Assessing Pandemic-Related Risks and Resilience of Danish Workforce: A Methodological Approach

Javakhishvili-Larsen, Nino and Bøje-Kovács, Bence János and Geerdsen, Lars Pico

Department of the Built Environment, Aalborg University, Denmark

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Authors: Nino Javakhishvili-Larsen*, Bence János Bøje-Kovács and Lars Pico Geerdsen
Department of the Built Environment, Aalborg University, Denmark
* Corresponding author: ninojl@build.aau.dk

Abstract

The restrictions during the Covid-19 pandemic brought repercussions for the employees. Most of the workplaces had to temporarily lockdown as a preventive measure to the virus spread. Those individuals who were able to continue working remotely faced a lower risk of job loss compared to those persons who could not. The main question, however, revolves around assessing risks and identifying resilient workers during these restrictive phases of the pandemic.

In this article, we propose a new Work-From-Home (WFH) index designed to assess individuals' likelihood of working from home. Utilizing quarterly Labour Force Survey data on the actual extent of remote work among Danish workers from 2008 to 2021, this new index can be employed in any dataset with access to the International Standard Classification of Occupation codes. A comparative analysis is conducted with the commonly applied indexes – the Home Office Index (HOI) and Lockdown Index (LDI) suggested by Faber et al. (2020) and Dingel and Neiman (2020). Our findings reveal that the WFH index offers greater variations by occupations, accounting for diverse outcomes of remote work across different economic sectors.

Using Pooled OLS models, the study examines factors influencing resilience and lockdown risks, considering demographics, socioeconomic status, residential location, and industry-related aspects. The results highlight the WFH index's accuracy in measuring remote work possibilities, providing a better-fitted model than in the case of HOI. The findings indicate that notably, male workers in middle to top-level positions, particularly in publicly-owned workplaces, exhibit positive outcomes in remote working and lower lockdown risks. This article not only contributes to future research on labour force resilience but also provides supplementary material for easy application to study labour market changes even in cases with limited data in other countries.

Keywords: Methodology, Remote Working, Work-From-Home, Lockdown, Pandemic Restrictions, Occupation ISCO

1. Introduction

The mandatory lockdowns and limitations on physical interactions during the COVID-19 pandemic brought challenges to many workplaces. In response, both individual workers and businesses had to devise alternative adaptation strategies to ensure their survival and continuity. Some occupations were able to shift to remote work. Others, whose jobs depended on close physical proximity with other people, faced the difficult choice of risking unemployment or reduced income during lockdown periods, as seen in the cases of waiters and shop assistants, among others. Certain critical sectors, such as public health and public transportation, compelled their workers to continue their duties despite the high risk of exposure to the virus due to the essentiality of their work for maintaining the life and well-being of general society.

In Denmark, the Covid restriction period commenced in March 2020 and extended until September 10, 2021[1], encompassing four cycles of lockdown and reopening. Everywhere in the world, as well as in Denmark, the COVID-19 restriction period has affected not only the global economy – production processes but also the local economies and the individuals in the labour markets.

The pandemic and the restrictions give rise to a lot of research questions (and a lot of research papers). For instance, which individuals were resilient during the pandemic restrictions? How can one measure and identify disruptive changes due to the large-scale obstacles to ordinary economic activities? How can we predict the consequences of future pandemics and epidemics on the labour markets and local economies?

This article aims to enhance the methodology used to assess the resilience of individual workers in the context of pandemic-related restrictions. This is accomplished through a three-step process:

1. Replicating existing methods from two distinct indexes, namely the Home-Office-Index (HOI) for remote work (Dingel and Neiman 2020) and the Lockdown Index (LDI) for pandemic-related lockdowns (Faber et al. 2020).
2. Improving the methodology for remote working by estimating the Working-From-Home (WFH) index, which is measured as the likelihood of an employee working remotely based on their occupation and the economic sector of their workplace, drawing on data from the Danish Labour Force Survey (2008/2021).
3. Analyzing micro register data of employment statistics in Denmark from 2020 and 2021 to examine and compare three indexes—HOI, WFH, and LDI. This analysis aims to explore the resilience of the labour force by considering individual demographic and socio-economic characteristics, assessing their ability to work from home, and evaluating their susceptibility to pandemic-related restrictions.

This study uses the Pooled OLS modelling technique to assess who is resilient and who faces the pandemic-related lockdown risks in the labour market. The analysis takes into account various factors such as workers' demographics, socioeconomic status, residential location, and industry-related considerations. The results suggest that in comparison to the Home-Office-Index (HOI), the Working-From-Home (WFH) index offers more data variations and improved measures for examining remote work possibilities in the labour force. Furthermore, the study concludes that male workers in their middle ages, holding middle or top-level positions, particularly in publicly-owned workplaces, exhibit positive outcomes in remote working. Additionally, this group faces lower risks of lockdown compared to the individuals with early-career, mid-level education, and service-skilled workers.

[1] https://covid19.ssi.dk/-/media/arkiv/subsites/covid19/presse/tidslinje-over-covid-19/covid-19-tidslinje-for-2020-2022-lang-version---version-1---april-2022.pdf?la=da

This study contributes to existing knowledge in three significant ways. Firstly, it introduces additional methods and measurement tools that are valuable not only in scientific research but also in policymaking and strategic planning for establishing resilient local economies. The article not only aligns with similar motivations and findings found in the scientific literature but enhances index construction methods by incorporating data from the Labour Force Survey. This survey provides a comprehensive range of responses regarding the remote working activities of Danish employees before and during COVID-19 restriction periods. Additionally, the article offers supplementary materials for methodology and index coding upon request. Secondly, this article contributes to our understanding of the resilience in the labour market, providing insights that can be valuable for anticipating future trends. Thirdly, the indexes are structured according to the International Standard Classification for Occupations (ISCO) and Economic Sectors (NACE), making them adaptable to other employment datasets containing ISCO and NACE information. This adaptability extends beyond Denmark to datasets in other countries with similar economies, such as those in Western Europe and Northern America.

This article is structured into five sections. The second section offers a brief overview of prior attempts to examine the impacts of remote work and lockdown measures during the COVID-19 restrictions. The third section elaborates on the methodology proposed for improvement. In the fourth section, the article presents an empirical comparison of these indexes and provides the assessment of Danish employees, their capacity for remote work and their vulnerability to being sent home while accounting for their demographic and socioeconomic characteristics. The fifth and final section offers concluding remarks.

2. Literature

Remote working is not a new phenomenon. Already, since the 90s, the rise of information and communication technologies (ICT) has led to the digitalisation and transformation of workplaces allowing remote working possibilities for some occupations. Such transformation has natural implications on the geographical distribution or re-distribution of economic activities and labour markets (Graham 1998; Cairncross 1997). New digital computing and communication technologies prepared society for a digitized daily existence, featuring teleworking, teleshopping, telebanking, and more.

Before the pandemic, in Denmark, hybrid working was relatively common, about 8 % of employees were working from home in 2019. During COVID-19 the number of hybrid workers increased by up to 17% in 2020 (LFS. Statistics Denmark, 2020). However, varied across the sectors. During this period, three primary work forms have emerged.

The first is full-time remote work, where employees do not require physical workplace visits. These employees can be considered highly resilient, as they not only maintain their employment and income but also have the freedom to reside in their preferred locations, even if these are far from the workplace, such as rural and peripheral areas. Additionally, they benefit from reduced commuting costs and the negative externalities of urban living, which often include high expenses. (Ramani and Bloom 2021).

