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A Study on the Matching Efficiency of Malaysia's Labor Market during the Covid-19 Pandemic using the DEA-Malmquist Productivity Index

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Abstract: This paper analyses the matching efficiency of the Malaysian labor market during the COVID-19 pandemic. Employing Malmquist DEA, the results indicate that from January 2020 to December 2021, the average total factor productivity change is 0.967. TFPCH declined and had an average growth rate of -3.3% during the sample period. Decomposing TFPCH into technical change (TECHCH) and efficiency change (EFFCH), low TECHCH, with an average growth rate of -10.2%, is the main reason why TFPCH is far from the effective frontier. The TFPCH of the mining and quarrying industry is the highest, with an average growth of 18.7%. The TFPCH of both manufacturing and construction industries are the lowest with average annual growths of -1.7% and -7.6% respectively. Overall, it can be concluded that one of the main drivers to enhance the matching efficiency of the labor market is technical change or technological progress. One way is to strengthen online platforms that can help the firm or industry to match job vacancies to job seekers, even during economic shocks.

Keywords: *Data Envelopment Analysis; Malmquist Productivity Index, Labor market efficiency.*

1. Introduction and Background

The COVID-19 pandemic has caused dramatic changes in every aspect of human life, especially health, economy, and social life. Because this virus is contagious, governments around the world have attempted to stop its spread through various policies. The Malaysian Government implemented several phases of Movement Control Order (MCO) (Table 1). During the first phase, the MCO, there were many restrictions, such as the general prohibition of mass movements and gatherings across the country. All business premises were closed, except for supermarkets, public markets, grocery stores, and convenience stores selling daily necessities. All government and private spaces were also closed, except those providing essential services. All public and private higher education institutions (IPTs) and skills training institutes nationwide were also closed, as were all kindergartens and public and private schools. Foreign visitors and tourists were also prohibited from entering the country.

During the Conditional Movement Control Order (CMCO) phase, most economic sectors and activities were permitted to operate, but they were required to comply with business standard operating procedures, such as social distancing and recording the names and telephone numbers of customers and the dates of their visit. In the Recovery Movement Control Order (RMCO) phase, the restrictions were loosened further. On 29th June 2020, the government announced that public and private pre-schools, kindergartens, nurseries, and daycare centers may return to operation from 1st July. In addition, spas, wellness and foot massage centers, cinemas, meetings, seminars, weddings, birthdays, and religious gatherings were among the enterprises and activities permitted during the RMCO. Swimming in public, hotel, condominium, gated community, and private pools were also allowed.

Table 1: Malaysia's MCO Phase

Date	Descriptive Statistics
March 2020 – May 2020	Movement Control Order (MCO)
May 2020 – June 2020	Conditional Movement Control Order (CMCO)
July 2020 – March 2021	Recovery Movement Control Order (RMCO)
January 2021 – May 2021	MCO by states
June 2021	Full Movement Control Order (FMCO)
June 2021 – December 2021	National Recovery Plan (NRP)

Source: National Security Council

A year later, approaching June 2021, the number of cases tremendously increased, forcing the government to announce a total lockdown or Full Movement Control Order (FMCO). Only essential economic and social services listed by the National Security Council were permitted to operate during this lockdown, such as food and beverage (F&B), banks, docks, airports, and transport related to cargo and commodities, land, air and water transport, construction and critical infrastructure works, and hotels used solely for quarantine. Restaurants may only open from 6 a.m. to 10 p.m. The government implemented the National Recovery Plan (NRP) as the final phase of MCO. At this stage, Malaysians were encouraged by the government to take two shots of vaccination to prevent the spread of the virus.

These policies have changed the labor market landscape drastically. The pandemic has led to massive job losses and economic slowdowns across the world. Malaysia in particular has seen considerable decline in both employment and productivity growth. Employment declined significantly from 15.1 million persons in 2019 to 14.9 million persons in the second quarter of 2020, as workers were laid off their contracts were not renewed and small businesses were impacted (Bank Negara Malaysia, 2021). During the COVID-19 pandemic, common reasons for job losses were business closure, downsizing, voluntary and mutual separation schemes (VSS/MSS), company financial difficulties, and constructive dismissal (MOHR, 2021).

