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On Covid-19: New Implications of Job Task Requirements and Spouse's Occupational Sorting

Warn N. Lekfuangfu, Suphanit Piyapromdee, Ponpoje Porapakkarm and Nada Wasi*

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Abstract

The Covid-19 pandemic has disrupted working life in many ways, the negative consequences of which may be distributed unevenly under lockdown regulations. In this paper, we construct a new set of pandemic-related indices from the Occupational Information Network (O*NET) using factor analysis. The indices capture two key dimensions of job task requirements: (i) the extent to which jobs can be adaptable to work from home; and (ii) the degree of infection risk at workplace. The interaction of these two dimensions help identify which groups of workers are more vulnerable to income losses, and which groups of occupations pose more risk to public health. This information is crucial for both designing appropriate supporting programs and finding a strategy to reopen the economy while controlling the spread of the virus. In our application, we map the indices to the labor force survey of a developing country, Thailand, to analyze these new labor market risks. We document differences in job characteristics across income groups, at both individual and household levels. First, low income individuals tend to work in occupations that require less physical interaction (lower risk of infection) but are less adaptable to work from home (higher risk of income/job loss) than high income people. Second, the positive occupational sorting among low-income couples amplifies these differences at the household level. Consequently, low-income families tend to face a disproportionately larger risk of income/job loss from lockdown measures. In addition, the different exposure to infection and income risks between income groups can play an important role in shaping up the timing and optimal strategies to unlock the economy.

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1. Introduction

Unlike previous economic shocks, Covid-19 has disrupted labor markets around the world along two new dimensions. First, workers in certain jobs are at higher risk of infection and transmission, particularly those working in close physical proximity to other people. Second, workers whose jobs are not adaptable to work from home may have a higher risk of income loss due to drastic measures (e.g. sectoral lockdowns and social distancing) to curb the spread of virus. Identifying the tradeoffs between the risks of economic loss and public health across occupations is essential to understanding the potentially heterogeneous impact across workers of Covid-19 and policies designed to contain it. At the household level, such risks may be intensified if both spouses sort into similar occupations, and so face common shocks. Socially desired exit strategies require a substantial balance between pandemic containment and economic burdens – both of which may involve rather different sets of stakeholders.

In this paper, we exploit the information on job task requirements of each occupation from the Occupational Information Network (O*NET) to construct a set of new pandemic-related indices using factor analysis. Specifically, these indices measure (i) the degree of job flexibility in terms of work location (due to job reliance on machinery or specific location; and adoption of ICT into task performance), and (ii) the extent to which jobs require the worker to perform tasks in close physical proximity with others. We show that these statistically-constructed indices can represent two important risks posed by the Covid-19 pandemic on workers: the risk of earnings losses when a worker is away from their regular workplace, and the risk of contracting or spreading the virus at the workplace.

Further, the interactions of these indices along the earnings distribution can be informative for designing programs to support different groups of affected workers as well as strategies to reopen the economy. For example, workers who cannot adapt to work from home may require more support than those who can, especially if work location flexibility is negatively correlated with earnings. On reopening the economy, the debate is around how to minimize the economic losses while controlling the spread of the virus. Our analysis suggests that workers in jobs which are not adaptable to work from home, but do not require frequent physical contact with others, should be allowed to return to their workplaces first. On the other hand, those who usually work in close physical proximity to others, but whose jobs are well-suited to work from home, may be the last to return to normalcy.

As an application, we focus our analysis of the impact of the pandemic on a developing economy. With relatively low social safety nets and large shares of workers in the informal sector with weak labor protections, workers in developing countries stand a higher risk of earnings loss in the presence of a global economic and public health crisis such as the Covid-19 pandemic. To investigate such potential impact, our analysis focuses on Thailand.¹ We map the latest release of Thailand's Labor Force Survey (2019) with the O*NET-derived indices, and evaluate the labor market risks arising from the Covid-19 crisis at both individual and household levels.² In developing countries, risk-sharing within households plays a central role in absorbing shocks (e.g., Chiappori et al. 2014, Samphantharak and Townsend

¹ Despite the relatively few Covid-19 cases at present, Thailand was one of the countries with the highest number of Covid-19 cases outside China at the onset of the crisis (January 2020), owing to the largest number of daily direct passenger flights from Wuhan. By mid-March of 2020, the Thai government declared a state of emergency – with the implementation of strict sectoral lockdown regulations, and social distancing practice.

² The structure variable definitions and survey conduct in the Thai Labor Force Survey are analogous to the European Union's Labor Force Survey (EU LFS) and the US's Current Population Survey (CPS). We use the third quarter data because it includes seasonal workers. Workers included in the LFS work in both formal and informal employment (defined by social security and health insurance status), as well as those in agricultural sector.

2018). Therefore, if Covid-19 exposes both primary earners in a household to common shocks, the impact on their livelihoods can be severe. Insights from our analysis on Thailand are highly relevant for other countries with similar labor market structures – specifically, a relatively large share of self-employment and low social safety net.

First, we document that there are noticeable differences in occupational indices among individuals from different income groups. Specifically, people with lower earnings tend to face a lower infection risk at the workplace, but a higher risk of income or job losses due to the difficulty in adjusting their working arrangement following a sectoral lockdown. Second, the occupational sorting within married couples reinforces these differences at the household level. Married couples from the lower end of earnings distribution are much more likely to sort into occupations with similar indices, and are highly concentrated in jobs not adaptable to work from home. In effect, earnings within low-income households are highly correlated, which can lead to large losses in household income during the lockdown regulations. This suggests that means-tested emergency relief programs would be more suitable than universal support programs in terms of targeting those working in most adversely affected occupations.

