Working from home in the midst of COVID-19: occupations and performance

Evidence from Hungary

Bence Kiss-Dobronyi[1], Márton Szekeres[1]

Abstract

In the world of strict measures against the COVID-19 pandemic including stay-at-home orders and lockdowns, working from home was part of the solutions to keep the economy running. In this paper we construct a simple measure of working from home potential using CEDEFOP's Skills Panorama data and test its relevance on survey data obtained during March-April 2020 in Hungary. Furthermore, we argue that even if working from home is possible, due to adverse factors it might not be the same in terms of performance as working under normal conditions. We present evidence from a sample of employees with tertiary education that this is indeed the case, highlighting the positive effect of previous remote work experience and the impact of changes in the nature of tasks to be done. This question is important for the long term as well: if working from home is perceived as decreasing employee performance in this situation it might hinder its future widespread adaptation as well. However, if we understand the factors influencing performance in this situation, we can find simple remedies.

[1] Corvinus University of Budapest, Hungary, Budapest

1. Introduction

In the beginning of 2020, the COVID-19 crisis had put governments into an uneasy position: in order to curb the spread of the pandemic, most of them have implemented strict measures asking or forcing residents to adopt social distancing and stay-at-home measures whenever they can. But these measures had adverse effects on the economy - restrictions were imposed on a substantial part of the labour force. This, as people were unable to work, have created a supply shock in the economy. At the same time, the same restrictions and behavioural responses have created a demand side shock as people significantly reduced their movements and have severely reduced their spending in many areas (e.g. tourism, transport, entertainment) (OECD, 2020).

By now we seen and understand some aspects of the overall economic effects COVID-19 and these measures. According to calculations by the IMF the global economy has shrank by about -3.1% (in GDP) (IMF, 2021). Meanwhile, given that adverse impacts were often hurting vulnerable and low-income groups the most, global employment has decreased by -3.5% according to the ILO (ILO, 2021). While the magnitude of these effects on the country and regional levels have been decided by multiple factors. It is still reasonable to say that for the supply shock two factors were probably among the most important drivers. The length and level of lockdown measures is one of these, while the other is the amount of supply substitution possible through working from home (WFH). Furthermore, what we see in terms of WFH adaptation can have long-term consequences as well, as many people experienced WFH for the first time. If it deemed feasible for jobs, where it was not standard practice before, it could lead to more widespread use. Nevertheless, if it is perceived as causing a performance issue among employees it can seriously hinder its adaptation in the future.

Literature quickly emerged when the COVID-19 pandemic and restrictive measures struck. Many of the studies focused on the potential rate of WFH across the economy. Starting with Dingel and Neiman (2020) multiple studies (del Rio-Chanona et al., 2020; Koren and Peto, 2020) have used the O*NET database for estimating the potential number of jobs that can be done from home either as a result or as an input to further modelling. Their methods have relied on programmatic and manual classification of occupations and industries, based on their main tasks and activities, to arrive at a score reflecting the plausibility of working from home. Results have ranged between 34%-44% for labour force in the US economy.

For countries other than the US Fadinger and Schymik (2020) have investigated the effects of costs and benefits of home office measures in Germany. They found, based on Eurostat data, that 42% of jobs can be done from home, putting their estimate in the range of US estimates. Adams-Prassl et al. (2020) reported, based on a recently conducted survey, that the average percent of tasks can be done from home differs quite significantly across occupations ranging between about 20-70% in both the US and UK.

While in developing markets, Saltiel (2020) have shown, based on the STEP survey, that WFH rates can be significantly lower, with large country differences. His definition of WFH follows Dingel and Neiman's (2020) decision, ruling out WFH "if workers either (not) use a computer at work, lift heavy objects, repair electronic equipment, operate heavy machinery or report that customer interaction is very important" (Saltiel, 2020, p. 105). His results show that on average 13% of jobs can be done from home in the studied countries, ranging between of 5.5% in Ghana and 23% in some Chinese provinces. This slightly differs from survey results from China - Zhang et al. (2020), based on a survey conducted in February, have reported that 38% of their respondents have worked from home, however their sample was not representative of the Chinese population and most of their respondents had completed tertiary education.

With the exception of Zhang et al. (2020), these studies focus on the *potential* for WFH, as their main question is usually the adverse supply shock that can be mitigated by substituting normal work practice to a WFH setting. However, it is not trivial to understand **how much of this potential was actually exploited during the pandemic (as is still exploited) and with what performance**. As Adams-Prassl et al. (2020) reports the share of tasks that can be done from home differs across occupations and there are also a large number of "first time" remote working employees, who could potentially face a challenge adapting to the new situation.