Table 2 shows job retrenchment data in 2020 and 2021. In 2020, the industries with the most job losses were manufacturing (23,281 jobs), wholesale and retail (15,023), and accommodation and F&B (14,427). In 2021, this trend continued, with manufacturing wholesale and retail industries seeing the most retrenchments.

Table 2: Job Retrenchment by Industry 2020 and 2021

Industry	2020	2021
Agriculture, forestry & fishing	867	504
Mining & quarrying	1620	732
Manufacturing	23281	13205
Construction	7878	4888
Electricity, gas, steam & air conditioning supply	520	510
Water, sewerage & waste	459	163
Wholesale & retail	15023	10613
Transportation	7064	3136
Accommodation and F&B	14427	4856
ICT	5734	4762
Financial & and insurance takaful	2793	2079
Real estate	2781	1739
Professional & Technical	10090	4986
Administrative & and support service	8378	4146
Defense compulsory social security	125	73
Education	2263	1764
Human Health and Social Work	769	612
Arts, entertainment & recreation	1348	637
Other services	1557	1909
Activities of households	12	3

Activities of extraterritorial	35	43
Total	107024	61360

Source: Perkeso & MOHR

By group of occupation, as shown in Table 3, professionals had the most retrenchments (2020: 28,116, 2021: 17,051). The data also shows that the most affected professionals, most of them were from the manufacturing sector (2020: 4,439, 2021: 2,758). The second most affected occupation was technicians and associate professionals (2020: 20,548, 2021: 12,187).

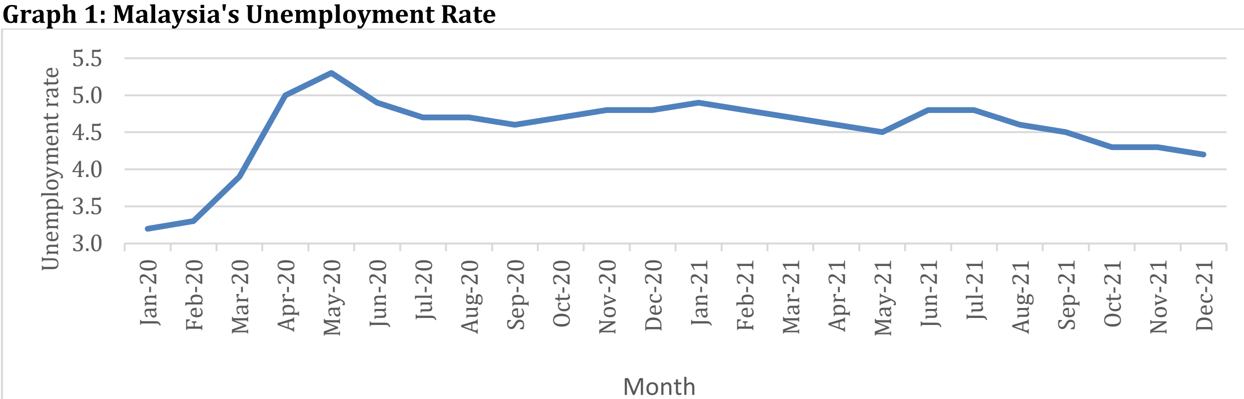
Table 3: Job Retrenchment by Group of Occupation 2020 and 2021

Types of Skills	Group of Occupation	2020	2021
High-skilled	Managers	14176	961
High-skilled	Professionals	28116	17051
High-skilled	Technicians & associate professionals	20548	12187
Middle-skilled	Clerical support workers	9249	5690
Middle-skilled	Service & and sales workers	11885	4319
Middle-skilled	Skilled agricultural, forestry, livestock & and fisheries workers	73	51
Middle-skilled	Craft & and related trades workers	2321	1105
Middle-skilled	Plant & and machine operators and assemblers	11826	6643
Low-skilled	Elementary occupations	7009	3934
Undefined		1821	763
Total		107024	61360

Source: Perkeso & MOHR.

