Jobs and COVID-19: Measuring Work-Related Physical Interaction

By Haroon Bhorat, Amy Thornton, Tim Köhler, and Morné Oosthuizen

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Abstract

Given the role of physical human proximity and contact in the spread of COVID-19, we build an index measuring the level of physical interaction for different occupations. Our Physical Interaction Index combines occupational work context information from O*NET and work travel information from the 2010 StatsSA Time Use Survey. We merge this with South African labour market data from 2018-2019 to explore the distribution of physical interaction across occupations and sectors shortly before the pandemic. The index provides some empirical evidence about a dimension of transmission risk that could inform how to calibrate the composition of economic sectors being phased back to work over the next few months. This short note introduces the index and provides some initial descriptive results for the South African labour market.

Keywords

COVID-19; occupations; Physical Interaction Index; South Africa; work from home; work travel

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1. Introduction

COVID-19 is a highly infectious virus that spreads from person to person when uninfected people come into contact with respiratory droplets from an infected person who coughs or sneezes (Naser et al., 2020). As such, the main tool policymakers have used to limit the spread of the virus has been to lockdown their populations to prevent as much as possible community transmission increasing exponentially and becoming unmanageable for the public health system (Alvarez et al., 2020). In South Africa, schools and universities have closed and a large portion of the employed have not been economically active since at least the 27th of March 2020 when the national lockdown began. Kerr and Thornton (2020) estimate this portion to be about two thirds of the employed, where the remaining third are either classified as essential services or could work from home.

From the 1st of May 2020, the South African government will begin carefully easing the lockdown according to areas where infection rates are lowest, and in industrial sectors where workers have a lower transmission risk in the workplace (President Ramaphosa, 2020). Evaluating which sectors put their workers at a higher or lower risk is an empirical question which could be answered using data. There are many dimensions to answering this question, some of which are epidemiological (infection rates per age), and others which are firm-specific (how easily the work environment can be adapted to safety protocols) or relate to the public health administration (the capacity of the public health system at a given point in time). What we focus on in this document is another important dimension of work-related transmission risk, and one about which we have data: the level of physical human interaction people have on the job or on their way to the job. Our aim is to provide some evidence-based insight into how physical human interaction was distributed across different sectors in South Africa just before the pandemic hit.

To do this, we build an index of physical interaction for different occupations. Information on physical interaction in the workplace comes from the Occupational Information Network (O*NET), an American survey of detailed occupational information collected by the Bureau of Labour Statistics. Examples include whether you share an office and how frequently you are speaking to other workers face-to-face. Information on physical interaction in work travel

comes from Statistics South Africa's latest Time Use Survey. The scores per occupation are then merged with South African labour market data in the Post-Apartheid Labour Market Series (PALMS) version of the Quarterly Labour Force Surveys for 2018 and first two quarters of 2019.

We are not the first to build an index of this type – see Avdiu and Nayyar (2020) and Lu (2020) – and we draw on these efforts in our work. Our index does differ from these other examples. We have tried to be clear about what we are, and are not, measuring. We are measuring human physical interaction based on data from a pre-pandemic world of work. This is related to, but is not the same thing as, transmission risk. As such, we have shied away from including other aspects known to be related to COVID-19 transmission risk but not explicitly about physical interaction, e.g. age distribution, occupations with contact with infectious diseases. We have also tried to be stricter in our definition of physical interaction and so we exclude the measures of team work and other contact included in other indices because these measures can include non-physical contact like email or phone.

2. The Index

The Physical Interaction Index varies between zero and one and increases with the level of physical interaction. There are three equally weighted dimensions: physical proximity (P), face-to-face discussions (F), and use of public transport (T). The first two are drawn from descriptions of occupational work contexts from O*NET, and the last is based on the 2010 Statistics South Africa Time Use Survey, based on our assumption that people who use public transport to get to work have more physical interaction than those using private transport. The definitions and scoring of each component are provided in Table 1. We impose explicit equal weighting of components, following the lead of the Multidmensional Poverty Index literature (Alkire & Foster, 2011). Explicit weighting keeps the index composition clear, and we believe equal weights are justified in the case of our index. The three components are combined as follows for occupation *i* at the four-digit level of occupation codes using the 2003 South African Standard Classification of Occupations (SASCO 2003):

$$\text{Physical Interaction}_i = (⅓ * P_i) + (⅓ * F_i) + (⅓ * T_i)$$

All components of the index are scaled to vary between zero and one. We first crosswalk the O*NET components into ISCO-88 before merging with the South African labour market data at the four-digit level (with adaption of Hardy's (2016) resource). The component from the StatsSA Time Use Survey naturally had compatible occupational codes and was directly merged into PALMS.