The second working form is hybrid remote working, also referred to as telecommuting (Aksoy et al. 2022; Sostero et al. 2020). These individuals must commute to the workplace on occasion, based on individual arrangements with their employers (Shirmohammadi et al. 2022; Neely 2021; Delventhal et al. 2022). They are less flexible since they need to remain in the geographical proximity of the workplace, but their commuting distances are typically longer than those required to be at the workplace every day. Gallent et al. (2023) highlighted that for many working individuals, transitioning to remote working practices during the pandemic, was due to the already existing experiences in such working form.

The final category represents the traditional form of work. These employees cannot work from home either full-time or in a hybrid manner. These individuals have an obligatory requirement to have physical proximity with other people (customers, colleagues, public) or operate the machinery or diverse equipment at the workplace (Faber et al. 2020). These persons have limited opportunities to work during the pandemic-related restrictions, cannot reside further than their acceptable level of distance and cost of daily commuting, and thus, exhibit the lowest level of resilience facing higher risk of being sent home without work or pay (*ibid.*).

The impact of COVID-19 on the labour market differs significantly from other economic crises, such as the financial crisis (Mongey et al. 2020). Due to the contagious nature of the Coronavirus, workplaces were mandated to implement lockdowns. Consequently, the occupations that typically required high physical proximity with others or physical presence in the workplace and had no capacity for remote work were hit the hardest (Mongey et al. 2020; Faber et al. 2020; Alstadsæter et al. 2020). Those employees faced layoffs or had to reduce their working hours, in some cases, temporarily, mainly during the lockdown months. Both workplaces and employees had to develop adaptive strategies to stay in business (Block et al. 2022; Faber et al. 2020; Béland et al. 2020; Alstadsæter et al. 2020). This strategy is sometimes referred to as "bootstrapping". As Block et al. (2022) noted in their research, "bootstrapping" is a commonly adopted method by companies during economic recessions and macro crises. With this approach, companies lay off or reduce the work hours of some employees during crisis periods to enhance their resilience to the shock and maintain operations, often at the expense of the remaining human capital (Block et al. 2022).

Since the initial pandemic-related involuntary lockdown in March 2020, there have been several methodologically similar efforts to explain these processes occurring in the labour market and local economies. Western European and Northern American researchers have developed two distinct indexes to help understand the pandemic-related changes in the labour market. One index, referred to as the Lockdown Index (LDI), considers the extent of physical contact required at work (Faber et al. 2020; Alstadsæter et al. 2020; Béland et al. 2020; Pouliakas and Branka 2020; Mongey et al. 2020).

The second index, known as the Home-Office Index (HOI), also called remote working and teleworking, is developed by evaluating whether a person can work remotely (Dingel and Neiman 2020; Aksoy et al. 2022; Faber et al. 2020; Redmond and McGuinness 2020; Sostero et al. 2020). Many of these studies focus on using either one of these indexes in their research. However, Faber et al. (2020) employ both indexes, arguing that they complement each other and provide a more comprehensive understanding of the transformative processes of the working forms due to the restrictive conditions.

In this article, we examine the HOI index on the actual frequency of remote working by each occupation using the Danish Labour Force Survey and provide suggestions for its improvement. The following section provides a detailed description of our data and methodology, which form the core of this study.

3. Data and methodology

3.1 Crosswalk LDIs and HOI from Swiss to Danish ISCO on the 5-6-digit level

As mentioned above, Faber et al. (2020) proposed the Lockdown Index (LDI) to estimate the economic impact of the Coronavirus. Their index was able to account for approximately 58% of short-term employment outcomes and roughly 20% of variations among Cantons (counties) in

Switzerland. To construct LDI, they relied on the measure of physical proximity requirements from the Occupational Information Network (O*NET) survey, primarily based on U.S. data. This measure was used to assign values ranging from 0 to 1 to various occupations, indicating the extent to which they were affected during the pandemic.

Specifically, they assigned a value of 0 to occupations with no close physical contact requirements, 0.5 to those with somewhat close contact (e.g., individuals working in the same room but not necessarily in proximity), and 1 to occupations who had an arm's length physical distance from others daily. Faber et al. (2020) excluded certain industries that had high levels of physical proximity requirements, but they could not shut down during the pandemic due to their critical role in the country's operations, such as delivery services, hospitals, passenger transport, pharmacies, food stores, and the public sector. Workers in these industries were assigned a value of 0.

Furthermore, Faber et al. (2020) mapped LDIs to the Swiss International Standard Classification of Occupations 2008 (ISCO-08 codes) at the 4-digit level. In addition to replicating the LDI approach with Swiss data, they also employed Dingel and Neiman's (2020) Home-Office Index (HOI) method to assess the possibility of remote work for various occupations, again based on the O*NET survey. Occupations, where respondents reported the need to operate machinery or had significant physical proximity requirements to perform daily tasks, were assigned an HOI of 0. Those who could telecommute were assigned an HOI of 0.5, and occupations not restricted to office settings and could potentially work anywhere were assigned an HOI of 1. For more details on this method, readers can refer to Dingel and Neiman (2020) and Faber et al. (2020).

The Lockdown Index (LDI) and Home-Office Index (HOI) developed by Faber et al. (2020) and Dingel and Neiman (2020) are constructed using hypothetical estimates based on respondents' claims regarding whether they work at a desk, have physical proximity requirements at work, or need to operate machinery or equipment to carry out their daily tasks. As a first step, we crosswalk their LDI and HOI indexes to the Danish employment data.

Regarding the lockdown index, our article follows the methodology developed by Faber et al. (2020). Since Denmark lacks a survey similar to O*NET, we adapt the LDI by cross-walking it from Swiss ISCO codes to the Danish occupation codes (DISCO). We assume that most of the occupations have similar tasks and work-related requirements both in Switzerland and Denmark. The Danish employment dataset contains DISCO codes up to the 6-digit level (in total 1290 unique codes), while Swiss LDI is developed for the occupations at the 4-digit level. Most of the indices are directly transferable to the Danish codes at the 4-digit level. We apply 4-digit level codes (573 unique codes) and decompose them further to 5- and 6-digit levels. Those Danish codes that we do not find in Faber et al.'s Swiss indexes at the 4-digit level (which is only 32 codes), then we decompose them with the unweighted average values of the indexes at the 3-digit level.

We apply the Lockdown Index (LDI) to the Danish employment dataset. The Danish LDI is equivalent to the Swiss LDI and is a continuous variable ranging from 0 to 1. Also, as in Swiss LDI, in Danish LDI a score of 0 indicates that the worker's occupation does not require physical proximity to carry out daily tasks, and therefore, they are not at risk of a lockdown. On the other hand, a score of 1 suggests that the worker's occupation necessitates physical proximity to others for their daily work. In this paper, we assign a value of 0 to certain critical sectors in Danish society, such as food stores, takeaway businesses, hospitals, pharmacies, etc., based on the assumption that these sectors were just as essential in Denmark as they were in Switzerland during the COVID-19 lockdown phases.

The same crosswalk method is applied to the HOI from Swiss ISCO 4-digit codes (Faber et al. 2020) to DISCO 5-digit. As explained by Faber et al (2020) and Dingel and Neiman (2020), the HOI is also a continuous variable between 0 to 1. In this context, a score of 0 signifies that the worker cannot perform their daily job tasks remotely, while a score of 1 indicates that the worker can complete all their daily work remotely. Occupations associated with critical sectors are assigned a value of 0. These workers were required to be always present at their workplaces, even during the lockdown phases, due to the essential nature of their work.