Retrenchments and the inability of job seekers to enter the labor market during the pandemic caused the unemployment rate to rise tremendously. As shown in Figure 1, the unemployment rate was around 3.3% in January 2020. When the government started to implement the restriction order, the rate surged to 5.3% in May 2020, stagnating around 4.6% for the remainder of the year. From the demand side, employers were unable to sustain their businesses. The former Entrepreneur Development and Cooperatives Minister, Tan Sri Noh Omar, said that about 37,415 businesses closed following the implementation of the Movement Control Order 3.0 (MCO 3.0) beginning in May 2021 (Nuradzimmah & Arfa, 2021).

Graph 1: Malaysia's Unemployment Rate



Sources: Department of Statistics Malaysia (DOSM)

However, many job vacancies were available in the market during the COVID-19 pandemic. Table 4 shows that the top three industries with the most job vacancies were manufacturing, wholesale and retail, and accommodation and F&B. Yet, as shown in Table 5, these job vacancies were mostly for elementary occupations, i.e., low-skilled jobs, which made up 25% of total job vacancies.

Table 4: Job Vacancies by Industry 2020 and 2021

Industry	2020	2021
Agriculture, forestry & fishing	18547	75676
Mining & quarrying	1325	9226
Manufacturing	190278	603216
Construction	55590	164651
Electricity, gas, steam & air conditioning supply	4322	14438
Water, sewerage & waste	4466	9376
Wholesale & retail	120587	249744
Transportation	35613	107741
Accommodation and F&B	79069	353624
ICT	27771	122975
Financial & and insurance takaful	15156	55901
Real estate	9116	16586
Professional & Technical	45099	171828
Administrative & and support service	70327	238594
Defence compulsory social security	4033	4167
Education	22235	105340
Human Health & Social Work	10406	60335
Arts, entertainment & recreation	3068	12746
Other services	21971	96681
Activities of households	5890	7570
Activities of extraterritorial	435	162
Total	745304	2480577

Source: Perkeso & MOHR

The concentration of job vacancies in middle- and low-skilled jobs made it difficult for job seekers, especially those previously working in high-skilled jobs and fresh university graduates, to enter the labor market during the pandemic. This led to the issue of a mismatch between demand and supply (Said et al., 2021).

Table 5: Job Vacancies by a Group of Occupations in 2020 and 2021

Types of skills	Group of occupation	2020	2021
High-skilled	Managers	35964	97700
High-skilled	Professionals	110175	457153
High-skilled	Technicians & associate professionals	89954	298578
Middle-skilled	Clerical support workers	55985	180164
Middle-skilled	Service & and sales workers	135058	395450
Middle-skilled	Skilled agricultural, forestry, livestock & fisheries workers	3846	8270
Middle-skilled	Craft & related trades workers	49426	176050
Middle-skilled	Plant & machine operators and assemblers	81418	220626
Low-skilled	Elementary occupations	183478	646586
Total		745304	2480577

Source: Perkeso & MOHR

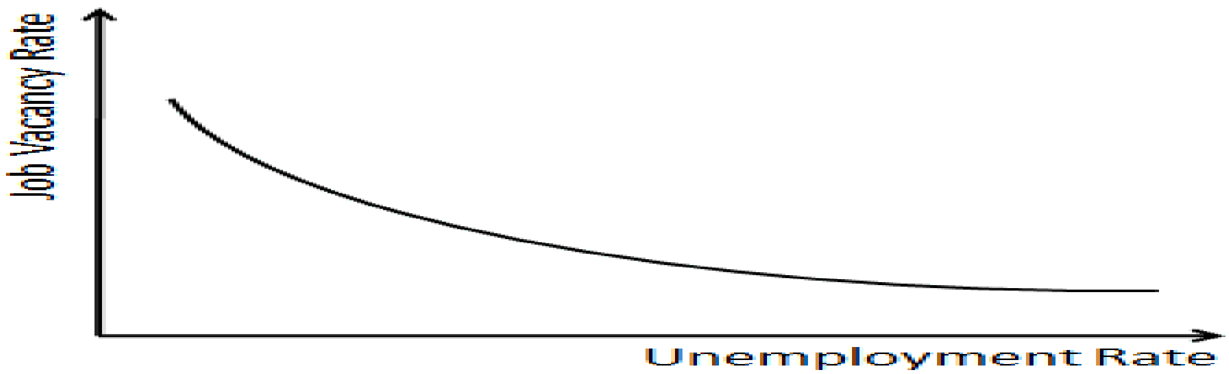
Against this background, this paper aims to analyze the matching efficiency of the labor market. In this context, efficiency refers to the speed with which the unemployed find jobs and vacancies match job seekers. The faster this occurs, the higher the matching efficiency and the lower the level of unemployment, assuming that other things are constant (Sheldon, 2003). Little research has measured the matching efficiency of the labor market, particularly during the COVID-19 pandemic. This study thus seeks to close this gap by merging the matching efficiency concept of labor economics with the methodology of efficiency measurement studies. We employ the DEA-Malmquist Productivity Index (MPI) using data from various government agencies to present a complete picture of how the pandemic has affected the labor market. The results are expected to further shed light on the difficulties faced by the Malaysian labor market during the pandemic and provide recommendations on how to improve its labor market. The findings may also be useful for other countries facing comparable problems.

