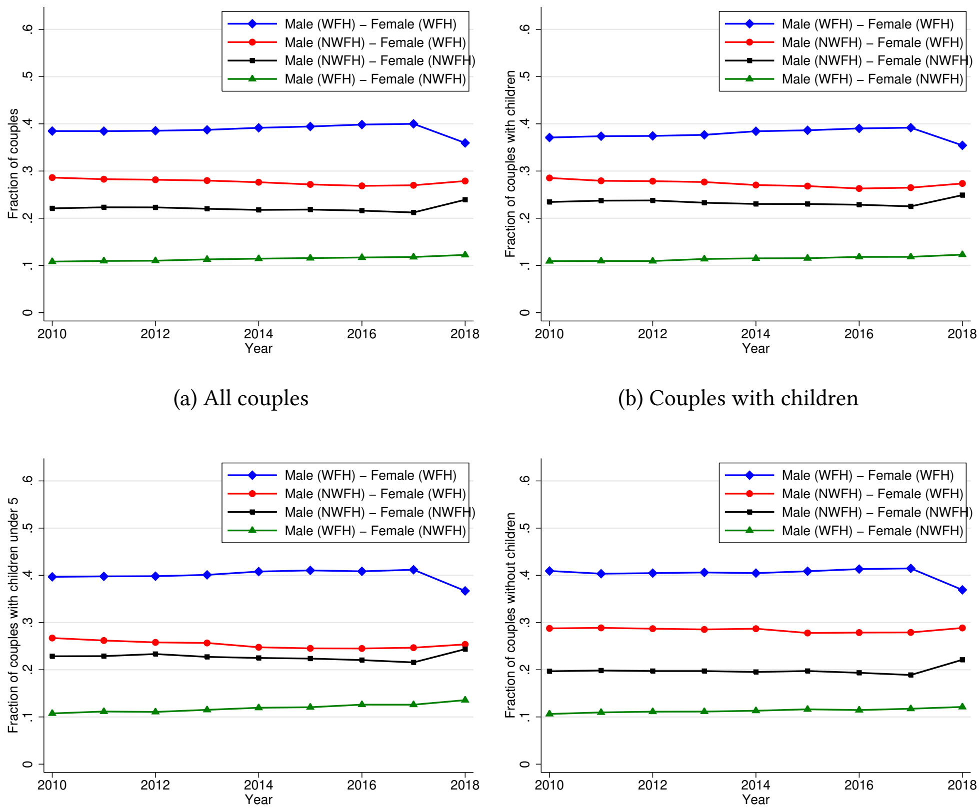
Online Appendix



(a) All couples

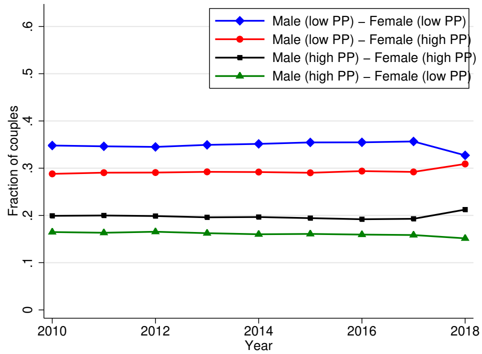
(b) Couples with children

(c) Couples with children under 5

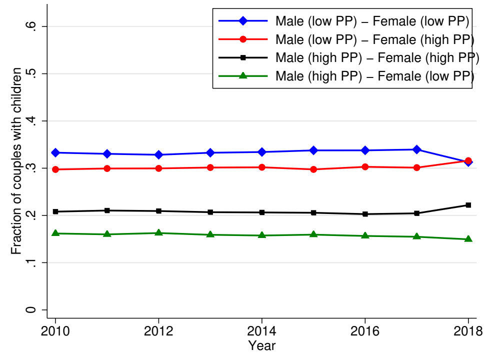
(d) Couples without children

Figure O.1: Distribution of WFH/NWFH occupations within dual-earner married couples

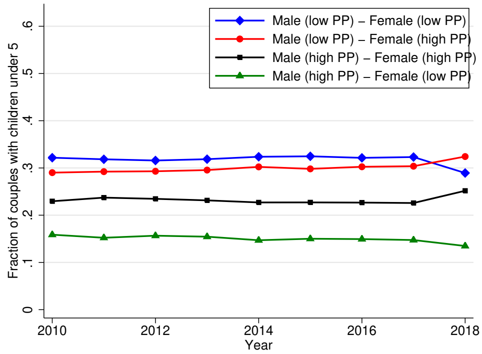
Note: We use 2010-2018 American Community Survey data to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Mongey et al. (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (not-work-from-home) stands for non-teleworkable occupations. To obtain the results, we use household weights provided by IPUMS.