This paper is closely related to works studying the labor market consequences of lockdown measures using occupational characteristics. Hicks (2020) recently uses the O*NET data on the degree of physical proximity to assess which occupations are more likely to be affected. Focusing on work flexibility characteristics, Dingle and Neiman (2020) and del Rio-Chanona et al. (2020) manually classify occupations into a binary variable whether they can be performed at home.³ Our main contribution is to show that (i) physical proximity, (ii) work-location flexibility and (iii) their interactions are crucial for impact evaluation and policy design in response to the pandemic. Our work is directly complementary to Adams-Prassl et al. (2020) which provides evidence from real-time surveys that workers with limited work arrangement are highly exposed to less favorable job outlooks. Additionally, we complement the assortative mating literature by showing that the labor market risk induced by Covid-19 at the household level can be mitigated or amplified depending on the occupational sorting pattern between husbands and wives.

The paper proceeds as follows: Section 2 describes how the indices are constructed using the O*NET. Section 3 applies the indices to evaluate labor market risks at individual and household levels in the Thai context. Section 4 discusses policy recommendations and Section 5 concludes.

2. Methodology

We select 24 task-based occupational variables from the O*NET data on ‘Work Context’ and ‘Work Activities’ to capture (i) the extent to which a job can be done at home, and (ii) whether a job requires working in close proximity with other people. The latter group of characteristics is particularly important for policy decision-making during the pandemic as the virus can easily be transmitted from person to person. (See the Appendix for the list of the selected O*NET variables.)

To reduce the dimensionality of the O*NET variables, we perform an exploratory factor analysis with rotation method to establish a factor retention criterion. We impose oblique rotation of factor loadings

³ Other papers using task characteristics to classify occupations to evaluate structural changes of labor markets include seminal work by Autor and Dorn (2013) and Blinder (2009).

to allow for correlation between the factors (Heckman et al., 2013). We retain three factors with eigenvalues greater than 2, following the criteria outlined by Gorsuch (1988).⁴ Table A1 in the Appendix presents the factor loadings on the predicted factors. A larger factor loading (in absolute terms) reflects higher correlation between the selected O*NET variable and the factors. The factors are standardized to have mean zero and standard deviation one.

The first factor encapsulates tasks related to repairing, maintaining, or inspecting equipment, structure or materials and operating vehicles or mechanized devices. Thus, we interpret this factor as a measure of both machine and location dependence of jobs. The second factor captures tasks that frequently utilise ICT - for example interacting with computer, analyzing data or processing information. The last factor captures whether the job often requires workers to perform tasks in close physical proximity to other people or to assist or care for others. For conciseness, in the rest of the paper, we will refer to these factors as indices for ‘machine-dependent’, ‘ICT-enabled’ and ‘physical proximity’, respectively.

We compute the three factor indices for over 900 detailed six-digit occupations (based on the US SOC 2010). We present a selected list of occupations with the highest and lowest scores in each factor in the Appendix. Note that the partial correlations of machine-dependent and ICT-enabled; machine-dependent and physical proximity; and ICT-enabled and physical proximity among the occupation list in the O*NET database are -0.40, 0.05, and 0.16 respectively. Small and statistically insignificant correlations of machine-dependent and physical proximity of occupations suggest that a lockdown restriction in response to the pandemic crisis may involve a trade-off along multiple dimensions, e.g. saving jobs versus preventing infection. The effects of the Covid-19 shock on jobs are therefore likely to be quite different from other economic shocks in past recessions.

Table 1 summarizes the average indices of the three factors derived from the O*NET by the broad occupation groups in columns 2, 3 and 5. While machine-dependent and ICT-enabled are separate factors, the ease of shifting work location from ‘office’ to home are highly depended on both factors in opposing directions.⁵ To ease our analysis, we also report an equally-weighted average of the scores of machine-dependent (reversed) and ICT-enabled factors in column 4, and refer to the additional index as the score of overall work-location flexibility. Broadly speaking, managers and professionals have relatively high degrees of work-location flexibility. Service and sale workers have the highest average indices of physical proximity.

The last three columns compare occupational compositions of workers in Thailand, EU-27 and the U.S. While the occupational shares of EU-27 and the U.S. are similar, the shares of Thailand reflect a common pattern of a middle-income economy – relatively large agricultural and manufacturing sectors with a lower share of workers in the high skill service sector (e.g. managers, professionals, technicians, and associated professionals).

Our analysis draws attention to the interaction between the degree of work-location flexibility and close physical proximity. While a lack of work-location flexibility indicates the risk of income losses due to the inability to work during a lockdown, the physical proximity factor emphasizes the risk of virus infection and transmission in performing such tasks. In the event of a pandemic, performing such tasks

⁴ Statistical criteria for factor retention include the Scree Test, Onatski’s Test and Horn’s Test.

⁵ For instance, a market research survey interviewer has a low index of machine-dependent, but because interviews were typically done face-to-face before the pandemic, this occupation is associated with a low score of ICT-enabled. Without ICT infrastructure, it is unlikely that these interviewers could easily perform their work from home.

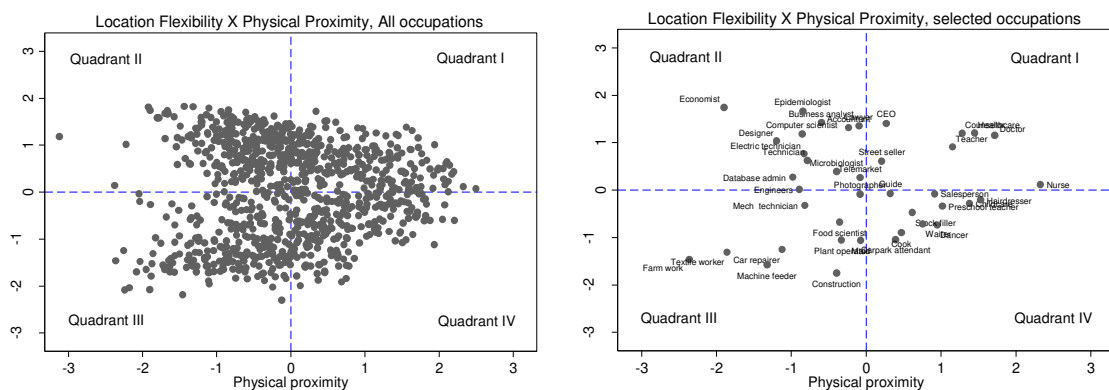
is seriously discouraged; therefore, jobs with a high value of physical proximity index may also be exposed to income losses.