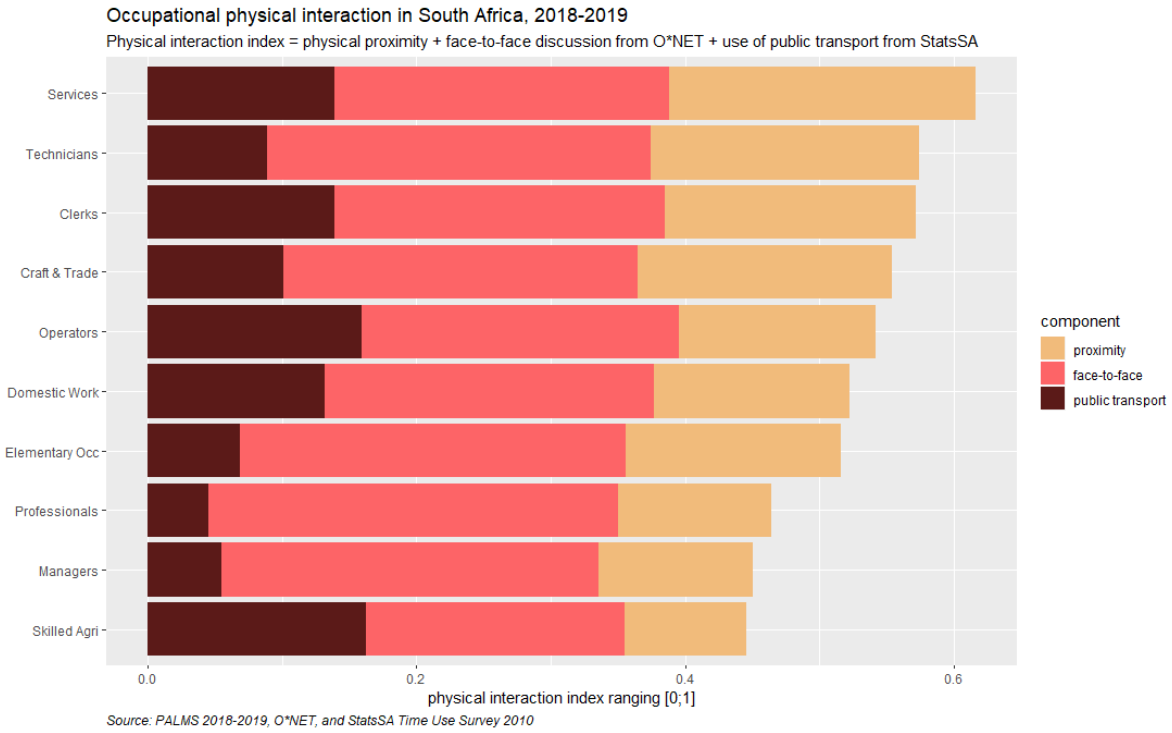
So far, we make only one adjustment of the American O*NET data for a South African context. Initial results scored domestic workers as one of the occupations with the lowest physical interaction scores driven by a low physical proximity score. In South Africa, domestic workers often perform a dual role of cleaning and child-minding leading us to think the physical proximity score was too low for our context (du Plessis, 2018). We adjusted the proximity score for domestic workers by replacing it with the mean of the physical proximity score for domestic workers from O*NET and the physical proximity score for child-care workers (SASCO code 5131). We believe this correction is justified given the importance and number of domestic workers.

Table 1. Defining the components of the Physical Interaction Index

Component	Definition	Scoring	Source
Physical proximity	1. I don't work near other people (beyond 100 ft.) 2. I work with others but not closely (e.g., private office) 3. Slightly close (e.g., shared office) 4. Moderately close (at arm's length) 5. Very close (near touching)	O*NET spreads 100 points across five levels per occupation. Our approach multiplies points by their category level and sums to get a score. We sum points in categories 3-5 only to reach a score out of 500 (the maximum feasible score). We rescale this to vary [0;1]	O*NET
Face-to-face discussions	1. Never 2. Once a year or more but not every month 3. Once a month or more but not every week 4. Once a week or more but not every day 5. Every day	O*NET spreads 100 points across five levels per occupation. Our approach multiplies points by their category level and sums to get a score. We sum points in categories 4-5 only to reach a score out of 500 (the maximum feasible score). We rescale this to vary [0;1]	O*NET
Public transport	Ever used any type of public transport to travel to work on a given day where public is defined as bus, taxi, train and other transport and private transport is defined as walking, cycling, or private vehicle.	Share per occupation. Varies [0,1]	StatsSA Time Use Survey, 2010