With the Lockdown Index (LDI) and Home-Office Index (HOI) applied to the Danish employment data, as a second step, our article improves upon previous studies by offering a more accurate measure of the ability to work from home. The next section of our study focuses on creating a new and more precise Work-From-Home Index (WFH) that aligns with the Danish working individuals, based on the Danish Labor Force Survey (LFS), where respondents explicitly state their actual remote work practices. This approach provides a more reliable estimation of individuals' ability to work from home.

3.2 Method for developing Work-from-Home (WFH) Index based on Danish LFS
Denmark, like all other European Union (EU) member countries, conducts the Labor Force Survey (LFS) and provides microdata, which serves as the foundation for labour market statistics in Eurostat. This microdata is made available to researchers who wish to conduct studies based on this dataset. The LFS dataset is carefully designed to be suitable for scientific research purposes while ensuring the protection of respondents' privacy by using "traditional statistical disclosure control methods." [2]

In the context of our study, this microdata is particularly significant because it includes a variable labelled HOMEWK, which specifies how frequently a person in a certain occupation works from home. The population selection criteria encompass "persons in employment," which also extends to self-employed individuals and travelling salespeople who do not require an office to prepare for meetings with clients. The survey in Denmark is conducted quarterly for employees aged between 15 and 89, with a sample size of approximately 30,000 persons. The sampling process is representative and random, although respondents who participated in the previous quarter were not selected for the subsequent quarter. The datasets are updated annually, covering the period from 2008 to 2021.

The HOMEWK variable has 5 answer codes for the frequency of working at home within a reference period of four weeks:

> **Ans. 1.** Persons usually work at home, i.e., working at home for half of the days of the working week.
> **Ans. 2.** Persons sometimes work at home, i.e., working at home less than half of the days of the working week.
> **Ans. 3.** Persons never work at home, i.e., working at home on no occasion in the reference period.
> **Ans. 9.** Persons who answer, “not applicable”.
> **Ans. bl.** Persons who leave blank with no answer.

(EUROSTAT, 2017; 2021)

Based on the responses provided in the LFS dataset, we assume that if a person with a certain occupation at any point in time (between 2008 and 2021) could typically or occasionally work from

[2] https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey

home, then that occupation likely had the potential to be adapted for remote working during the mandatory lockdown phase of pandemic. Consequently, we create a binary dummy variable for Remote Work using the following conditions:

Remote Work=1, i.e., remote workers: if a person **usually (ans. 1)** or **sometimes (ans. 2)** works at home,
Remote Work=0, i.e., non-remote workers: if a person **never (ans. 3)** works at home, or answers "**not applicable**" **(ans. 9)** or leaves it **blank (ans.bl.).**

Figure A1 in the Appendix shows the percentage of the respondents working remotely before and during the COVID-19. There is a clear pandemic effect observed in the data, when up to 25 % of respondents worked remotely before the pandemic, and this number increased up to 35 % during the lockdown phases. Similar trends of remote working are observed in other EU member states as well (Sostero, et al. 2020).

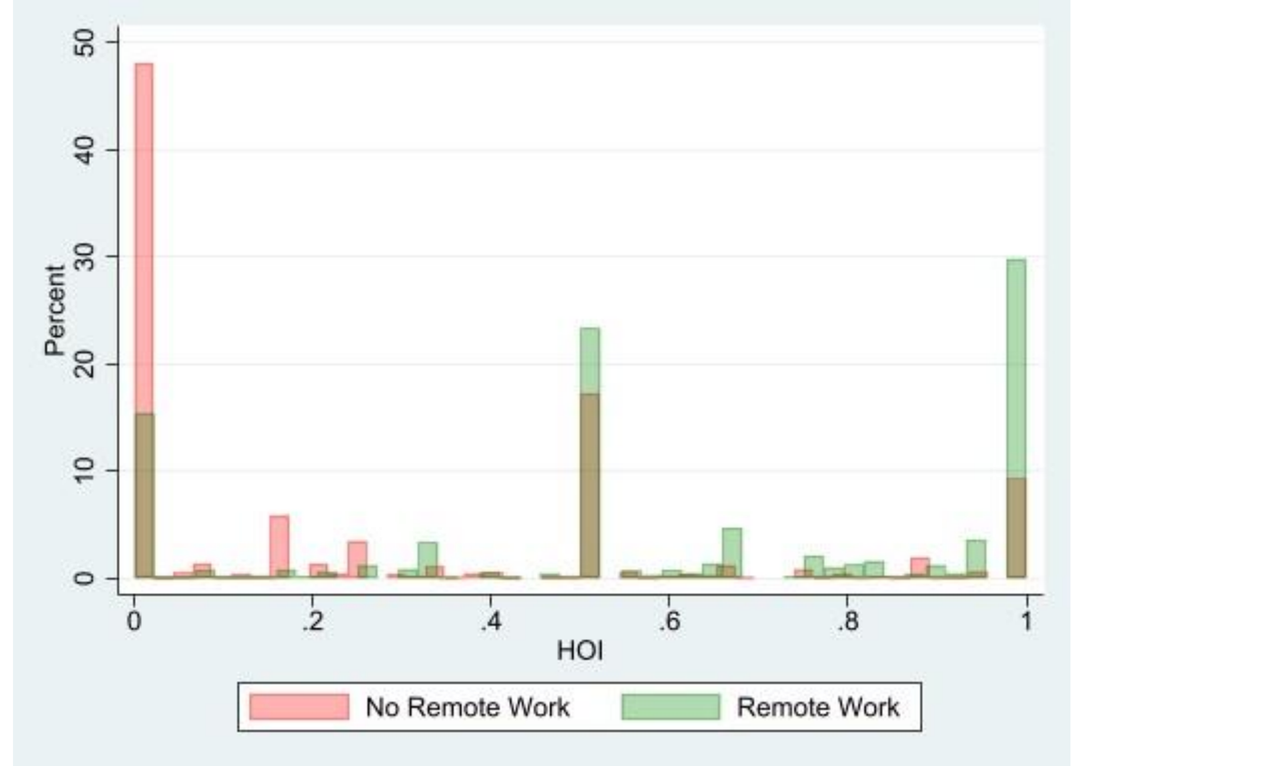
The LFS dataset contains various explanatory variables per person, among others, the International Standard Classification of Occupations (ISCO) codes up to a 4-digit level and The Statistical Classification of Economic Activities (NACE) at the 3-digit level. Since the LFS serves as our sample dataset, we undertake several data transformations: we convert quarterly data into yearly data, combine all years from 2008 to 2021, and extract unique observations that encompass HOMEWK, ISCO, NACE, and a binary dummy variable representing Remote Work.

In the next step, we assess the Home-Office-Index (HOI) derived from Faber et al (2020) and Dingel and Neiman (2020), cross-referenced with the Remote Work dummy variable, constructed from the respondents' answers in LFS. It becomes apparent that HOI successfully identifies certain instances of remote work in the dataset; nevertheless, there exist notable gaps. Figure 1 describes these discrepancies by illustrating the distribution of HOI on a scale from 0 to 1 under two conditions: 1) individuals with identical ISCO codes who answered they did not work remotely (i.e., Remote Work=0), and 2) individuals with identical ISCO codes who answered they worked remotely (i.e., Remote Work=1) in 2020 and 2021.