Table 1. Average Score of Factors and Occupational Distribution

| Occupational Groups (1 Digit) | Work Location-Flexibility Indices | | | Physical Proximity | Share of workers, 2019 (%) | | |
|--|-----------------------------------|---------------------|-----------------------|--------------------|----------------------------|-------|----------|
| | i. Machine-Dependent (-) | ii. ICT-Enabled (+) | Average of [-2] & [3] | | US | EU-27 | Thailand |
| [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| 1. Managers | -0.22 | 0.87 | 0.67 | 0.56 | 11.07 | 4.23 | 3.66 |
| 2. Professionals | -0.73 | 0.66 | 0.85 | -0.01 | 22.65 | 19.38 | 5.41 |
| 3. Technicians and associate professionals | 0.09 | 0.35 | 0.16 | 0.33 | 14.28 | 17.81 | 4.32 |
| 4. Clerical support workers | -0.74 | -0.14 | 0.36 | 0.09 | 9.89 | 10.89 | 4.42 |
| 5. Service and sales workers | -0.16 | -0.61 | -0.28 | 0.79 | 17.89 | 16.69 | 20.06 |
| 6. Skilled agricultural, forestry, fishery workers | 0.99 | -0.92 | -1.17 | -0.86 | 0.17 | 0.95 | 31.50 |
| 7. Craft and related trades workers | 0.73 | -0.98 | -1.05 | -0.41 | 8.38 | 11.53 | 10.59 |
| 8. Plant and machine operators, assemblers | 1 | -1.23 | -1.36 | -0.59 | 5.76 | 8.54 | 9.40 |
| 9. Elementary occupations | 0.54 | -1.25 | -1.09 | -0.35 | 9.90 | 9.97 | 10.64 |

Note: The indices are standardized to have mean zero and standard deviation one. Source: EU-27 occupational shares come from EU Statistics, US shares come from Bureau of Labor Statistics, and Thailand shares come from Thai Labor Force Survey.

Figure 1: Occupation Classification



Note: Factors are standardized to have mean zero and standard deviation one.

Figure 1 depicts the interactions between these two indices. The vertical axis represents the degree of work-location flexibility, and the horizontal axis shows the degree of physical proximity. The left panel illustrates that the 968 occupations from O*NET are distributed across all the quadrants. The right panel shows a selected list of occupations in each quadrant. Workers with occupations in quadrant IV (bottom-

right) are arguably the most vulnerable group with respect to both income losses and getting infected at workplaces because they have relatively low degree of work-location flexibility and high degree of physical proximity. Workers with occupations in quadrant III (bottom-left) are also limited in their work arrangements but have jobs with less physical contact and correspondingly lower infection risk at their workplaces. Those in quadrants I and II (top-right and top-left) have jobs which are more flexible. We discuss the policy implications in more detail in Section 4.

3. Evaluating the New Labor Market Risks

Our analysis focuses on measuring supply-side labor market risks associated with various measures to slow down the infection rates. These include closing businesses in some or most sectors and requiring non-essential workers to work from home. We focus our study on potential labor market risks at occupation level using our occupation classification.⁶ Our case study is based on Thailand. Despite the relatively low official number of infections, the country mobilized to slow down the outbreak of Covid-19 by imposing strict sectoral lockdowns and campaigning for social distancing in late March 2020.

In section 3.1, we analyze the potential risks at the individual level. In section 3.2, we extend our analysis to households. Incorporating the role of assortative marriage, this section assesses to what extent occupational sorting of spouses amplifies or attenuates the income risk among different types of households. Insights from our analysis on Thailand are highly relevant for other countries with similar labor market structures – specifically, a relatively large share of self-employment and low social safety net. In term of marriage patterns, Thailand has seen increasing assortative marriage over the past decades, a pattern common to many developed and developing countries (see Chiappori, 2017 for a review).

We map the indices to the Thai 2019 Labor Force Survey (LFS), a quarterly nationally representative sample. For each sampling household, detailed information from all members is collected. This includes demographic characteristics, marital status, employment status, work hours, occupations and sectors. While the complete information on occupation is available for all types of workers (wage or salary workers, self-employed and unpaid workers), earnings data were collected only for wage or salary workers. For individual analysis, we restrict the sample to workers aged between 15 and 65 years old. For household analysis, we further use the subsample of married couples.

3.1 Individual Heterogeneity

Table 2 reports the average indices across genders, age groups and education levels. On average, occupations held by older and lower educated workers tend to be more machine-dependent, less ICT-enabled, and have a lower degree of close physical proximity. On average, jobs held by Thai men are less flexible but require less physical contact than jobs held by Thai women. This is because a higher proportion of men work as assemblers or machine operators in factories and agricultural activities, while a higher proportion of women are in sales and services.

⁶ Because the actual lockdown sectors differ across countries, we do not explicitly incorporate the sectoral lockdown to analyze the labor market risks. See a companion analysis in Lekfuangfu et al. (2020), where we documented the differences in the lockdown sectors in Thailand and European countries.