3. Results: how does physical interaction vary across main occupations?

We use a sample of the employed in the four quarters of 2018 and the first two quarters of 2019 to analyse our index. In the figure below, we collapse the index to the main occupational code level. In this way we lose a lot of detail in the aggregation process, but this is still a useful first exercise. As we would expect, people working in services have more physical interaction than managers. We colour the bars with the contribution of each component. This allows us to see that the use of public transport increases physical interaction for skilled agricultural workers, whereas face-to-face discussions increases physical interaction for managers.



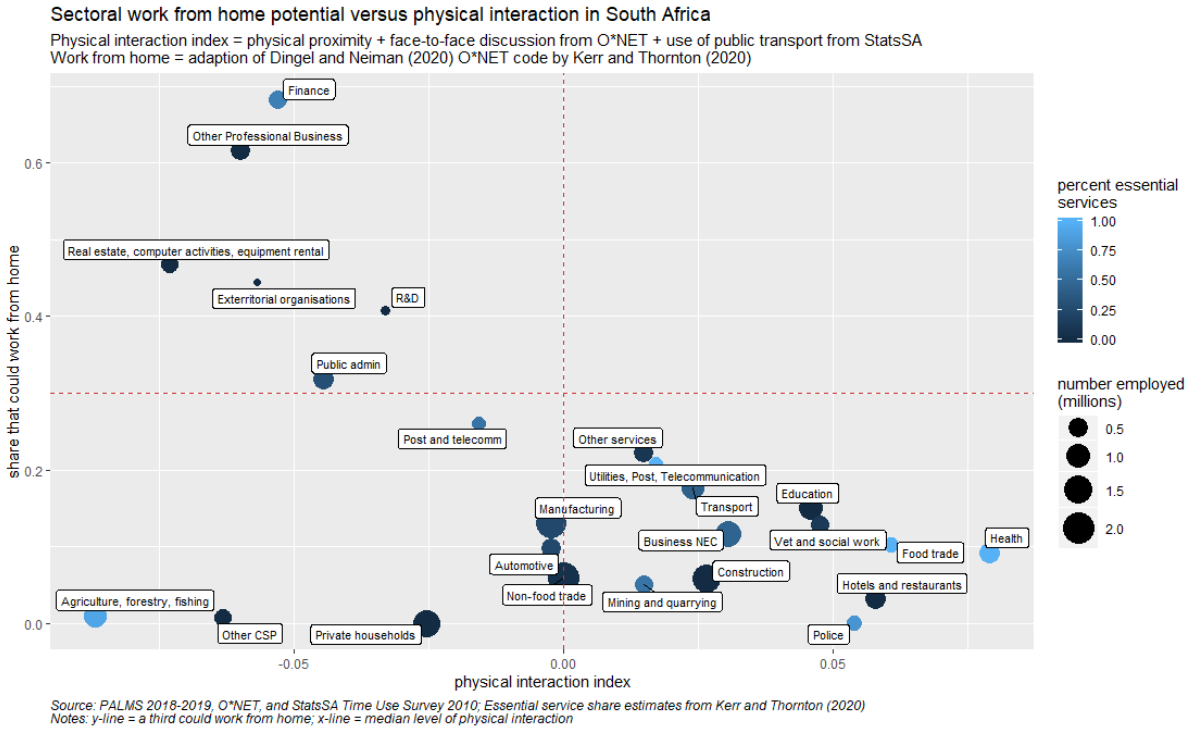
4. Results: how does physical interaction vary with the ability to work from home?

Dingel and Neiman (2020) use O*NET to classify whether occupations can work from home or not for the United States. Kerr and Thornton (2020) adapt this for the South African context and also use the gazetted list of essential services to classify industries as essential or not at the three-digit industry code level. In the figure below, we cross-reference our physical

interaction index with their estimates for the ability to work from home for 25 sector categories. The bubbles are weighted by employment share and coloured by the share of essential workers in that sectoral category. We plot the data around the median for the physical interaction index.