Figure 1 illustrates overlapping observations, where HOI = 0 assumes that persons with certain occupations cannot work remotely based on Dingel and Neiman's (2020) estimation. However, the data from the LFS dataset reveals that only about 48% of respondents with the same occupations reported not having remote work, while approximately 15% indicated that they did work remotely. In another example, when HOI = 1, assuming individuals with certain occupations working fully remotely. Contrary to this, our data indicates that only 30% of respondents with the same occupations worked remotely, while 9% reported not working remotely. Consequently, Figure 1 demonstrates that, although HOI is a well-developed index, it only aligns on average with approximately 40% of the actual remote working data. As a result, to enhance the accuracy of remote working estimations in Denmark, we apply the LFS dataset and Remote Work binary dummy to calculate predictive values for occupations with a more accurate likelihood for remote working activities.

Notably, certain ISCO codes may exhibit both 0 and 1 values for Remote Work. This occurrence is influenced by the specific sector in which job occupations are situated. In some sectors, similar occupations may have the potential to work from home, while in other sectors, this opportunity might not be as prevalent, thus we can observe that remote working is sector specific.

Figure 1. Cross-reference of HOI with remote working data from LFS



***Source**: LFS dataset and authors' calculation*

Consequently, we perform a linear regression in which we control for NACE 3-digit codes and generate predicted values for each ISCO code up to a 4-digit level, ranging from 0 to 1. These predicted values are assigned to the 360 distinct ISCO codes, forming a new variable referred to as "WFH" (Work-From-Home). Subsequently, we integrate these "WFH" predicted values into the Danish micro register data for the years 2020 and 2021.

Considering that Danish employment data contains unique 1-, 2-, 3-, 4-, 5- and 6-digit level codes for the Danish ISCO (DISCO) variable, and in total 1290, we disaggregate WFH predicted values from 360 to 1290 codes. The DISCO codes in the 4-, 5- and 6-digit levels get directly the WFH predicted values from the LFS-ISCO4. However, more aggregated occupations at the 1-, 2- and 3 digits will have assigned the non-weighted average of predicted value (μ) of the values at the closest digit level between 1 to 3 digits. Table 1 demonstrates this procedure.

Table 1. Aggregating/disaggregating the values from 4-digit to 6-digit DISCO codes

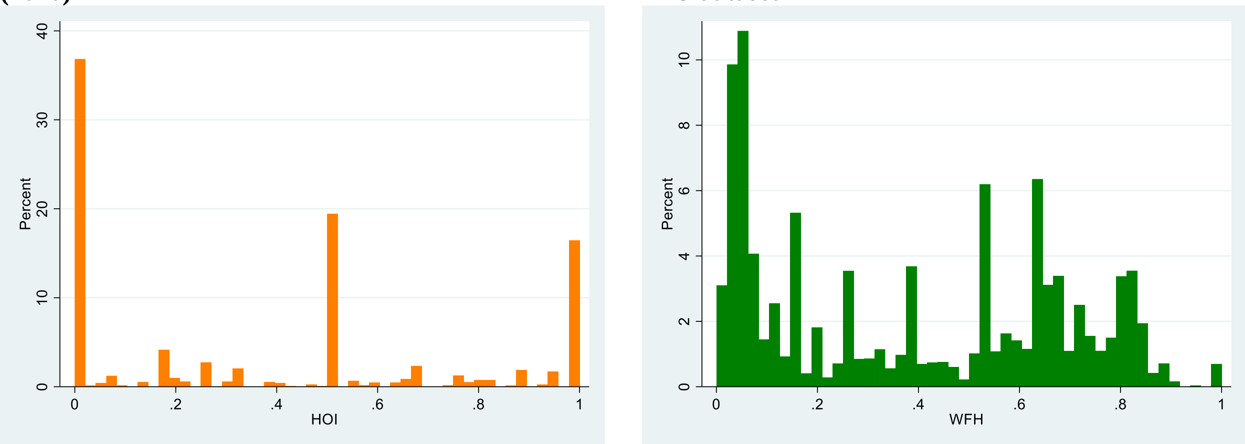
LFS-ISCO4 (4-digit)	**DISCO 1-6 digits (micro register dataset)**	**Predicted values n: WFH**
Range: 1000 - 1999	100000	μ. n {ISCO4: 1000-1999}
Range: 1100 - 1200	110000	μ. n {ISCO4: 1100-1200}
Range: 1110 - 1120	111000	μ. n {ISCO4: 1110-1120}
1111	111100	n {ISCO4: 1111}
1111	111110	n {ISCO4: 1111}
1111	111111	n {ISCO4: 1111}

When comparing two indexes related to remote work, namely the replicated HOI and our newly developed remote working index (WFH) based on the Danish Labor Force Survey, a substantial correlation of 0.77 is observed between them. The strong correlation suggests that these indexes can be used interchangeably, particularly in situations where remote working data is not available. However, it is essential to recognize that the WFH index, derived from responses in the Danish Survey, is better suited for evaluating remote work. This distinction becomes evident when examining comparative histograms, revealing that the WFH index demonstrates a broader range of variations compared to the HOI (Figure 2).

Figure 2 displays histograms of the HOI and WFH represented in percentages. Consequently, it becomes apparent that the predictive values associated with remote working possibilities based on occupation and economic sector differences, the WFH index holds greater descriptive power compared to the HOI.

Figure 2. The HOI and WFH histograms

Distribution of the HOI based on Dingel and Neiman (2020) **Distribution of the WFH Index based on the Danish LFS dataset**



***Source**: LFS dataset and authors' calculation*

Given that the WFH index considers not only occupation (ISCO) but also economic sector (NACE) codes, a comparison between HOI and WFH based on these characteristics will demonstrate to what extent these indexes overlap. Consequently, we decompose the indexes and examine the difference between HOI and WFH using an unpaired (Independent) T-test across 13 sector groups in Table 2 and 9 occupation (ISCO) groups in Table 3.

Table 2. Unpaired (Independent) T-test of means of HOI and WFH by economic sectors.

	obs	Mean: HOI	Mean: WFH	dif	St Err	t value	p-value
1. Primary (A-B)	580	.229	.339	-.11	.011	-10.55	0
2. Manufacturing (C)	9192	.269	.343	-.074	.003	-26	0
3. Provision (D-E)	659	.404	.406	-.002	.011	-.2	.836
4. Construction (F)	4192	.132	.211	-.08	.003	-33.1	0
5. Sales (G)	9709	.326	.284	.042	.003	17.7	0
6. Transport (H)	3002	.433	.256	.178	.004	45.3	0
7. Hotel-rest (I)	1826	.135	.141	-.006	.004	-1.45	.144
8. Info-communication (J)	2946	.73	.666	.064	.005	14.55	0
9. Finance-real-estate (K-L)	3326	.658	.595	.064	.005	14.75	0
10. Business services (M-N)	8116	.448	.445	.004	.003	1.25	.206
11. Public (O,P,Q)	29455	.416	.412	.004	.002	3.2	.002
12. Culture, sport, org. R	1281	.404	.418	-.015	.007	-2.15	.03
13. Private service (S-T)	1591	.454	.461	-.006	.006	-1.05	.285

***Source**: LFS dataset and authors' calculation*

In Table 2, the distributions of HOI and WFH significantly differ (p<0.1) across most economic sectors, with exceptions in 3. Provision (D-E), 7. Hotel and Restauration (I), 10. Business services (M-N), and 13. Private services (S-T). Table 3 shows that the distributions of HOI and WFH also significantly differ (p<0.1) across all 9 occupation groups. Based on these analyses, we consider adopting the WFH index for examining the Danish labour force and its individual and regional variations during the primary restriction period of the COVID-19 pandemic in 2020 and 2021.