Morikawa (2020) explores this issue in an article based on interviews within a Japanese economic research institute finding a lower productivity in the WFH setting. He highlights some contributing factors: new software and hardware that the employees need to learn to use, work that cannot be done from home because of security reasons or a poor working environment. Contrasting that in an earlier experiment conducted with Chinese call centre employees, unrelated to the current crisis, Bloom et al. (2015) found a positive effect of WFH on productivity. However, this was a special setting, because as they write call centre work does not involve "teamwork" and their performance can be clearly tracked. Results from Rymaniak et al. (2021) on the perceived "quality" of one's work across three countries (Poland, Spain, Estonia) show that these impacts can even be mixed across countries. While in Estonia as a result of the mandatory telework, they find a perceived increase in the work quality, in Poland and Spain, the same indicator shows a decrease.

However, as Morikawa (2020) proposed, certain, often crisis-specific, factors might be responsible for this change. Some employees might not have the necessary equipment (like a computer or suitable desk and place within their home) to engage in WFH or to perform their tasks properly, which can further suggest that the assumed *potential* substitution is not possible. Carillo et al. (2021) studies the adjustment of employees to remote work in France during the pandemic. They propose and confirm that there are various factors on various conceptual levels (individual, job, organizational level and crisis and non-crisis specific) that influence whether the adjustment is seamless or not (i.e. there is no or only minor performance change). They point to WFH environment, previous WFH experience, ICT proficiency, the length of the adjustment period, but also to professional isolation as main drivers that can hinder the adjustment. From these elements, they define the environment, duration and professional isolation as specific to the crisis. Van Zoonen et al. (2021), analysing a Finnish sample of employees during early stages of the pandemic, have also found strong support for the notion that these contextual factors (e.g. change in the working environment, disruptions, new tasks) have adversely effected the ease of adjustment to the WFH situation.

Therefore, we think it is important not just to know how well WFH indices represent actual behaviour, but also to understand whether these factors (such as earlier experience of environmental factors) have an adverse effect on productivity in this new situation. Our contribution to the literature is therefore twofold: first, based on survey data collected among Hungarian employees in March-April 2020 we conduct an empirical testing of a simple WFH index, derived from the data of CEDEFOP's Skills Panorama (CEDEFOP, 2020) project. Second, we analyse two ideas: (1) there could be a divergence from reaching the potential WFH rate due to adverse factors (such as lack of technical equipment, employer decisions, etc), (2) even when controlling for these adverse factors the performance of WFH is not necessarily in line with the occupational possibility of WFH. We focus on whether the employees have previous experience with working from home as it is shown to be an important driver in other studies (Carillo et al., 2021; van Zoonen et al., 2021).

The rest of the paper proceeds in the following way: Section 2 introduces a simple WFH potential index that we use for measuring occupational WFH potential. Section 3 briefly presents the survey that has been conducted and serves as a basis for the empirical analysis. Section 4 describes our assessment of the WFH potential index against observed behaviour, while Section 5 investigates employee performance change in the WFH context. Finally, in Section 6 a brief conclusion summarizes the paper.

2. A simple WFH potential index

As it was discussed there were multiple indices used by different papers estimating WFH potential. Here we implement a definition very similar to Saltiel (2020), we base our estimation on Skills Panorama (CEDEFOP, 2020) data and use their broad occupational level (corresponding to ESCO[2] occupations, covering 40 occupations) skills index to determine our own WFH index, in a way similar to Rio-Chanona et al. (2020) remote labour index (RLI). We define a negative case for working from home using the following characteristics of the occupations: 'strength', 'use of machine' and 'service and attend', 'use of ICT', 'gather and evaluate information'.

The Skills Panorama dataset provides a value between 0-1 for each of these characteristics, indicating how important they are for the given occupation. We calculate the WFH as an average

[2] European Skills, Competences, Qualifications and Occupations, see: https://ec.europa.eu/esco/portal/occupation

of these characteristics, taking the ‘inverse’ (1-x) value of all, but the latter two – as presented in equation (1).

$$\text{(1)} \qquad WFH\ score = \frac{\begin{pmatrix}[Use\ of\ ICT] + [Gather\ and\ eval.\ inf.] + [Strength\ (rev)] \\ +[Use\ of\ machine\ (rev)] + [Service\ and\ attend\ (rev)]\end{pmatrix}}{5}$$

With this we gain an index which supposedly increases as the feasibility of working from home increase. For example for *ICT professionals* we calculate the score as follows:

$$\text{(2)} \qquad \frac{0.85 + 0.74 + (1 - 0.04) + (1 - 0.13) + (1 - 0.23)}{5} = 0.84$$

One clear advantage of this method, beyond its simplicity, is that the Skills Panorama dataset provides data for all European Union member states therefore it is quite straightforward to replicate this calculation for other member states.