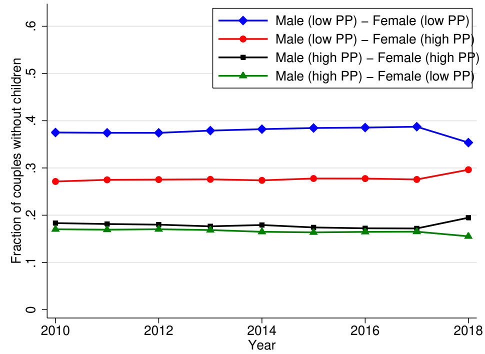
(a) All couples



(b) Couples with children



(c) Couples with children under 5



(d) Couples without children

Figure O.2: Distribution of low PP/high PP occupations within dual-earner married couples

Note: We use 2010-2018 American Community Survey data 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 close physical proximity at the workplace. High PP (high-physical-proximity) stands for occupations that require close physical proximity at the workplace. To obtain the results, we use household weights provided by IPUMS.

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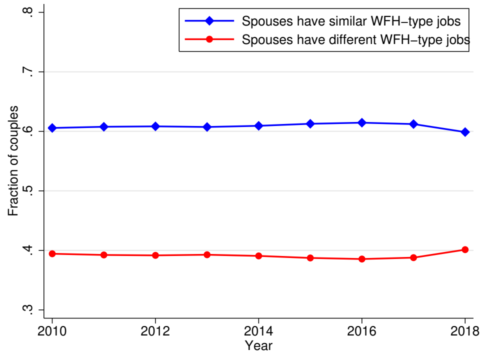
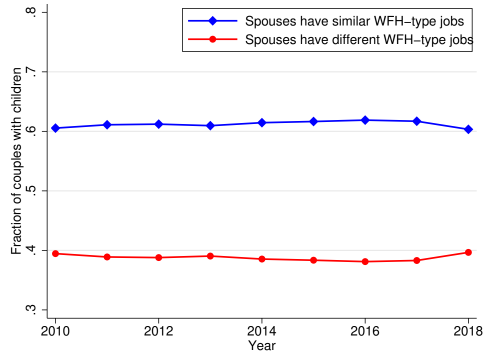
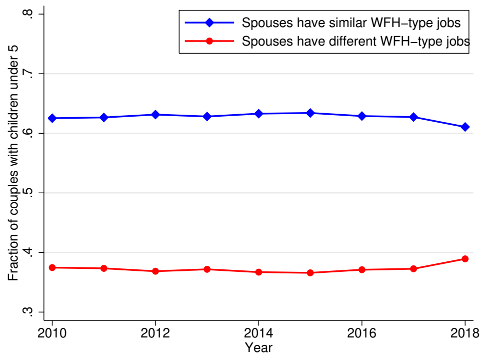


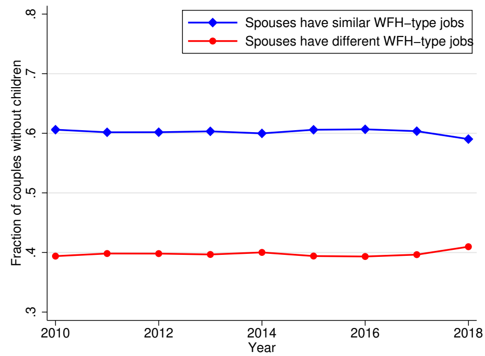
(a) All couples



(b) Couples with children



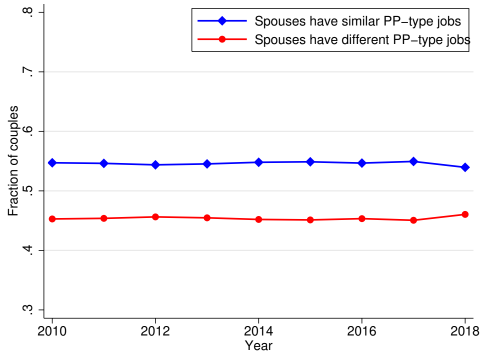
(c) Couples with children under 5



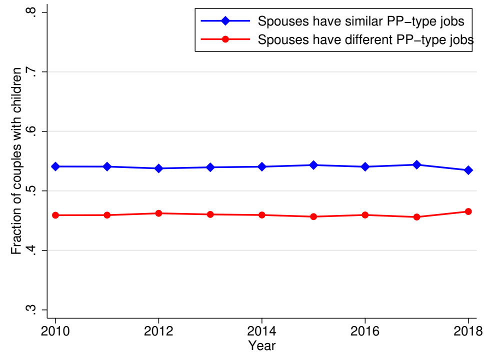
(d) Couples without children

Figure O.3: Fraction of dual-earner married couples where spouses have similar/different WFH-type jobs