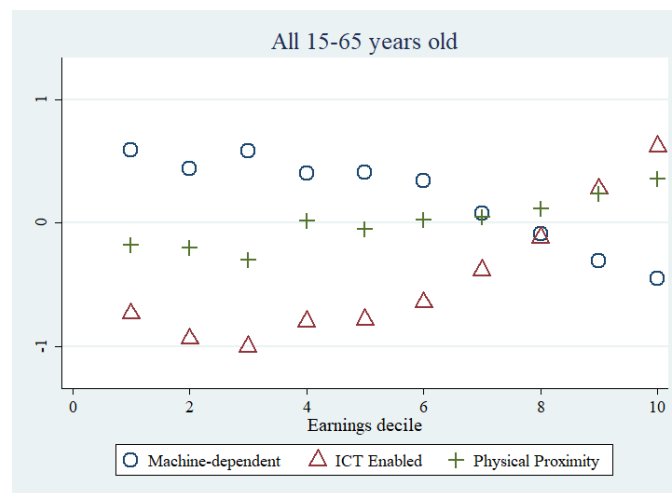
Table 2. Average Factors by Worker Characteristics

| | Work-Location Flexibility Indices | | | Physical Proximity | Total number of workers (millions, %) |
|-------------------------|-----------------------------------|---------------------|---------------|--------------------|---------------------------------------|
| | i. Machine-Dependent (-) | ii. ICT-Enabled (+) | Average Index | | |
| National | 0.41 | -0.61 | -0.62 | -0.25 | 37.3 |
| Gender | | | | | |
| Male | 0.60 | -0.59 | -0.73 | -0.30 | 20.4 (55%) |
| Female | 0.17 | -0.63 | -0.49 | -0.19 | 17.1 (45%) |
| Age groups | | | | | |
| 15-25 | 0.41 | -0.75 | -0.71 | -0.22 | 4.3 (12%) |
| 26-35 | 0.21 | -0.51 | -0.43 | -0.09 | 8.3 (23%) |
| 36-45 | 0.31 | -0.53 | -0.51 | -0.18 | 8.7 (24%) |
| 46-55 | 0.40 | -0.61 | -0.67 | -0.39 | 8.8 (25%) |
| 56-65 | 0.62 | -0.72 | -0.82 | -0.46 | 5.5 (16%) |
| Education Levels | | | | | |
| Secondary or lower | 0.53 | -0.73 | -0.77 | -0.28 | 31.6 (85%) |
| College | -0.47 | 0.25 | 0.44 | 0.29 | 6.1 (15%) |

Notes: The indices are standardized to have mean zero and standard deviation one.

To understand how the job task requirements are mapped into earnings, **Figure 2** plots the indices across earnings deciles. Workers with lower earnings work in occupations that are more machine-dependent and less ICT-enabled, making them less flexible to work remotely. Thus, lower earning workers are more exposed to the risk of losing income during the pandemic than higher earning workers. The degree of physical proximity, however, is reversed. Lower paid workers tend to be the laborers (e.g., fixing streets, construction site) and those who work in factories whose work naturally involves less close physical interaction.

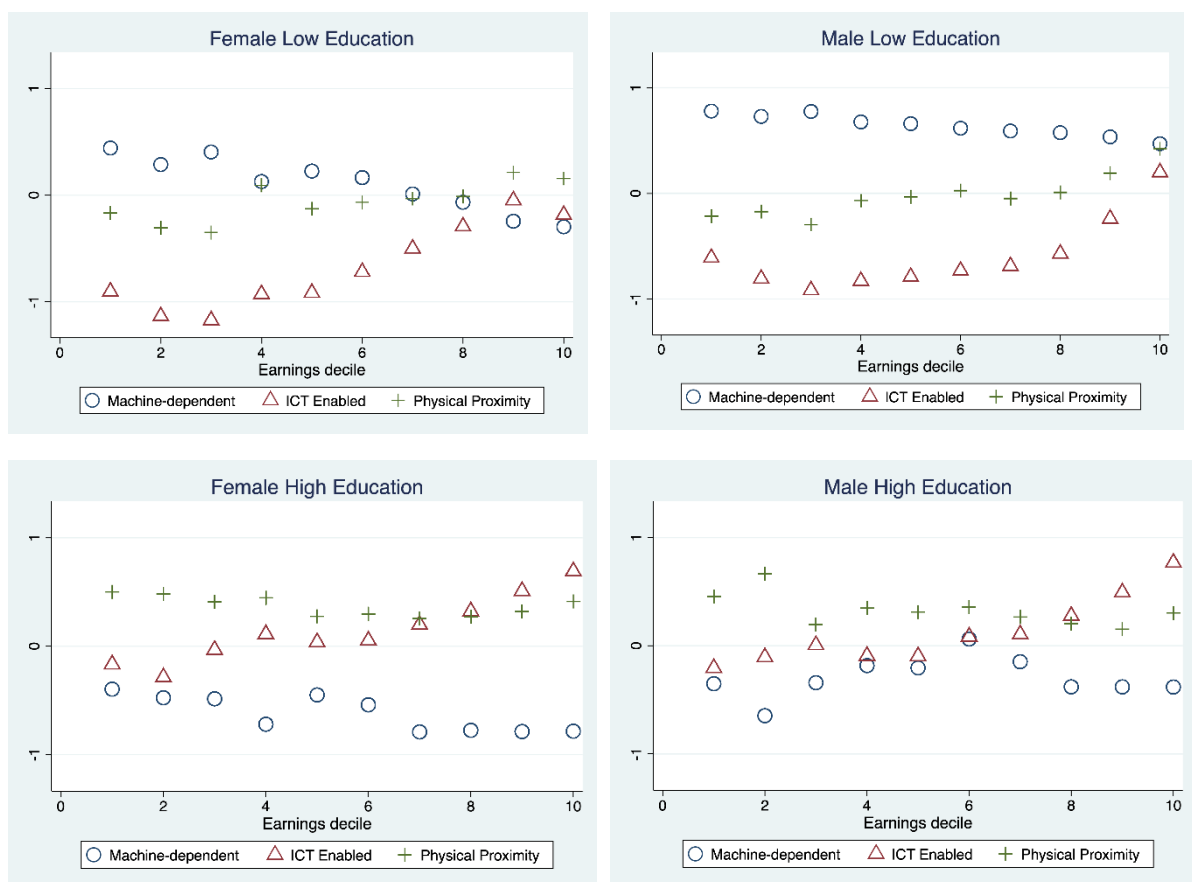
Figure 2. Work Characteristics by Earnings Decile