The calculation gives us a list of negative WFH scores by occupation, therefore the higher the score the less likely it is for an occupation to be feasible in a WFH setting, the mean of the calculated score is 0.60. We are going to use these occupational level scores later. We can also apply a simple binary classification to decide whether an occupation is feasible to be done from home or not - after inspecting the generated scores (see Table 2.1) and ranking the occupations by the scores it seems acceptable to classify every occupation over the mean to be not feasible for WFH.

Occupation	WFH score	WFH feasible
ICT professionals	0.84	yes
Office professionals	0.77	yes
ICT technicians	0.77	yes
…		
Legal & social associate professionals	0.63	yes
Health professionals	0.62	yes
Hospitality & retail managers	0.59	no
Health associate professionals	0.59	no
…		
Technical labourers	0.48	no
Agricultural labourers	0.47	no
Cleaners and helpers	0.47	no

Table 2.1 - Sample of calculated WFH scores

Then using Skills Panorama data we have applied these binary WFH classifications on the overall occupational structure of the Hungarian economy and calculated the sectoral shares of *potential WFH* (share of people holding an occupation in the given sector which can be done from home) and the total economy wide WFH potential. **We estimate that about 38% of jobs can be potentially done in a WFH situation in Hungary.** Putting this estimate into context: US estimates were between 34-44%, Germany 42%.

It needs to be noted here that while this calculation does give us a share of people holding occupations which are feasible to be done from home it does not account for those jobs which cannot be done from home, because of the sector that *they are in*. An example of this would be a retail manager, who by their occupation could potentially work from home, but given that *other people who they manage* cannot work from home their role comes into question. However, there is a high potential for changes in task structures, which we investigate further in this paper later.

Nevertheless, this rate is in line with reported rates of home working due to the coronavirus in Hungary. A representative public opinion survey by the Publicus Institute (Publicus Institute and Népszava, 2020) has recently found that about 41% of Hungarians are working from home (however this survey was not representative in terms of sectors or occupations). Nevertheless, we are interested in not only the total rate, but also whether the WFH index is a fitting predictor on the occupational level. For this we use responses from an online survey collected through March-April 2020, where we asked employees about their work related experiences during the pandemic situation.

3. Survey[3]

We have conducted an online survey[4], from March 27 to Apr 27, collecting 1074 responses altogether. For this analysis we have limited our scope to respondents who are between 16 and 65 years old, are currently working in Hungary, are employed or were employed recently and have provided their position (employment position). Due to data limitations and to have a more homogenous sample we have also excluded respondents without tertiary education, leaving 469 observations to work with. This also means that we are working with a sample whose potential for holding jobs where WFH is feasible is higher. The dataset is close to being representative without weights, but using a simple raking method we have created a weighted version of the dataset bringing our sample within ±5% of the target population in terms of gender, age group, region and broad occupational group.

In the survey data we have a high share of respondents who said that they were working (even before this situation) from home. A weighted share of 54% have said that they were working from

[3] In the creation of the survey we have received valuable advice from the Institute of Informatics at Corvinus University of Budapest, IFUA Horvath & Partners and the Competitiveness Research Center.

[4] The survey was organised by Zoltán Bakonyi and Bence Kiss-Dobronyi. Further results and details are available at: http://tavmunka-kutatas.hu/

home in the last one year, this is a much larger share than what has been reported by the Hungarian Central Statistical Office (2020) for 2018 Q1 - about 10% for residents with tertiary education. This can be explained by multiple factors: increase in the last two years could be a contributor, but more importantly the different wording of our question can drive the difference - we captured respondents who *have worked in any situation* from home, not only those who reported '*working from home*'.

We also got a high ratio of people saying that they are working from home in this new situation. Due to the crisis about 85% of our respondents are currently working from home - this is a slightly higher ratio than what was reported by Publicus (73%) (Publicus Institute and Népszava, 2020). This again can be explained by differences in the questions asked.