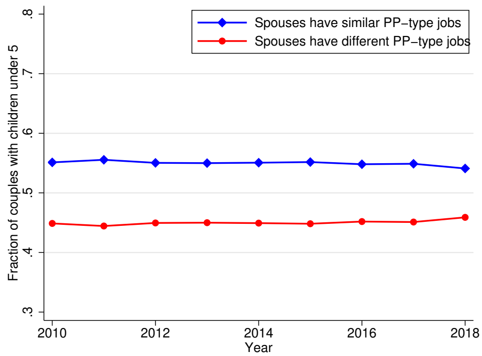
Note: We use 2010-2018 American Community Survey data to construct these figures. Occupations are defined at the 3-digit Census OCC level. The classification of occupations in terms of teleworkability (WFH/NWFH) is from Mongey et al. (2020). WFH (work-from-home) stands for teleworkable occupations. NWFH (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. To obtain the results, we use household weights provided by IPUMS.



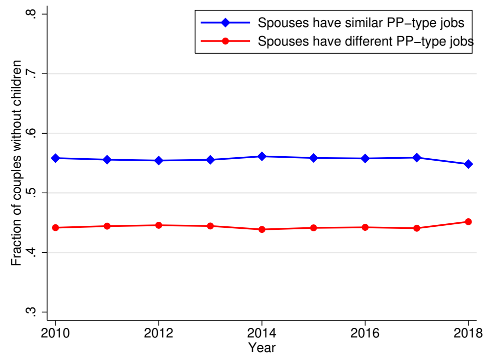
(a) All couples



(b) Couples with children



(c) Couples with children under 5



(d) Couples without children

Figure O.4: Fraction of dual-earner married couples where spouses have similar/different PP-type jobs

Note: We use 2010-2018 American Community Survey data 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 close physical proximity at the workplace. High PP (high-physical-proximity) stands for occupations that require close physical proximity 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. To obtain the results, we use household weights provided by IPUMS.

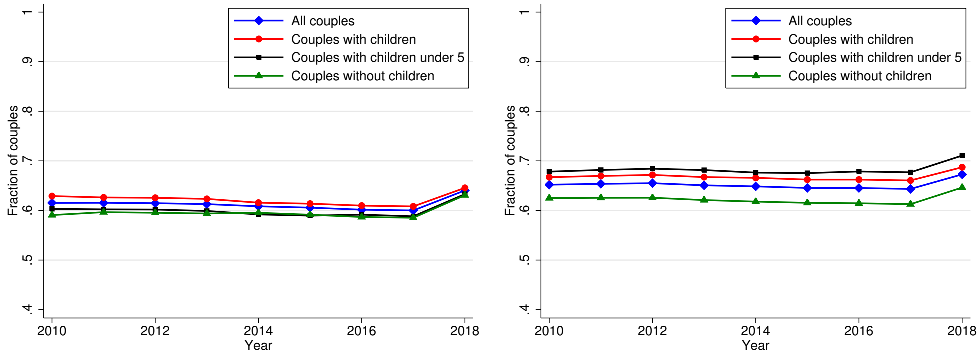


Figure O.5: Left panel — Fraction of dual-earner married couples where at least one spouse cannot work from home (has NWFH job). Right panel — Fraction of dual-earner married couples where at least one spouse should work in physical proximity (has high PP job)

Note: We use 2010-2018 American Community Survey data 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). To obtain the results, we use household weights provided by IPUMS.