Notes: The figure shows average score in each factor index along the earnings distribution. The horizontal axis is the ranking position of individual wage earners on the earnings distribution of all wage earners observed in the LFS 2019, quarter 3.

Since the Covid-19 shock adversely affected people’s health and income, it creates political tensions between people from different groups which can play an important role in shaping policy in response to the crisis. Glover, et al. (2020) emphasize the tension between people outside the labor market (“the old”) and those participating in the labor market (“the young”). The old face a higher mortality risk of being infected but little (or no) earnings risk; the opposite is true for the young. Consequently, the old may prefer more drastic measures or delays to opening the economy. Our findings reveal an additional tension among workers in the labor market which has not previously been discussed. While those from a lower earnings bracket face a lower infection risk, they may endure a larger economic loss from having a lockdown imposed on them due to the difficulty in adjusting their work arrangements. Therefore, these workers would prefer an earlier removal of the lockdown. The opposite may be true for the high-income group.

Figure 3. Work Characteristics by Gender and Education



Notes: We use common earnings decile as in Figure 2.

Figure 3 plots the indices across earnings decile conditional on gender interacted with education level. There are stark differences between occupational characteristics of workers with and without a college degree along the earnings distribution. The average indices shown in Table 2 capture the characteristics of workers with at most secondary education who have a much larger share in the workforce. However, conditional on having a college degree or higher, the differences between occupations of males and females are modest. Nevertheless, the pandemic-induced risk of earnings losses at the household level depends on *the composition of the household*. That is, households with more *dissimilarity of*

occupations with respect to the flexibility to work from home and physical proximity are in a better position to smooth the negative income shock. On the other hand, households with both primary earners working in low physical proximity and flexible jobs would be best off, while households with both partners having limited work-location flexibility would face much harsher economic implications.⁷

3.2 Household’s Correlated Risks

The impact of the pandemic on individuals’ earnings discussed in the previous section can be either mitigated or magnified at the household level through occupational sorting within households. We examine this point by focusing our analysis on households in which both spouses work. To shed light on the pattern of occupational sorting, we report the correlation of each index between the husband’s and wife’s job separately for different types of households.

To account for a large share of Thailand’s informal sector (33% self-employed, 17% unpaid workers and 47% paid employees), we classify working married couples in our sample into four types as the following:

- Type A: both work as employees
- Type B: one as employee, another as self-employed
- Type C: both spouses are self-employed
- Type D: both work, and at least one works as unpaid family worker ⁸

Table 3 displays the spousal correlations of each pandemic-related index (machine-dependent, ICT-enabled, physical proximity). For households of types A and D (76.4% of total), the correlations between indices of jobs held by married couples of all three factors are highly positive. For households of type D, the spousal correlations are close to one – suggesting that most unpaid workers tend to work in the same or similar jobs as their spouses. Thus, for type D, the occupational impact at the household level would be similar to that at the individual level. For type B (one spouse is self-employed), the negative correlations of machine-dependent and physical proximity factors indicate that these households may have a higher degree of risk diversification through less assortative occupational choices.

Table 3. Married couple correlations by types of employment

| Types of households | Total married workers in millions (%) | Machine-dependent | ICT Enabled | Physical Proximity |
|---------------------------------------|--|--------------------------|--------------------|---------------------------|
| A. Both as employees | 4.1 (30) | 0.39 | 0.56 | 0.44 |
| B. One employee and one self-employed | 1.9 (15.3) | -0.05 | 0.11 | -0.03 |
| C. Both as self-employed | 1.1 (8.3) | 0.19 | 0.08 | 0.15 |
| D. One or both as unpaid workers | 6.2 (46.4) | 0.9 | 0.92 | 0.97 |
| All households | 13.3 (100) | 0.51 | 0.61 | 0.66 |