4. WFH potential and observed behaviour

We will use our survey results to test the proposed WFH index. In the survey we have asked our respondents to indicate their employment position - we received nearly as many position names as respondents. To consolidate this, we have first used the fuzzywuzzy (SeatGeek, 2011) package available in Python, which is able to combine results of multiple matching mechanisms (e.g. Levenshtein distance) for a first round of matching these free-text answers to ESCO occupations. Then we carried out a manual checking of all entries and matches to arrive at a complete set of matches between positions in the responses and ESCO occupations.

We use this matched dataset to calculate the WFH share of each occupation and to compare it to the calculated WFH scores. The correlation between the score and share is 0.58. This indicates that on the occupation level there is a connection between the WFH score and the actual observed values, therefore the WFH index is potentially a fine predictor.

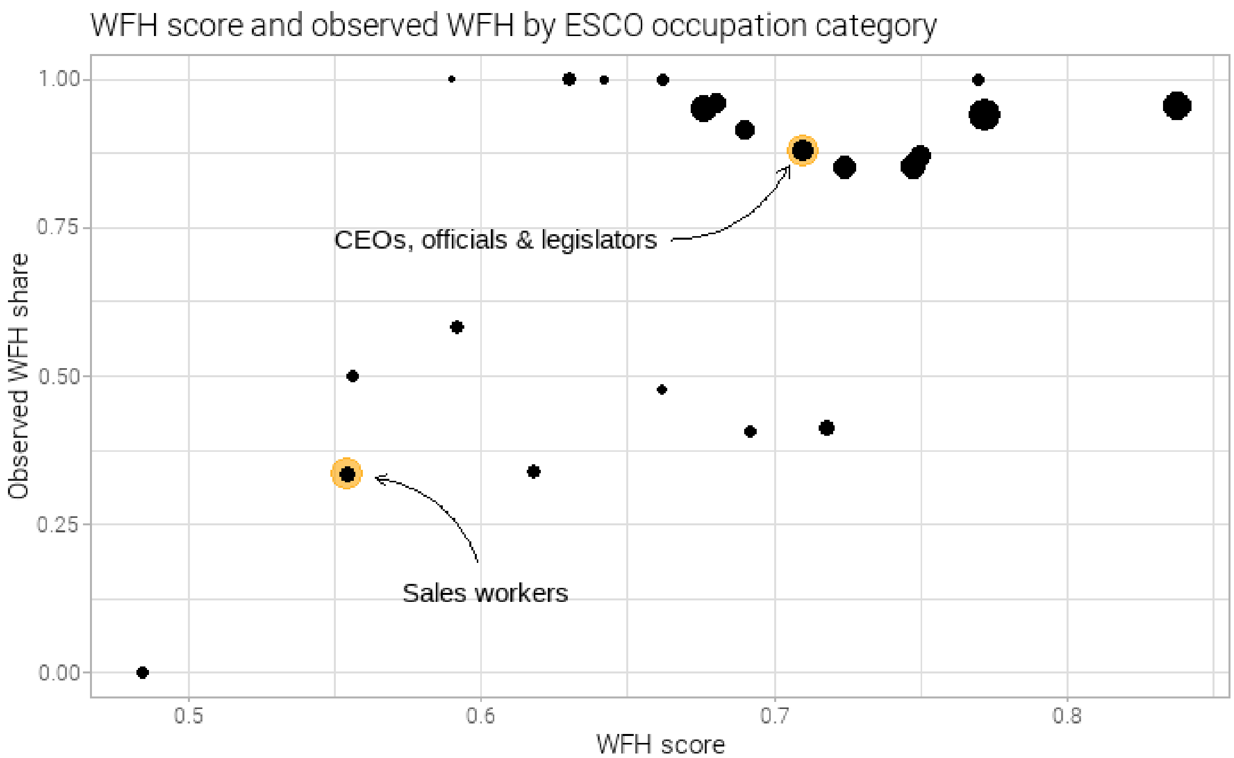

Figure 4.1 - WFH score and observed WFH by ESCO occupation category, 40 ESCO occupation groups shown, size of the circles represents the number of employees in each group.

To investigate the strength of the relationship further and to account for potential confounders on observation level we specify a probit model with various controls. We specify the probability of working from home in the recent weeks as:

$$Y_i^*(obs_{recent} = 1) = \alpha + \beta \times WFH_i + \epsilon_i \quad (3)$$

where Y_i is the probability of working from home, α is a constant, WFH_i refers to the observed index score for the given occupation and ϵ_i is the error term. The survey weighted version of this model is estimated on the data. The estimation results (presented in Table 4.1) show that the WFH score significantly affects the probability of working from home recently, the effect is robust for including demographic dummy variables (age, gender, not shown in results table).