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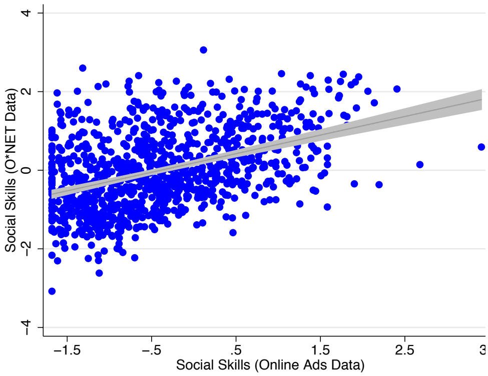
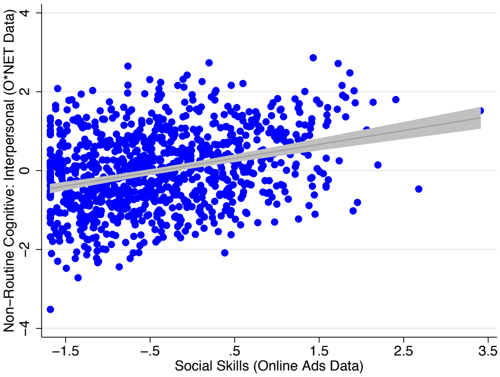
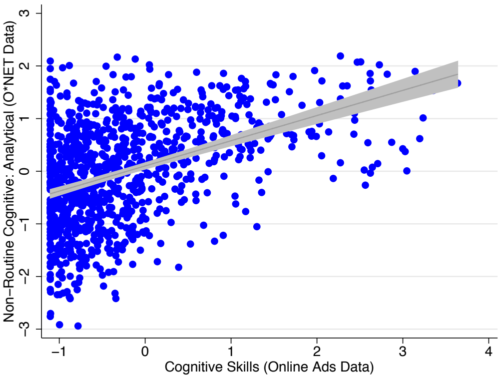


(a) Social skills



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



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

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

Note: Blue dots represent occupations defined at O*NET SOC level. The grey shaded area represents the 95% confidence interval. In these figures, we 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 O.6a, corresponds to the measure used by Deming (2017). Non-routine cognitive measures, interpersonal and analytical, from O*NET data, used in Figure O.6b and Figure O.6c, correspond to the measures proposed by Acemoglu and Autor (2011).

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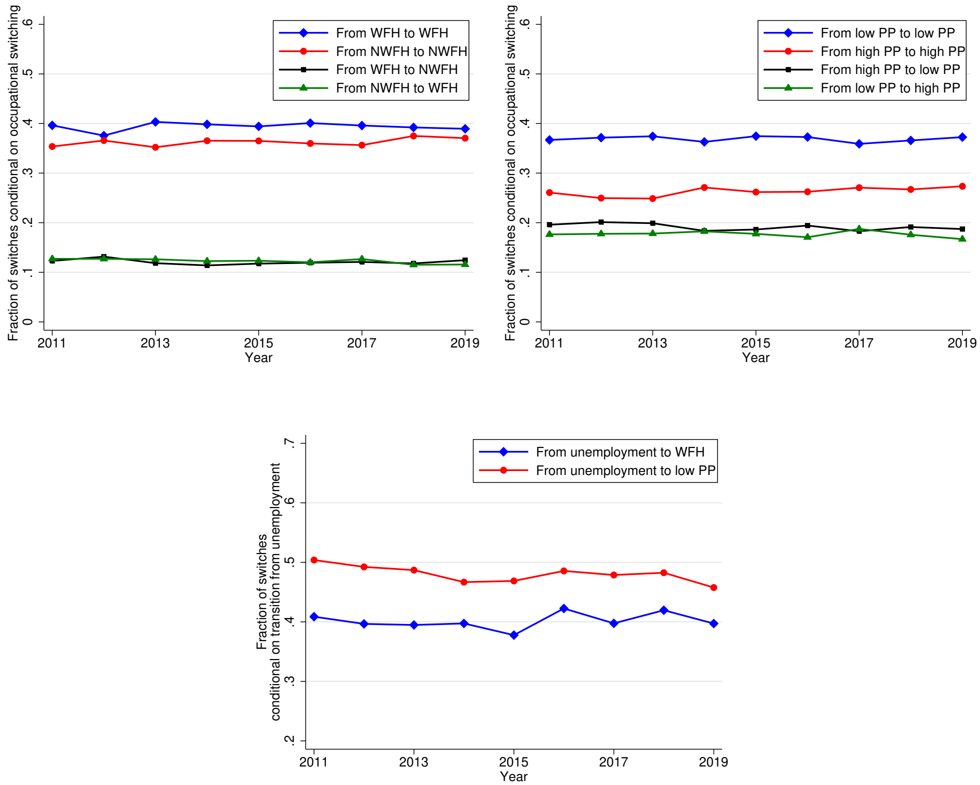

Figure O.7: Left upper panel — Distribution of occupational switching over teleworkable (WFH) and non-teleworkable (NFWH) occupations. Right upper panel — Distribution of occupational switching over occupations that require (high PP) and do not require (low PP) close physical proximity at the workplace. Bottom panel — Distribution of unemployment-to-employment transitions

Note: We use 2011-2019 Annual Social and Economic Supplement of the Current Population Survey data 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). To obtain the results, we use ASEC individual weights.

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