Table 3. Unpaired (Independent) T-test of means of HOI and WFH by occupations.

	obs	Mean: HOI	Mean: WFH	dif	St Err	t value	p-value
1. Managers	3445	.747	.718	.03	.005	5.95	0
2. Professionals	25229	.581	.617	-.036	.002	-25.75	0
3. Technicians	9264	.554	.484	.07	.004	18	0
4. Clerks	7627	.511	.48	.031	.003	12.4	0
5. Sales/Service	13749	.159	.104	.054	.002	36.15	0
6. Agro-skills	385	.066	.303	-.238	.007	-32.1	0
7. Craftsmen	6093	.022	.166	-.144	.003	-57.65	0
8. Machine Operator	3766	.153	.047	.106	.004	31.9	0
9. Elementary	6317	.065	.044	.02	.002	12.3	0

***Source**: LFS dataset and authors' calculation*

These findings lead us to infer that the WFH index[3] offers a more precise and nuanced measure of remote work when compared to the HOI.

To understand the dynamics of remote work opportunities and identify those workers whose jobs were involuntarily lockdown, we explore the individual and geographical heterogeneity of Danish workers based on the WFH and LDI indexes in the following section.

3.3 Data processing

To investigate the pandemic-related adaptation of Danish working individuals, we utilize a comprehensive micro dataset derived from the population and employment statistics. This dataset, provided by Statistics Denmark (DST), encompasses information about every individual (approximately 5.6 million people) with a registered residential address in Denmark. It comprises a wide array of personal, socioeconomic, and labour market details for each individual, including age, gender, family composition, ethnic background, educational attainment, place of residence, workplace location, economic sector of employment, occupation, salary, hourly wage rate, workplace type (public or private), and socioeconomic status (e.g., employed, student, retired, etc.). We select data from 2020 and 2021. Table 4 presents key statistics regarding Denmark's population, employment, and unemployment.

Table 4. Denmark's population and labour market

	Population	Primary Employment	Employment rate %	Activity rate %	Unemployed No.	Unemployment rate %
2020	5822763	2924122	75,1	77,7	94594	3,1
2021	5840045	2906044	74,5	77,7	115857	3,8

***Source**: RAS dataset, StatBank, Statistics Denmark (DST)*

To prepare the dataset for our study, we undertake a series of data-cleaning steps. We exclude individuals who are not employed during 2020 and 2021, those with addresses outside Denmark but working within the country (e.g., cross-border commuters), and individuals working abroad (e.g., at Danish embassies or on North Sea oil platforms).

Furthermore, we filter out individuals who are under 18 and those over 67 years of age. While the official retirement age in Denmark is 65, it's common for individuals aged 65 to 67 to remain in the job market, particularly those with high-skilled occupations. Additionally, we remove individuals

[3] The WFH indexes at the ISCO 4-digit and NACE 3-digit level codes are available upon request.

with occupations (defined by ISCO-88 codes) in the military and those whose occupations are not registered in official statistics.

From the remaining dataset, we retain only primary employment records, which include self-employment. This means we exclude records of secondary employment or other types of economic activities, such as owning a business in addition to a primary job.
In the end, our dataset comprises the primary employment records of individuals aged 18 to 67, with registered occupational (ISCO) codes. Table 5 provides an overview of the final number of observations, which account for approximately 79% of the total employed individuals per year. This subset offers a genuine representative sample of Danish workers for our methodology and analyses.

Table 5. Number of observations per year after data cleaning

	Primary Employment (official)	**Number of observations**	**% of the total employed**
2020	2924122	2308622	79
2021	2906044	2300934	79
Source: *DST datasets and own calculations*			

Using micro register data and the developed indexes, the paper provides a detailed assessment of the pandemic-related risks and resilience of the workers considering their ability to Work-From-Home and the risks to be sent home due to mandatory lockdown of workplaces. The next section of this period is devoted to assessing and analysing workers' individual and regional differences concerning COVID-19 resilience. Tables A1 and A2 in the Appendix provide the full list of demographic and socioeconomic variables applied in this paper.

4. Individual and regional differences by HOI, WFH and LDI in Denmark

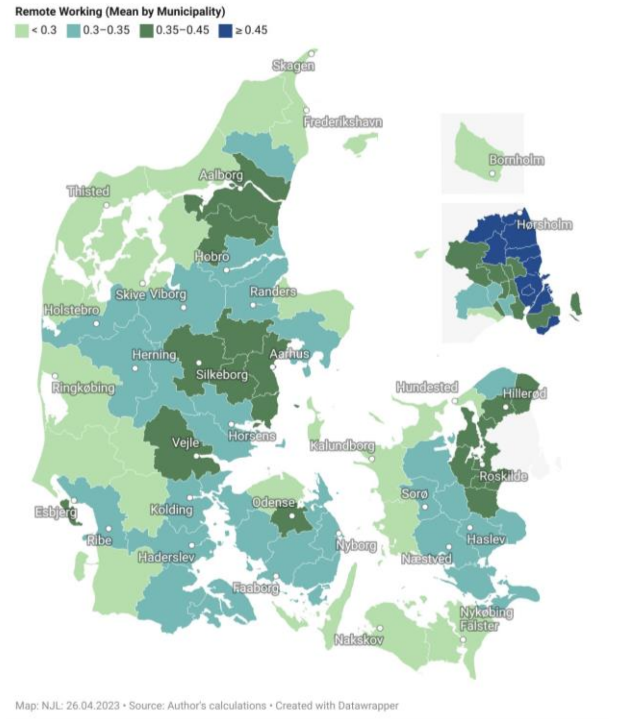
In this chapter, we compare the HOI, WFH, and LDI indexes by exploring the demographic, socioeconomic, and locational attributes of individuals who can work remotely (i.e., are resilient), and those who were at risk (i.e., being affected by lockdowns) during mandatory COVID-19 lockdown phases. To accomplish this, we construct a cross-sectional dataset based on the microregister data for 2020 and 2021 and apply a pooled Ordinary Least Squares (OLS) multiple linear regression.

As explained in the Methodology section, a strong correlation of 77% exists between the HOI and WFH indexes. Consequently, it is reasonable to anticipate that the individual and regional differences among workers are similar in both cases, with only marginal variations in certain worker categories, thus they can be used as substitutes. The WFH and LDI indexes, on the other hand, overlap only less degree. Their correlation of -0.43 suggests that these indexes share some similarities but are not entirely interchangeable. Consequently, they exhibit more of a complementary relationship rather than being direct substitutes. Consequently, we examine these indexes individually in three models to gain a deeper understanding of their distinctiveness based on the Danish data. Herein, the Home-Office-Index is studied in Model 1 where Y_1=HOI, the probability of Working-From-Home in Model 2 where Y_2=WFH and the risk of being sent home due to lockdown in Model 3 where Y_3=LDI. All three models share the same dataset and explanatory variables, which encompass workers' demographic and socioeconomic characteristics and are summarized in Table A2 in the Appendix.