It is still significant (however only at the 10% significance level) if we include a dummy variable indicating that the person in question has not worked from home before, however if both the demographic variables (gender, age) and the previous WFH experience is included it loses its significance in the model. This indicates that whether the respondent was working previously from home is a better indicator of whether they are going to work from home, than their occupation. However, we believe this factor is correlated with the occupation (as a high WFH is also a good predictor of prior WFH experience[5]), therefore does not invalidate our general finding that in occupations with higher WFH scores it is more likely to switch to WFH in a situation like this.

The average marginal effects of the model (2) indicate that if the person has not worked from home their chances of doing that now are reduced by -23%, while 0.01 increase in the WFH score increases the chances of working from home now by 0.6%.

Figure 4.3 shows the fit of the predicted values (from model 2) against observed behaviour - working from home in the last few weeks.

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[5] We have also tested a model specification, where we investigated the effect of occupational WFH score on the probability of prior WFH experience – results indicate a clear connection – but that just confirms that employees in occupations with higher WFH scores are more likely to have WFH opportunities even without an epidemic.

	Dependent variable:		
	WFH recently (yes)		
	(1)	(2)	(3)
	Average marginal effects		
WFH score	1.30^{***}	0.61^{*}	0.60
	(0.38)	(0.36)	(0.37)
No prior WFH experience		-0.23^{***}	-0.23^{***}
		(0.05)	(0.05)
Further controls (gender, age)			X
χ^2	35.63^{***}	79.79^{***}	85.02^{***}
Pseudo R^2 (Nagelkerke)	0.08	0.16	0.17

Note: *p<0.1; **p<0.05; ***p<0.01

All regressions use probit, weighted for design effects. *N*=466. Standard errors in parentheses.

Table 4.1 - Probit estimation results, WFH recently as a function of WFH score and prior experience