There is a negative correlation in the figure below meaning less physical interaction in the workplace is associated with higher work-from-home potential. However, there is also a cluster of sectors in the bottom left-hand corner where both physical interaction and the ability to work from home are low. These sectors cover workers in agriculture; other community, social, and personal services (many of the workers making up this bubble are street sweepers); and slightly further up the physical interaction index, private households including domestic workers.

The health sector has the highest score for physical interaction. It also has a very high share of essential workers. Food trade and hotels and restaurants also rank highly in the physical interaction index. By contrast, private households have the lowest score, and none of these workers are classified as essential in the current lockdown (Alert Level 5). The finance sector has a low level of physical interaction and the highest share of workers who could work from home. This suggests that working from home would be a good strategy to keep transmission risk low for this group. Manufacturing, the automotive trade sector, and non-food trade have median levels of physical interaction, but very low shares of these sectors could work from home.



*Source: PALMS 2018-2019, O*NET, and StatsSA Time Use Survey 2010; Essential service share estimates from Kerr and Thornton (2020)*
Notes: y-line = a third could work from home; x-line = median level of physical interaction

5. Conclusion

We believe our index is a useful method for providing some indication of where COVID-19 tranmission risk may be highest because of its allignment with physical interaction. As mentioned previously, this index measures one aspect of transmission risk but is not an index of transmission risk, itself. Other aspects may come into play. For example, it may be harder to implement work safety protocols in a private household than a restaurant. These other dimensions may ultimately reorder which occupations and sectors have a higher transmission risk. Physical interaction though remains a key input into our understanding of how COVID-19 spreads, and so we think providing some data on this topic may be helpful when choosing the composition of sectors to phase back to work as the lockdown is eased. There are many more potential applications this index could be used for, and interested researchers should please contact the authors via amy.thornton@uct.ac.za.

6. References

Alkire, S. and Foster, J. E. (2011). "Counting and multidimensional poverty measurement." *Journal of Public Economics*, 95(7): 476–487.

Alvarez, F. E., Argente, D., and Lippi, F. (2020). A simple planning problem for covid-19 lockdown (No. w26981). National Bureau of Economic Research.

Avdiu, B. and Nayyar, G. (2020) When face-to-face interactions become an occupational hazard: jobs in the time of COVID-19. Brookings Future Development Article. Available: https://www.brookings.edu/blog/future-development/2020/03/30/when-face-to-face-interactions-become-an-occupational-hazard-jobs-in-the-time-of-covid-19/

Dingel, J. and Neiman, B. (2020). How Many Jobs Can be Done at Home? Available: https://bfi.uchicago.edu/wp-content/uploads/BFI_White-Paper_Dingel_Neiman_3.2020.pdf

du Plessis, A. (2018). The role of domestic workers, as child carers, in the stimulation of motor development of preschool children in Bloemfontein, South Africa. Master's thesis. School of Allied Health Sciences, University of the Free State.

Hardy, W. (2016). Occupation classification crosswalks – from O*NET-SOC to ISCO. Institute for Structural Research (IBS), Warsaw, Poland. Available online: https://ibs.org.pl/en/resources/occupationclassifications-crosswalks-from-onet-soc-to-isco/

Kerr, A., Lam, D. and Wittenberg, M. (2019). Post-Apartheid Labour Market Series [dataset]. Version 3.3. Cape Town: DataFirst [producer and distributor], 2019.

Kerr, A. and Thornton, A. (2020). Essential workers, working from home and job loss vulnerability in South Africa. A DataFirst Technical Paper 41. Cape Town: DataFirst, University of Cape Town.

Lu, M. (2020). The Front Line: Visualising the Occupations with the Highest COVID-19 Risk. Visual Capitalist.com. Available: https://www.visualcapitalist.com/the-front-line-visualizing-the-occupations-with-the-highest-covid-19-risk/

Naser, N., Masic, I., and Zildzic, M. (2020). Public Health Aspects of COVID-19 Infection with Focus on Cardiovascular Diseases. *Mater Sociomed*, 32(1): 71-76

National Center for O*NET Development. O*NET OnLine. Retrieved April 24, 2020, from https://www.onetonline.org/

President Ramaphosa, C. (2020) Televised address to the nation: 23 April 2020.

Statistics South Africa (2014). Time Use Survey 2010. [Dataset] Government of South Africa. Pretoria.

Statistics South Africa (2003). South African Standard Classification of Occupations (SASCO). Available: http://www.statssa.gov.za/classifications/codelists/SASCO_2003.pdf

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