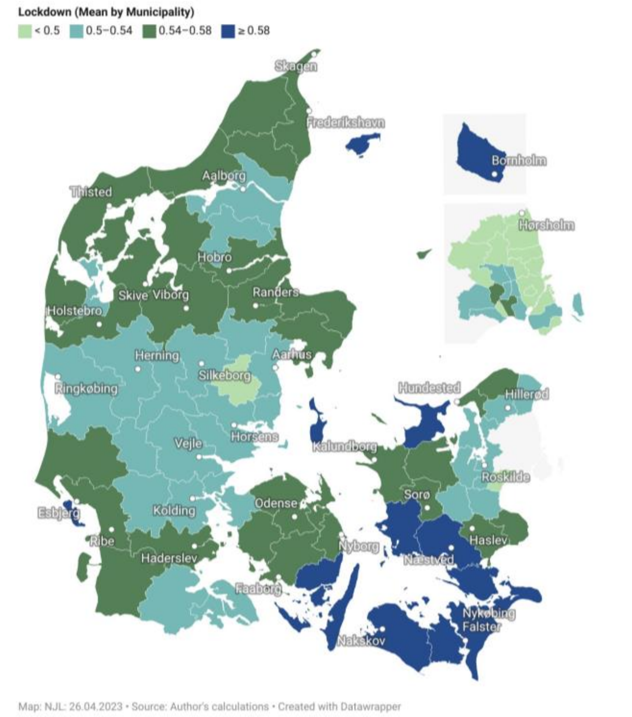
Before engaging in regression analyses, we investigate whether there is regional heterogeneity in the residential locations of workers, considering their capacity to work from home or their risk of workplace lockdowns. The data indicates that the regional distribution of WFH and LDI indexes is contingent upon the composition of local economies. Figure 3 visually illustrates the average WFH and LDI indexes among workers based on their residential municipalities.

Figure 3. The regional distribution of average (a)WFH and (b)LDI by residential municipality in Denmark.

(a) Average WFH index by the residential municipality in Denmark in 2020 and 2021



(b) Average LDI index by the residential municipality in Denmark in 2020 and 2021



In Figure 3. a, the map reveals that the municipalities with the highest average WFH values (over the national average of 0.35) are the Copenhagen metropolitan area and its surroundings, along with the larger cities in Denmark, such as Aarhus and its neighbouring municipalities. Additionally, municipalities that serve as regional administrative centres, such as Aalborg, Odense, and Vejle, also exhibit high WFH values. In contrast, the lowest potential for remote work is observed in the rural and peripheral municipalities throughout Denmark.

Conversely, in Figure 3. b, the highest average LDI values (over the national average of 0.54) are predominantly found in the peripheral and rural municipalities. These observations underline the disparities in remote working and lockdown possibilities across various regions of Denmark, highlighting a more pandemic-resilient working population in urban areas.

Considering that there is unobserved heterogeneity across the residential municipalities, such as local economic composition, municipality amenities, urbanisation grade, natural amenities, etc. it becomes imperative to account for these spatial variations while exploring our indexes in OLS regression.

Given that both WFH and LDI are influenced by industry-specific factors and that the same occupations can vary in terms of work-related tasks within different industries (as explained in section 3.2), it is important to recognize that certain industries may be more favourable to remote work or lockdown measures compared to others. Furthermore, changes and fluctuations within industries can significantly impact the outcomes. This observation is consistent with the results presented in studies by Faber et al. (2020) and Sostero et al. (2020).

To address this, we integrate controls for unobserved heterogeneity across diverse industry types, including the primary sector, manufacturing, and services (A full list of industries is in Table A2 in the Appendix). This approach allows us to account for the industry-specific factors that may influence the probability of working from home or being subject to lockdown.

Thus, by controlling the place and industry unobservable factors, as well as controlling for the individual and socioeconomic characteristics of workers, we construct the Pooled OLS models to explore what characterizes the workers who face the pandemic-related risks (LDI) and have resilience (HOI and WFH) on the labour market:

$$Y_i = \beta_0 + \beta \cdot \sum X_i + \gamma \cdot \sum Z_i + \mu_i + \sigma_i + \varepsilon_i$$

Where,

Y_i is the dependent variables 1) HOI, 2) WFH and 3) LDI by individual i.
X_i is the vector of individual characteristics as the explanatory variables, such as gender, age, family type, ethnicity, and living conditions.
Z_i is the vector of socioeconomic variables, such as education, salary level, skills, full-time work, and public/private workplace.
σ_i is the control of industrial heterogeneity of 13 economic sector groups by individual's workplace.
μ_i is the control of spatial heterogeneity of municipalities by individual's residential municipality.
ε_i is the error term.

The corresponding outcomes of the three models for Y_1=HOI, Y_2=WFH, and Y_3=LDI are illustrated in Table 6 (Summary statistics of dependent variables are provided in Appendix Table A1). The reference levels for each explanatory variable are shaded in grey in Table A2 and summarized in Table A3 in the Appendix. The reference worker is selected as the individual whose work we assume (based on the register data, previous literature, as well as urban myths and media) was most hindered by the COVID-19 restrictions.

Table 6. Comparison of HOI, WFH and LDI based on the pooled OLS analyses for 2020/2021

MODELS: EXPLANATORY VARIABLES:	Model 1: HOI	Model 2: WFH	Model 3: LDI
Male vs. Female	-0.001***	0.023***	-0.009***
	(0.000)	(0.000)	(0.000)
Age (25/34) vs. (18/24)	0.019***	0.011***	-0.024***
	(0.001)	(0.000)	(0.000)
Age (35/49) vs. (18/24)	0.022***	0.012***	-0.028***
	(0.001)	(0.000)	(0.000)
Age (50/67) vs. (18/24)	0.019***	0.012***	-0.042***
	(0.001)	(0.000)	(0.000)
Married or Partnership vs. Single	-0.001	0.002***	-0.005***
	(0.000)	(0.000)	(0.000)
Danish vs. Descendant	0.029***	0.022***	-0.017***
	(0.001)	(0.001)	(0.001)
Migrants vs. Descendant	0.006***	-0.002**	-0.039***
	(0.001)	(0.001)	(0.001)
Detached housing vs. Other housing	0.003***	0.004***	-0.000

	(0.000)	(0.000)	(0.000)
Vocational (ISCED 2-4) vs. ISCED 1-2	0.012***	0.009***	0.001**
	(0.000)	(0.000)	(0.000)
Short High (ISCED 4) vs. ISCED 1-2	-0.002**	0.025***	-0.025***
	(0.001)	(0.000)	(0.001)
Middle High (ISCED 5-6) vs. ISCED 1-2	-0.063***	0.014***	0.088***
	(0.001)	(0.000)	(0.000)
Long High (ISCED 7-8) vs. ISCED 1-2	0.070***	0.127***	-0.072***
	(0.001)	(0.000)	(0.001)
Commuter vs. Non-commuter	0.005***	0.011***	-0.013***
	(0.000)	(0.000)	(0.000)
Salary:13.2-27 K EURO vs. <13.2 K EURO	-0.008***	-0.003***	0.011***
	(0.001)	(0.000)	(0.000)
27-40 K EURO vs. <13.2 K EURO	-0.013***	-0.015***	0.006***
	(0.001)	(0.000)	(0.000)
40-54 K EURO vs. <13.2 K EURO	-0.004***	-0.005***	0.013***
	(0.001)	(0.000)	(0.000)
54-67 K EURO vs. <13.2 K EURO	0.004***	0.025***	-0.013***
	(0.001)	(0.000)	(0.001)
67< K EURO vs. <13.2 K EURO	0.042***	0.054***	-0.069***
	(0.001)	(0.000)	(0.001)
High-skilled vs. Manual-skilled	0.512***	0.461***	-0.083***
	(0.000)	(0.000)	(0.000)
Service-skilled vs. Manual-skilled	0.216***	0.178***	0.069***
	(0.000)	(0.000)	(0.000)
Private workplace vs. Public workplace	0.017***	-0.044***	0.001
	(0.001)	(0.000)	(0.001)
Full-time work vs. Part-time	0.022***	0.022***	-0.014***
	(0.000)	(0.000)	(0.000)
Constant	-0.083***	-0.017***	0.607***
	(0.001)	(0.001)	(0.001)
Control: Residential Municipality	Yes	Yes	yes
Control: Industry	Yes	Yes	Yes
Observations	4,609,488	4,609,488	4,609,488
R-squared	0.419	0.640	0.397

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Source*: Register dataset from Statistics Denmark, and authors' calculations*

Table 6 presents the robust OLS results illustrating the relation between HOI, WFH, and LDI indexes and the demographic and socioeconomic characteristics of Danish workers. This analysis incorporates controls for both the economic sectors of the workplace and the residential municipality. The table shows coefficients that can be interpreted as percentage-point values.