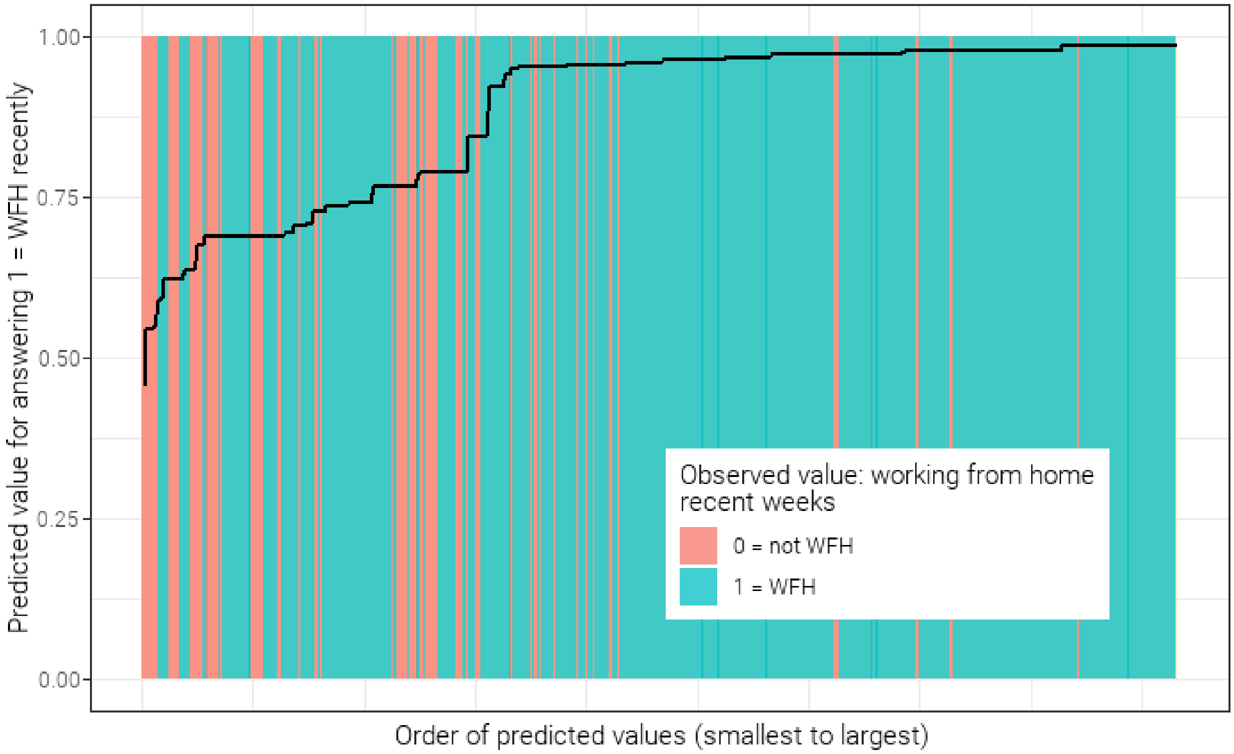

Figure 4.3 - Comparison of predicted and observed WFH in recent weeks

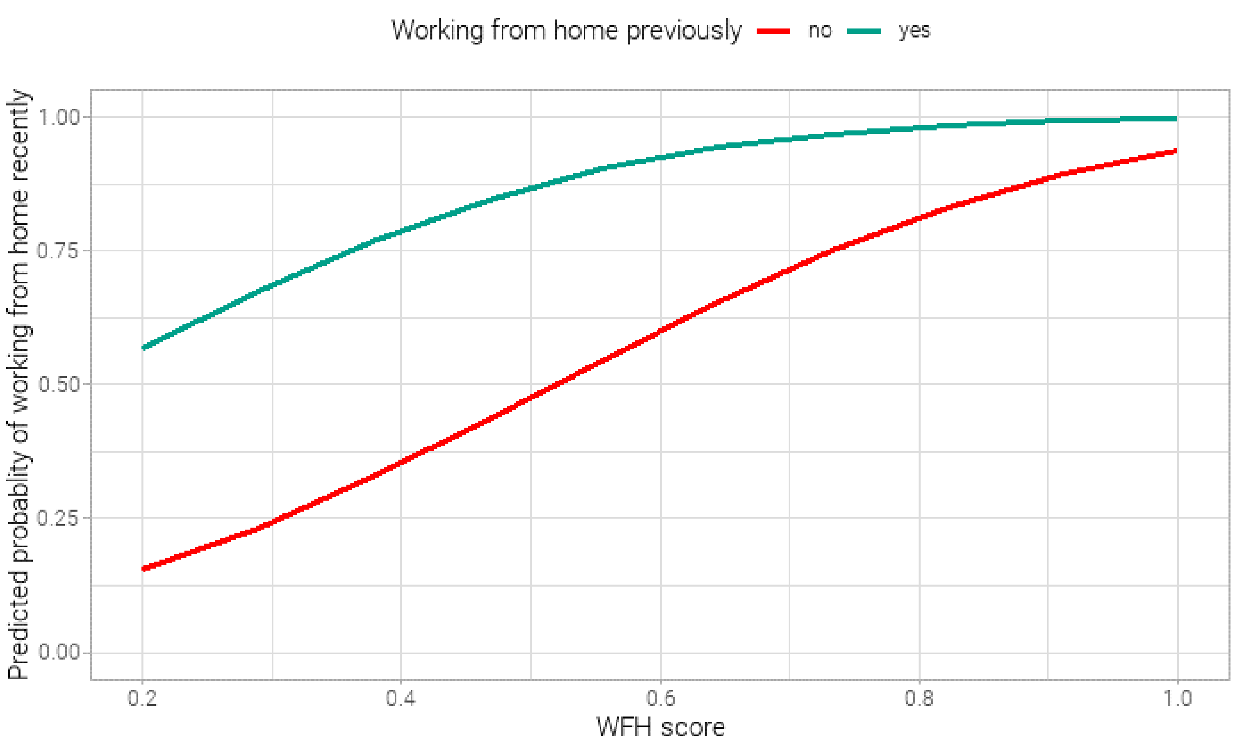

Figure 4.2 - Predicted probability of working from home recently conditional on WFH score, by previous WFH experience

This indicates (at least considering this population) that the WFH score proposed here is a relevant measure of potential for working from home. Comparing marginal effects at different probabilities (Figure 4.2) it can be seen that the effect of the occupation, captured in the WFH score is much higher for those who were not working from home previously - this is in line with the notion that there are jobs where working from home is (and likely was) possible, but was not available for (or chosen by) the employees for reasons unknown to us.

5. WFH and performance

Another important point that we have raised earlier is the performance of the employees in a WFH setting. In our survey we have asked the respondents to rate how well they are able to perform in the WFH setting compared to a “normal” work setting. The respondents were asked to use a four choice scale with choices “Not at all”, “Less well”, “Nearly as well”, “Totally”. For this analysis we constructed a binary variable from these choices - one category for weaker and one category for nearly as good performance. These scores are of course subjective perceptions of the employees, but can give an indication about the general level of performance.