2. Literature Review

Theoretical Review

The Theory of the Beveridge Curve: Introduced by British Economist William Beveridge, the theory of The Beveridge Curve describes how job vacancies and unemployment vary along a curve (Figure 1). When economic growth is high, job vacancies tend to be high, and unemployment tends to be low. At one point, the number of job vacancies might exceed the number of unemployment, and vice versa.

Figure 1: The Beveridge Curve



(**Source:** Borjas, 2015)

All points where unemployment is equal to the number of vacancies are shown by the 45-degree line from the origin. If the Beveridge curve shifts outwards, two possibilities have taken place in the labor market. Firstly, it could be due to a decline in search effectiveness among the unemployed. Secondly, there could be an increase in mismatches between the patterns of unemployment and vacancies across sectors, as employers are posting more job openings, but potential employees possess inadequate or wrong skills. When a mismatch happens, it would decrease the rate of hires given the labor market tightness. Subsequently, the curve shifts outwards of the origin (Wall & Zoega, 2002; Albaek & Hansen, 2004; Shibata, 2013).

However, the change in the curve pattern is not necessarily a sign of rising structural unemployment or mismatch. Firstly, it could be due to unemployment insurance: the unemployment rate remains high because workers are unwilling to look for jobs. Secondly, employers may be posting more vacancies but are not yet interested in hiring. The movement along the curve is associated with the state of the business cycle (Arpaia et al., 2014). When a recession happens, employers tend to cut costs and are unwilling to hire new employees. There are no new open vacancies, leading to a higher unemployment rate. At this state, equilibrium unemployment moves down the curve.

Empirical Review

Methods to Measure Matching Efficiency: Matching efficiency is the productivity of the process of matching job seekers to available job vacancies. Among the reasons contributing to the mismatch is the decline in matching efficiency (Erken et al., 2015). Job seeker characteristics, job vacancy characteristics, recruitment or hiring practices, job matching technology, and search channels are among the determinants of matching efficiency. A decline in matching efficiency means a lower chance for a match to form between firms and job seekers. Since job creation is motivated by search and matching frictions, it is relevant for explaining unemployment, mainly through changes in matching efficiency (Cheremukhin & Restrepo-Echavarria, 2014).

There are several methods to measure efficiency. Its measurement follows the same principles as measuring a Hicks-neutral index of productivity in the production function (Hall & Schulhofer-Wohl, 2018). The measurement of efficiency based on the efficient frontier involves either parametric or non-parametric methods. Some examples of parametric methods are Stochastic Frontier Analysis (SFA), Thick Frontier Approach (TFA), and Distribution Free Approach (DFA). The econometric theory is used to estimate pre-specified functional forms, and inefficiency is modeled as an additional stochastic term. For non-parametric methods, Data Envelopment Analysis (DEA) or Free Disposal Hull (FDH) are among the most popular.

Ilmakunnas and Pesola (2003) analyze efficiency using the parametric method SFA. Ilmakunnas and Pesola (2003) analyze efficiency using the parametric method SFA. The authors find that the returns to scale are close to constant in the frontier estimation. This method was later followed by Němec (2015) and Hynninen et al. (2009), who respectively attempted to measure the efficiency of the Czech and Finnish labor markets. Meanwhile, Sheldon (2003) measures the efficiency of public employment services in Switzerland by employing the non-parametric method DEA. Du and Seo (2022) use the same method to analyze the efficiency of R&D activities of universities in China.