In Table 6, the first two models (HOI and WFH) are designed to compare how the workers' characteristics can explain each remote working index. Positive coefficients signify an increase in the probability of remote work for each unit increase in each category, relative to the threshold category for a worker. It is crucial to remember that given the strong correlation between HOI and WFH indexes, the results for these two should be very similar. However, if we argue that WFH is an improved index, based on actual data on remote working compared to HOI, which only assumes a person's ability to work remotely, we can analyse the differences between these indexes in relation to workers' demographic and socioeconomic characteristics, holding all other factors constant.

When comparing the HOI and WFH indexes, it appears that WFH provides a more fitting model with an R-squared of 0.64, which is better than the HOI's R-squared of 0.42 for HOI. Even though most coefficients are similar in both models, varying only in size, there are still a few categories of workers that have different outcomes between HOI and WFH.

For instance, in the HOI model, male workers show a significant negative correlation compared to females, whereas in the WFH model, the correlation is significantly positive. A similar distinction is observed in the outcomes for workers with Short Higher and Middle Higher education compared to those with only Primary education (ISCED 1-2), whose correlation is negative in the HOI-model and positive in the WFH-model.

Another difference emerges in terms of workers' family types. According to Table 6, being married or living in a partnership, compared to single individuals, does not exhibit a significant impact on remote working in the HOI model, whereas it shows a significantly positive outcome in the WFH model.

Regarding the ethnic categories of workers, ethnically Danish workers, when compared to 2nd generation descendants, demonstrate similarly significant positive outcomes for remote working in both models. However, migrant workers, when compared to descendants, exhibit a significantly positive outcome in the HOI model, while displaying a positively negative outcome in the WFH model. This pattern corresponds to workers in privately owned workplaces, who, when compared to those in publicly owned workplaces, show similarly contrasting results.

The comparison between the HOI and WFH models distinctly highlights both overlapping and divergent results concerning the probabilities of working from home, offering valuable insights for future research on remote work. However, our current study focuses further on investigating the demographic and socioeconomic characteristics of workers with high resilience - specifically, those with a high probability of working from home, by using WFH index (model 2) - and low risks, denoting a low probability of being sent home due to workplace lockdown, by using LDI index (model 3).

To summarize the findings on remote working (model 2) from Table 6, we observe that workers who exhibit a positive and significant correlation with WFH, indicate resilience to pandemic-related restrictions. These workers are predominantly male, older, living in a partnership, ethnically Danish, residing in detached (one-family) housing, having education beyond the primary level, commuting to work, earning an annual income exceeding 54 thousand Euros, employed in high-skilled and service-skilled occupations as opposed to manual-skilled jobs, working in publicly owned workplaces, and engaging in full-time employment.

In the third column (model 3) of Table 6, the coefficients of the LDI model are presented, aiming to investigate which workers are most vulnerable to being sent home during periods of pandemic-related restrictions. Similar to the other models, the coefficients in the LDI model can be interpreted as percentage-point values. However, in contrast to the previous models, in the LDI model, positive coefficients indicate an increase in the probability of the risk of lockdown for each unit increase in each category compared to the threshold category of workers, while negative coefficients signify a lower risk of lockdown. As previously mentioned, there is an overlap of about -43% between the

WFH and LDI indexes, indicating some similarities in the results. However, more than half of the observations provide different outcomes.

In summary of the findings on lockdown risk (LDI model) from Table 6, it is evident that negative and significant coefficients in relation to LDI, indicate lower risks of workplace closure during pandemic-related restrictions. These workers are characterised as predominantly male, aged 25 and older, living in a partnership, ethnically Danish as well as migrants compared to descendants, holding Short Higher and Long Higher education, commuting to work, earning an annual income exceeding 54 thousand Euros, employed in high-skilled jobs, and working full-time. However, higher risks of lockdown are observed among workers with Vocational and Middle Higher education, and lower income levels working in service-skilled jobs and privately owned workplaces.

Hence, this section provides both a comparison of the two different indexes for measuring remote working and the explorative assessment of pandemic-related risks and resilience of Danish workers.

5. Concluding remarks and future considerations

This article explores the challenges posed by the COVID-19 pandemic, during which workplaces had to adapt to lockdowns and restrictions on physical interactions. While some occupations shifted to remote work, others faced unemployment or reduced income due to the obstacles of being physically at work. Critical sectors continued to operate despite the increased risk of virus exposure. The pandemic continued in Denmark for approximately two years, involving multiple cycles of lockdowns and reopening. Such global events are expected to become more frequent due to factors such as pandemics, economic volatility, disruptive innovations, and crises related to climate change.

The study introduces three key indexes: the Home-Office-Index (HOI), the Work-from-Home (WFH) index, which both estimate the likelihood of remote work and the Lockdown (LDI) index, which measures the likelihood of being sent home during pandemic-related restrictions. It examines Danish employment data from 2020 and 2021, alongside Labor Force Survey data from 2008 to 2021, to evaluate the resilience of the labour force based on demographic and socioeconomic factors.

A significant contribution of this study is the replication, development, and comparative assessment of indexes structured according to the International Standard Classification for Occupations (ISCO), making them adaptable for use in similar datasets from other countries. It replicates and improves existing methods for constructing these indexes and provides insights into significant demographic, socioeconomic and spatial differences of the workers regarding their pandemic-related resilience and risks. Furthermore, it offers valuable tools for research and policymaking aimed at building resilient local economies.

To achieve this, the study employs microregister data, Labour Force Survey data and Pooled OLS models to assess each index, where Model 1 measures HOI, Model 2 – WFH and Model 3 – LDI. The comparison between the HOI and WFH models reveals both overlapping and divergent outcomes concerning the probabilities of working from home. Notable distinctions appear in gender, education, family and ethnicity types, providing valuable insights for future research on remote work.

The findings from WFH and LDI models show that the workers in the middle and top career levels in publicly owned, high-skilled jobs are more resilient than those workers that are in the early-career and privately owned service-skilled jobs. Their resilience strengthens further if the workers are also ethnically Danish and live together with a partner or spouse, preferably in detached one-family housing. However, the paper also suggests that there is a spatial difference between the WFH and LDI outcomes, and to capture these differences and urban/rural dichotomy in the workers' pandemic-related resilience, we will require further research.

While the study provides valuable insights into the factors influencing remote work possibilities and lockdown risks, it is essential to note that the results specifically describe the Danish working population during the COVID-19 pandemic. However, considering previous studies, these findings shed light on the importance of demographic, socioeconomic, and industry-related factors in shaping working conditions during a pandemic. Importantly, the results align with prior methodological studies (Faber et al. 2020; Sostero et al. 2020; Alstadsætter et al. 2020), suggesting that labour market structures are comparable within Western European countries, even during pandemic-related shocks.