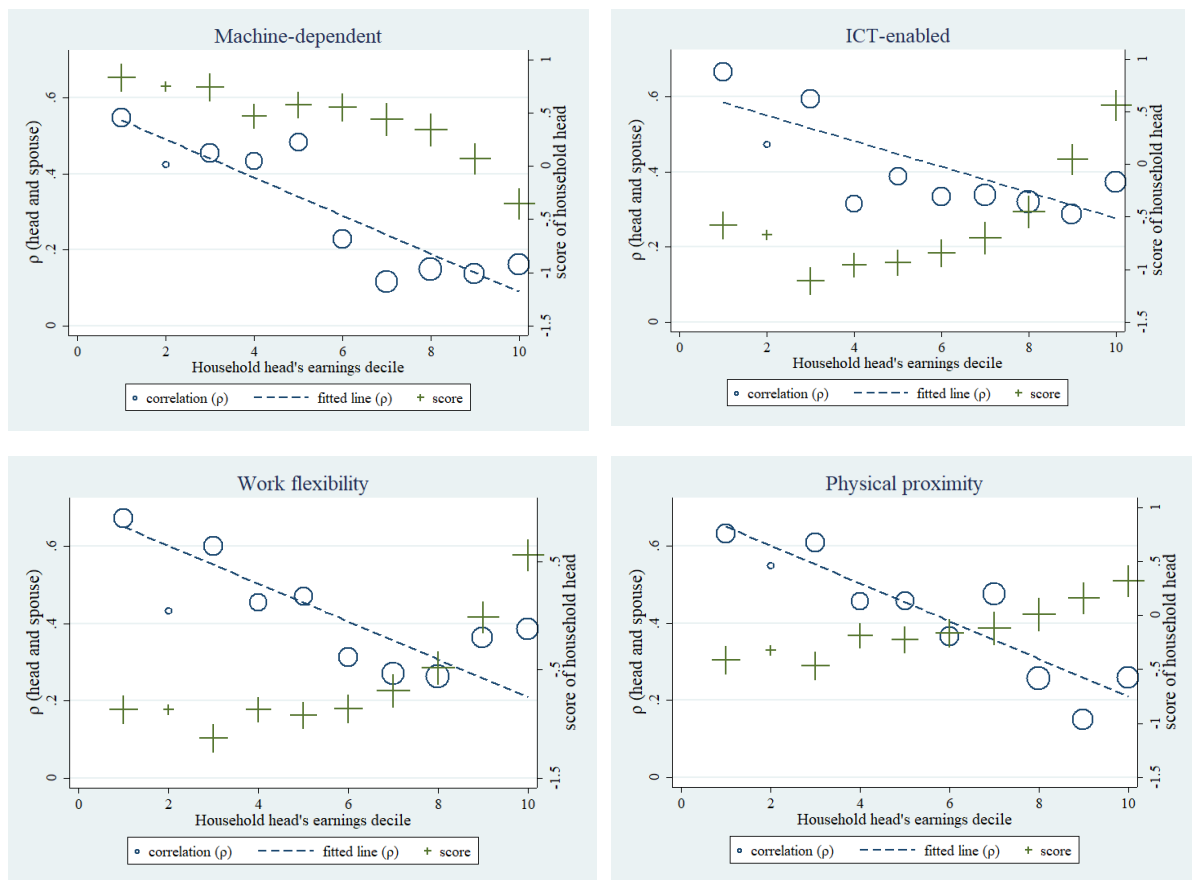
Notes: The correlations are weighted by the sum of individual survey weight of the head and of the spouse.

⁷ Moreover, other structures of households, such as whether there are young children or not, could be vital. Given school and day care closures, mothers are more likely to be affected. Being able to work from home might alleviate the impact (see Alon et al. (2020) for a discussion).

⁸ Unpaid family workers are people working without actual pay in an enterprise or farm owned by a family member.

Whether the positive spousal correlations for the job flexibility or physical proximity factors reflect the scale of labor market risk depends predominantly on the magnitude of these indices. For instance, a household is better insulated from a negative shock from lockdown measures when at least one spouse is in an occupation with a low degree of machine dependent and/or high degree of ICT-enabled - which implies a higher probability of being able to work from home. In contrast, the Covid-19 crisis could cause larger losses in household's income if both spouses lose their jobs because they cannot work from home. Moreover, the impact can substantially worsen income and consumption inequalities if such positive occupational sorting (into jobs with limited locational flexibility) is more prevalent among poor households.

Figure 4. Type A household: both are employees



Notes: The figures show spousal correlations in each factor index. The horizontal axis is the ranking position of household heads on the earnings distribution of all wage earning individuals observed in the LFS 2019 (quarter 3). On the horizontal axis, we use the common earnings decile as in Figures 2 and 3.

In what follows, we investigate the pattern of spousal correlations along the earnings distribution. We focus on households of type A for which earnings of both spouses are observed in the data. **Figure 4** depicts the spousal correlations of their occupational factor (on the left vertical axis), and the average

score of household head for a given factor (the right vertical axis).⁹ It shows that the spousal correlations are strongly positive particularly at the lower-end of the earnings distribution. This suggests that married couples from low-income households work in occupations with common levels of machine-dependent, ICT-enabled and physical proximity. Further, the size of the positive correlation decreases along the earnings decile, in particular for machine-dependent factor. These plots present compelling evidence that labor market risks due to the Covid-19 are heterogeneous across households – and that those at the bottom-end of the earnings distribution are more at risk to the pandemic shock than others.

4. Policy Implications

In response to the Covid-19 pandemic, affected countries around the world have introduced various forms of supports to aid their citizens, including emergency cash transfer programs, social assistance, in-kind food and utility and financial obligation waivers. The cash transfer programs appear to be most common with some countries launching a one-off universal transfer whereas others used a means-tested cash transfer, i.e., the cash amount is conditional on household’s income or people working in certain occupations (Gentilini et al., 2020).

In Section 3, we show that the degree of potential impacts of Covid-19 on workers depend on the two new dimensions of their job characteristics (the degrees of work-location flexibility and close physical proximity), and these impacts can be intensified by occupational sorting in marriage. Our findings can be used to guide efficient supporting schemes for different targeted groups of workers, and strategies for reopening the economy. At the time of writing, some countries announced that they have been able to slow down the virus outbreak; thus, the recent debate has shifted towards how to open up the economy without jeopardizing the public health systems.

Table 4 demonstrates examples of occupations in the four quadrants deriving from the cross-dimensionality between work-location flexibility and physical proximity (as seen in **Figure 1**). Workers with occupations in quadrant IV (bottom-right) are the most vulnerable group. Due to the high degree of close physical proximity, these jobs have been the first to be restricted, and potentially will be the last to return to normalcy. Unlike workers in quadrants I and II (top-right and top-left), workers in quadrant III (bottom-left) could ‘produce’ only if they are allowed to return to their workplaces. In fact, those in quadrant II (top-left) may experience relatively mild impacts from the lockdown measures since their jobs are more flexible and do not require frequent physical contact with others.