We use the WFH scores once more to show how performance relates to the potential of the given occupations. This analysis is concluded on a limited sample as for this we can only consider respondents who have worked from home in the recent weeks. Here we exploit that in the current situation it is likely that WFH is not a *choice* for most employees, but rather a necessity, therefore we do not expect the otherwise important self-selection mechanism (those who expect the same performance while working home will choose to work from home) to play a role. We model the effect of WFH score of occupations on the working from home performance indicator using, once more, a probit model specified as follows:

$$Y_i^*(performance_{WFH} = 1) = \alpha + \beta \times WFH_i + \epsilon_i \quad (4)$$

where Y_i^* is the probability of performance loss when working from home, α is a constant, WFH_i refers to the observed index score for the given occupation and ϵ_i is the error term. The model is estimated on a sample of 407 answers. We estimate four specifications: (1) a simple specification with on the WFH score as an independent variable, (2) a specification similar to our model from earlier: where a dummy variable indicating whether the person has worked from home previously is added, (3) a model with another added dummy indicating whether the tasks of the employee has changed as they switched to working from home and finally (4) a model where we add yet another dummy variable controlling for whether the employee has employer provided equipment.

Results of the models are presented in Table 5.1 and shown in Figure 5.1. Model 1 indicates that working from home in lower WFH score occupations could mean a lower performance, and this effect stays significant even with the introduction of the lack of prior WFH experience. However, as we can see in Model 3 the effect of WFH score will become insignificant once we also control for significant change in tasks done.

Therefore, from these results it seems that there is a WFH penalty, but not necessarily on the occupation level. Those who have not worked before in this setting could see a drop in performance as well as those whose tasks have changed. Furthermore, those who have employer provided equipment, which we can assume sufficient for the tasks, have a lower probability of performance drop. The good news is that all these factors can easily be changed - WFH experience can be gained (and should - even before situations where it becomes a must - as it turns out from this analysis) and hopefully employees can adapt to new tasks. It also seems like employers can help mitigate the productivity loss - we investigated one factor here - the providing of suitable equipment, but there could be more ways for this. But overall, in this sample, we do see a loss of productivity due to the novel WFH setting, with the lack of prior experience and a change in tasks being significant contributors to this.

	Dependent variable:			
	Weaker performance in WFH (yes)			
	(1)	(2)	(3)	(4)
	Average marginal effects			
WFH score	-2.21*** (0.57)	-1.51** (0.59)	-0.91 (0.66)	-0.93 (0.64)
No prior WFH experience		0.24*** (0.07)	0.19*** (0.06)	0.19*** (0.06)
Significant change in tasks			0.26*** (0.07)	0.25*** (0.07)
Equipement provided by employer				-0.10* (0.06)
Further controls (gender, age)			X	X
χ^2	44.36***	67.78***	96.58***	102.46***
Pseudo R^2 (Nagelkerke)	0.10	0.15	0.21	0.22

Note: *p<0.1; **p<0.05; ***p<0.01
All regressions use probit, weighted for design effects. *N*=407. Standard errors in parentheses.