In summary, this study offers several significant contributions. Firstly, it develops the methodology by introducing an improved Work-from-Home (WFH) index based on survey responses, providing a more accurate measure and more variation across occupations compared to previous methodologies. This index serves as a robust foundation for future research exploring the short- and long-term resilience of labour markets in the face of macroeconomic disruptions.

Secondly, the study provides essential measurement tools for assessing the resilience of the labour force based on geographical distribution, enabling policymakers to tailor policies to specific regions and individuals.

Thirdly, the study contributes to the development of measures based on the international classification of occupations (ISCO), facilitating research in other countries even in the absence of remote work or lockdown survey data.

There are some limitations to this approach. While the Work-from-Home (WFH) index relies on survey data, which is an improvement over previous attempts, the Lockdown (LDI) index is an estimated proxy adapted from the Swiss LDI. Refinement of the Danish LDI based on responses from national surveys is needed, which are currently underway. These surveys specifically investigate whether workplaces were closed during COVID-19 restriction phases, providing more accurate data in the Danish labour market context.

Nonetheless, the empirical findings suggest that the Work-from-Home (WFH) and Lockdown (LDI) indexes examined in this study lay a solid foundation for future research into the long-term impact of pandemics on the labour market, local economies, and regional resilience.

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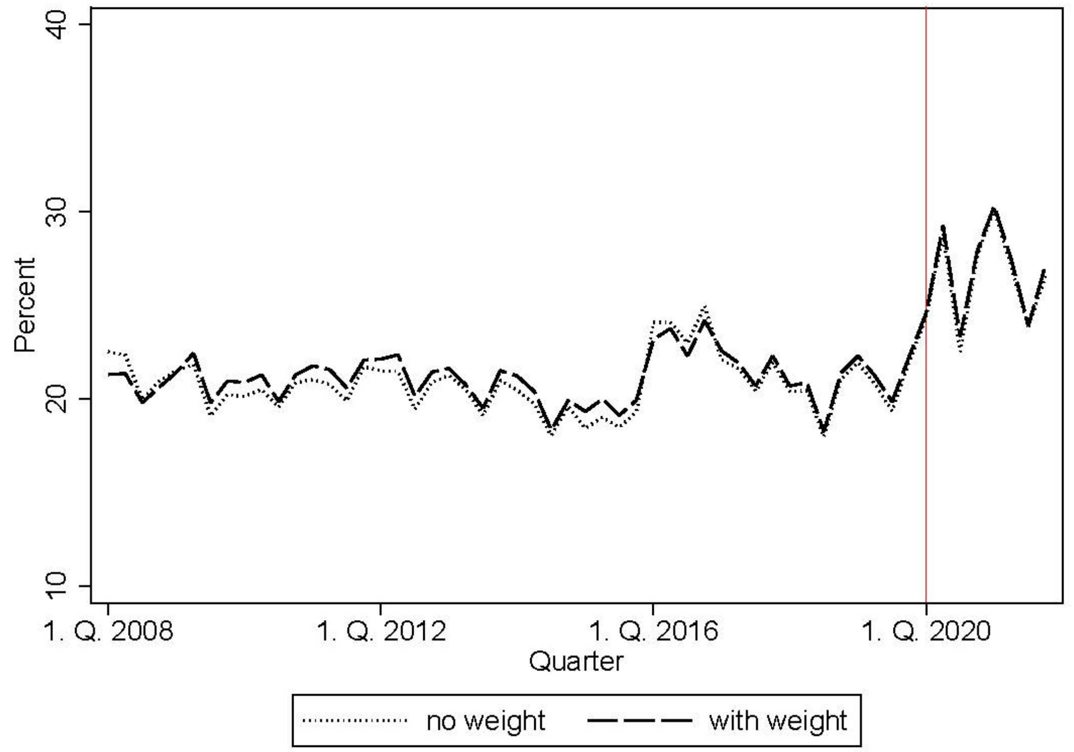
Appendix

Figure A1. Remote Working in Denmark between 2008 to 2021



Source: LFS data and authors' calculations

Table A1. Summary of dependent variables (DV)

Variable	Obs.:	Mean:	SD.:	Min.	Max.
WFH	4,609,488	0.37	0.30	0.0009637	1
HOI	4,609,488	0.38	0.38	0	1
LDI	4,609,488	0.52	0.32	0	1

Table A2. Summary of the Independent Dummy Variables

	Category	*Mean*	*Std.dev*	*min*	*max*
Gender	Male	0,50	0,50	0	1
	Female	0,50	0,50	0	1
Age groups	Age (18/24)	0,11	0,32	0	1
	Age (25/34)	0,22	0,41	0	1
	Age (35/49)	0,33	0,47	0	1
	Age (50/67)	0,33	0,47	0	1
Family types	Married or in partnership	0,69	0,46	0	1
	Single or Child	0,31	0,46	0	1
Ethnicity groups	Danish	0,87	0,33	0	1
	Migrants	0,11	0,31	0	1
	Descendants	0,02	0,14	0	1
Living conditions	Other types of houses	0,51	0,50	0	1
	One-family detached houses	0,49	0,50	0	1
	Primary/secondary (ISCED1-3)	0,22	0,41	0	1

Education groups	Vocational (ISCED 2-4)	0,35	0,48	0	1
	Short High (ISCED 4)	0,06	0,24	0	1
	Middle High (ISCED 5-6)	0,21	0,41	0	1
	Long High (ISCED 7-8)	0,15	0,35	0	1
Labour mobility	Non-commuter	0,51	0,50	0	1
	Commuter	0,49	0,50	0	1
Wage categories (K=1000)	<13.2 K EURO	0,15	0,36	0	1
	13.2-27K EURO	0,11	0,31	0	1
	27-40K EURO	0,14	0,34	0	1
	40-54K EURO	0,24	0,43	0	1
	54-67K EURO	0,17	0,38	0	1
	67< K EURO	0,19	0,39	0	1
Economic Sectors	1. Primary (A-B)	0,01	0,08	0	1
	2. Manufacturing (C)	0,12	0,32	0	1
	3. Provision (D-E)	0,01	0,09	0	1
	4. Construction (F)	0,06	0,24	0	1
	5. Sales (G)	0,14	0,35	0	1
	6. Transport (H)	0,04	0,20	0	1
	7. Hotel-rest (I)	0,03	0,17	0	1
	8. Info-communication (J)	0,04	0,20	0	1
	9. Finance-real-estate (K-L)	0,04	0,21	0	1
	10. Business services (M-N)	0,11	0,32	0	1
	11. Public (O,P,Q)	0,36	0,48	0	1
	12. Culture, sport, org. R	0,02	0,13	0	1
	13. Private service (S-T)	0,02	0,14	0	1
	14. Other and unknown (U)	0,00	0,00	0	1
Sector-ownership types	Public	0,36	0,48	0	1
	Private	0,61	0,49	0	1
	Abroad/Unknown	0,03	0,17	0	1
Job occupations	High Skilled	0,47	0,50	0	1
	Service Skilled	0,29	0,45	0	1
	Manual Skilled	0,24	0,43	0	1
Part/Full-time work	Part-time work	0,23	0,42	0	1
	Full-time work	0,77	0,42	0	1

Table A3. Summary of reference group characteristics

Demographic characteristics reference	**Socioeconomic characteristics reference**
Is female, age between 18/24, lives alone, is the descendent of the immigrant parents, does not live in a detached one-family house.	With primary education, is a non-commuter, earns less than 13.2K EURO per year, works in manual skilled occupations, works in a publicly owned sector, at a part-time job.