⁹ We define household head as the highest earner of the couple. The horizontal axis in Figure 4 represents earnings decile, calculated from all wage workers aged 15-65 years old.

Table 4: Selected occupations in four impact groups

| Work Location Flexibility | Physical Proximity | |
|---------------------------|--|---------------------------------------|
| | Low | High |
| High | Quadrant II: Mild impact | Quadrant I: Medium impact |
| | Sociologist | Human resources manager |
| | Programmer | Fitness manager |
| | Website developer | Business strategy manager |
| | Economist | Information coordinator |
| | Financial advisor | Head hunter |
| Legal councillor | Secondary school teacher | |
| Low | Quadrant III: Medium impact | Quadrant IV: Severe impact |
| | Garment factory worker | Cleaner |
| | Metal worker | Restaurant server |
| | Planter, Grower | Travel organiser |
| | Construction worker | preschool teacher |
| | Machine controller | Tour guide |
| | Production worker | Dentist |
| Painter and polisher | Veterinarian | |

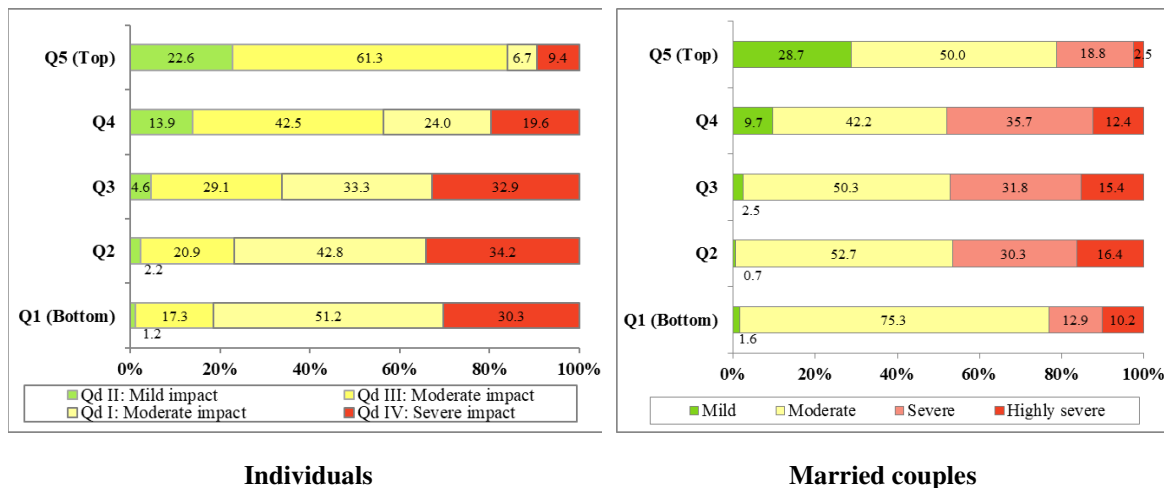
Notes: The impact level is derived based on the interactions of work location flexibility and physical proximity.

The composition of workers across the four quantiles is not equally distributed on the earnings distribution. As can be seen in the left panel of **Figure 5**, there is a substantially larger fraction of workers with occupations in quadrant IV (red) — the severely impacted group— at the lower-end of the earnings distribution. In contrast, workers at the top quintile have the largest share of jobs considered to be mildly affected by the pandemic crisis (based on our occupational classifications) in the short run. This means that without adequate government intervention to support income or employment for the poor, the adverse impact of Covid-19 could worsen income inequality.

The findings suggest that mitigation interventions should be targeted based on job characteristics when possible.¹⁰ For example, ICT-related support would assist those in quadrant I (top-right) to maintain their work activities. In contrast, the measure would be less effective for those in quadrant III (bottom-left) since their jobs are required to be performed at specific locations. In effect, potential schemes providing substitutions for income losses would be more suited for workers holding jobs in quadrants III and IV. Given that the Covid-19 pandemic is likely to disproportionately affect the low earners, the introduction of means-tested relief programs targeting those working in most adversely affected occupations, rather than a universal program, would be socially desirable.

¹⁰ In some sectors such as finance, businesses can continue without all workers being able to work from home since core and non-core activities are divisible e.g. face-to-face customer relation activities can be put on hold while main banking activities can run remotely. However, in some other sectors such as hotels and restaurants, this kind of division is unlikely to be possible. Although their managers and sales may be able to work from home, most service staff work in close physical proximity to others.

Figure 5. Fraction of the derived impact levels by earnings distribution



Notes: The left panel shows the proportion of wage earning individuals by the derived impact level (based on the interactions of work location flexibility and physical proximity) for each earnings quintile. The right panel shows the proportion of married couples in wage earning employment by the derived impact level. ‘Mild’ is for households with both spouses’ jobs in quadrant II; ‘moderate’ when no spouse’ jobs in quadrant IV; ‘severe’ when one spouse’s job in quadrant IV; ‘highly severe’ when both spouses’ jobs in quadrant IV. For both panels, the ranking position is based on the earnings distribution of all wage earning individuals observed in the LFS 2019 (quarter 3).

The above argument is reinforced when taking into account the high degree of occupational sorting among married couples at the bottom-end of the earnings distribution (as discussed in Section 3.2). The right panel in **Figure 5** shows the fractions of at-work married couples (household-level) according to the derived severity of the pandemic impact on their jobs. In this case, we define impact as ‘mild’ (green) for households with both spouses in jobs of quadrant II, ‘moderate’ (yellow) for households without any spouse’s job in quadrant IV; ‘severe’ (orange) for households with one spouse’s job in quadrant IV, and ‘highly severe’ (red) when both spouses’ jobs are in quadrant IV.