Table 5.1 - Probit estimation results, weaker performance

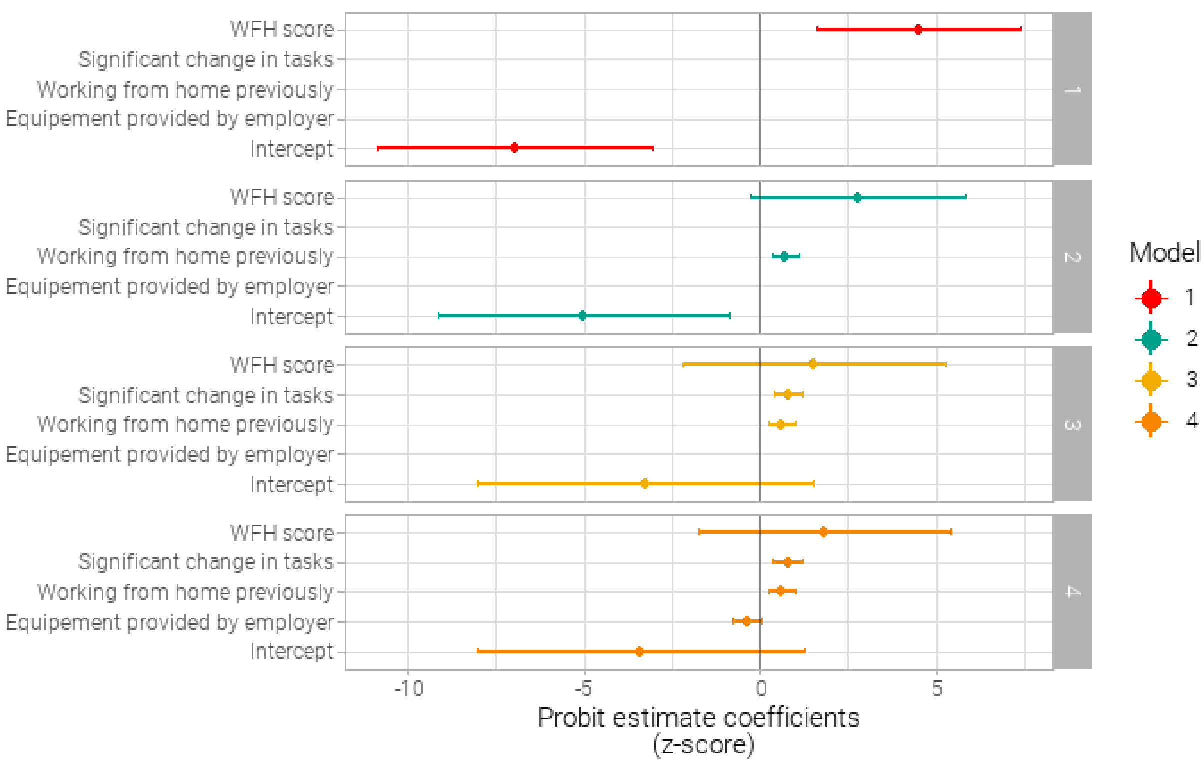

Figure 5.1 - Probit estimation coefficients with different model specifications

6. Conclusion

Stay-at-home policies provide a means to fight the virus, but they also come at a cost. Working from home is not possible for many employees and in many occupations. In this paper we presented a simple occupation level WFH index based on CEDEFOP's Skills Panorama data. Using survey data collected among Hungarian employees with tertiary education during March-April 2020 we showed that the WFH index is an acceptable predictor of WFH probability. However, previous experience with WFH can be an even better predictor.

We have also proposed that WFH, even if possible, can have an effect on employee performance. Using the aforementioned survey data we have shown in the paper that this is indeed the case. Not having prior WFH work experience or significant changes in the tasks being done can cause employees to perform weaker. However, we have also seen that support from the employer, such as sufficient equipment, can decrease the probability of this performance loss.

Based on these results, we believe that although WFH is possible - and its feasibility is related to those factors that are represented in our WFH index - not all WFH experiences are the same. Those who had previous experience with WFH are taking this obstacle easier as well as those who are technically supported by their employer. Which brings us to a point that should be important for employers even in "normal times": those employers who allowed their employees to try out working from home before the pandemic seen a lesser drop of productivity now.

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8. Annex

Table 8.1 - Composition of the limited sample, only ISCED11 5-8 categories, N=469

Sex	population	unweighted sample	weighted sample
Male	0.45	0.36	0.45
Female	0.55	0.64	0.55

Age	population	unweighted sample	weighted sample
15-24	0.02	0.03	0.02
25-54	0.84	0.90	0.84
55-64	0.14	0.07	0.14

Region	population	unweighted sample	weighted sample
Budapest	0.33	0.61	0.33
Pest	0.14	0.04	0.14
Kozep-Dunantul	0.09	0.03	0.09
Nyugat-Dunantul	0.09	0.11	0.09
Del-Dunantul	0.06	0.05	0.06
Eszak-Magyarorszag	0.07	0.05	0.07
Eszak-Alfold	0.11	0.05	0.11
Del-Alfold	0.10	0.08	0.10

Occupation	population	unweighted sample	weighted sample
Managers	0.09	0.27	0.10
Professionals	0.57	0.58	0.59
Technicians and associate professionals	0.19	0.09	0.20
Clerical support workers	0.06	0.05	0.06
Service and sales workers	0.05	0.01	0.05
Skilled agricultural, forestry and fishery workers	0.01	0.00	0.00
Craft and related trades workers	0.01	0.00	0.00
Plant and machine operators and assemblers	0.01	0.00	0.00
Elementary occupations	0.00	0.00	0.00
Armed forces occupations	0.00	0.00	0.00