The top earnings quintile has noticeably the largest fraction of households classified as mildly impacted (green) and the smallest fraction of households classified as ‘highly severe’ (red). In contrast, married couples who both work in occupations in quadrant IV are of the highest fraction in the middle quintile groups. A large fraction of the bottom quintile couples are classified as moderate impact because many low wage occupations are based in factories which require less physical interaction. Overall, our findings suggest that suitable relief schemes, for instance income transfers, should be means-tested with criteria based on specific occupational characteristics as well as joint household earnings.

As for reopening the economy, other things being equal (for instance, health, age of household members, the infection rate and healthcare capacity in the area), our results and the application of the occupation indices, discussed earlier, indicate that the highest priority to relax lockdown regulations should be given to workers in occupations in quadrant III (bottom-left). Without returning to their workplace, these workers face a high risk of income losses. Additionally, allowing them to return to work may involve minimal infection transmission risk since their works require limited physical contact with others.

5. Conclusion

The Covid-19 pandemic has posed new types of risks on workers around the world. Given the rapid transmission from person to person of the virus, drastic measures such as lockdowns and social distancing have been imposed to control the spread of infection. Despite differences in the scope of sectoral lockdowns across countries, these measures undoubtedly come with sizable costs to the economy.

The direct effect of a lockdown can have different impacts on workers with different job characteristics. To understand such heterogeneous impacts, we use a factor analysis to construct a set of occupational indices that are general but relevant to study the impacts of the Covid-19 pandemic. These indices feature two key dimensions of job task requirements: the degrees of work-location flexibility and working in close physical proximity to others. The former captures the risk of the worker's income loss, and the latter captures the infection risk posed to the worker and the public. We show that occupations in the O*NET are broadly distributed over these two dimensions.

Using the data from Thailand, we document that low earners tend to work in occupations that are less adaptable to work from home, but their jobs usually do not require frequent physical interaction with others. Furthermore, we show evidence that spouses in low-income households sort into jobs with similar characteristics. This occupational sorting amplifies income risk at the household level during the lockdown period. Our findings offer evidence supporting the use of *means-testing* in assistance programs to ease the burden of those immediately affected by the drastic measures. Our indices can also be useful when designing a policy to reopen the economy with the goal of minimizing the income and job losses while controlling the spread of the virus.

Finally, our study takes the first step to analyzing the impact of the pandemic from the labor supply side. Fruitful avenues for future research include (i) incorporating the labor demand side (incorporating, for example, the decline in consumption and supply-chain effects); (ii) allowing for substitutions – cases in which workers switch to jobs requiring similar skills or, over the longer term, adjust their skills; and (iii) using our constructed indices as supplementary classifications of jobs in order to further track the labor market adjustments as a result of the pandemic in the long run.

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Appendix: Construction of the indices from O*NET variables

We select a list of *Work Activities* (14 items) and *Work Context* (14) from the O*NET work characteristics as described in Table A1.

Table A1. Selected O*NET variables

| Work Activities variables: we take the Importance Score of each activity (measured on the 0-100 scale). | Work Context variables: we use the original scale (0,25,75,100) ¹¹ |
|---|---|
| <ul style="list-style-type: none"> • Assisting and Caring for Others • Performing for or Working Directly with the Public • Repairing and Maintaining Electronic Equipment • Repairing and Maintaining Mechanical Equipment • Operating Vehicles, Mechanized Devices, or Equipment • Performing General Physical Activities • Interacting With Computers • Handling and Moving Objects • Documenting or Recording Information • Controlling Machines and Processes • Thinking Creatively • Processing Information • Analyzing Data or Information • Inspecting Equipment, Structures, or Material | <ul style="list-style-type: none"> • Structured versus Unstructured Work • Pace Determined by Speed of Equipment • Freedom to Make Decisions • Spend Time Walking and Running • Physical Proximity • Outdoors, Under Cover • Outdoors, Exposed to Weather • Telephone • Work With Work Group or Team • Public Speaking • Responsible for Others' Health and Safety • Electronic Mail • Face-to-Face Discussions • Contact With Others |

Table A2: Selected list of occupations with highest and lowest scores (3 factors)

| Machine-Dependent | ICT-Enabled | Physical Proximity |
|-------------------------------|------------------------------|------------------------------------|
| Panel A: Top scores | | |
| Metal workers | Chemical engineers | Nurses* |
| Fire-fighters* | Chief executives | Personal care workers |
| Refrigeration mechanics | Community leaders | Child care services managers |
| Well drillers | Mining engineers | Midwives* |
| Freight handlers | Supply distribution managers | Traditional medicine professionals |
| Miners and quarries | Police officers* | Ambulance workers* |
| Ships' engineers | Inspectors and detectives | Customs and border inspectors* |
| Boiler operators | Mechanical engineers | Paramedical practitioners* |
| Electronics mechanics | Biologists | Veterinarians* |
| Forestry plant operators | Services managers | Police officers* |
| Panel B: Bottom scores | | |
| Legal professionals | Weaving machine operators | Visual artists |
| Economists | Laundry machine operators | Livestock farm laborers* |
| Mathematicians | Shoemaking operators | Subsistence crop farmers* |
| Credit and loans officers | Subsistence crop farmers | Weaving machine operators |
| Higher education instructors | Livestock farm labourers | Shoemaking machine operators |
| Health professionals* | Tobacco products makers | Economists |
| Arts teachers | Pelt dressers | Garment makers |
| Language teachers | Sewing machine operators | Sewing machine operators |
| Human resource managers | Horticultural labourers | Subsistence fishers* |
| Survey interviewers | Fibre machine operators | Hunters and trappers |

Notes: *denote occupations regarded as 'essential' in the Covid-19 pandemic.

¹¹ The scale indicates either the frequency of task, or the importance of the task required in each occupation.