Labor Market during Covid-19: Lemieux et al. (2020) examine the initial effects of the COVID-19 pandemic on the Canadian labor market, focusing on changes in employment and total hours worked between February and April 2020. Due to the distribution of lost labor, the authors find that COVID-19 caused a 32% drop in the total number of hours worked per week among employees aged 20 to 64, along with a 15% decline in employment. Those most impacted by COVID-19 are younger workers, hourly-paid employees, non-union workers and employees in public-facing positions in the industries most impacted by closures (accommodation and food services). In the United Kingdom, Costa Dias et al. (2020) find that COVID-19 has caused substantial drops in labor demand in numerous economic sectors and initial severe labor shortages in other sectors. The current crisis differs significantly from traditional downturns in that it involves not only a general slowdown in economic activity but also a drastic short-term change in the mix of economic activities.

A recent study by Adamowicz (2022) shows that the pandemic has disruptive, immediate and long-term repercussions on the Polish labor market. The pandemic has caused a widespread economic downturn and has permanently altered Poland's labor market. The use of technological instruments, such as the digitalization of the economy and society, e-commerce, remote learning, and remote working, is important to aid the labor market in adapting to the new crisis conditions. In Malaysia, Habibullah et al. (2021) examine the impact of lockdown measures undertaken by the Malaysian Government on employment outcomes. The authors find that loss of employment is significantly related to lockdown measures, with a reduction in employment and income for workers in non-essential sectors. The study emphasizes the need for policymakers to consider targeted measures to support affected workers and sectors to mitigate the negative effects of the pandemic on the labor market.

Rahman et al. (2020) find that the COVID-19 pandemic has caused a substantial increase in unemployment and a decline in labor force participation in Malaysia. They identify four main factors that contribute to job vulnerability during the pandemic: the nature of the job, industry characteristics, worker demographics, and geographic location. Workers in the services sector are the most vulnerable to job losses, particularly those employed in the accommodation and F&B and wholesale and retail industries. Workers in the manufacturing and construction sectors are also at risk, but to a lesser extent. In terms of worker demographics, young workers and those with low education levels are most vulnerable to job losses.

3. Research Methodology

Sources of Data: One input and one output are used to find matching efficiency change. Labor market tightness, measured as the number of vacancies divided by the number of unemployed, is the input, and job finding rate is the output. The job-finding rate is expressed as the number of unemployed persons who manage to secure a job in a given year divided by the number of unemployed persons. Generally, the job-finding rate would increase when there are fewer unemployed workers and more job vacancies, which would create more new successful matches.

The data are monthly data from January 2020 to December 2021, when the COVID-19 virus started to hit the economy. Data on the number of vacancies, number of retrenchments, and number of new placements for all 19 industries are collected from the Ministry of Human Resources. The data are estimated from Sistem Insurans Pekerjaan (SIP) and Perkhidmatan Maklumat dan Analisa Pekerjaan (EIAS). Specifically, the number of vacancies is estimated based on the vacancies dataset on My Future Jobs. My Future Jobs is the Malaysian National Employment portal for all job seekers and employers. This portal provides the most accurate job match data based on jobseekers' abilities and competencies using AI technology and a validated matching algorithm. The number of retrenchments is estimated based on the loss of employment dataset, and the number of new placements is estimated based on the placement dataset.

Methodology: This method combines the matching efficiency concept of labor economics with the methodology of efficiency measurement studies following Said et al. (2021) and Sheldon (2003). To estimate the matching efficiency, the non-parametric DEA-Malmquist productivity index (MPI) is employed. Initially introduced by Caves et al. (1982), MPI has been used by others (see Färe et al. (1992); Färe et al. (1994)). The selection of inputs and outputs in the analysis must be based on the designated rule of thumb (Cooper et al. 2002; Banker & Datar, 1989). The sample size must abide by the rules before continuing with the DEA analysis: $n \geq \max \{m \times s, 3(m + s)\}$ (1)

Where:
n = number of decision-making units (DMUs)
m = number of inputs
s = number of outputs

In this study, total factor productivity changes for all 19 industries are measured using output-oriented MPI. Change in total factor productivity (TFPCH) is decomposed into efficiency change (EFFCH) and technical change (TECHCH). Change in efficiency change (EFFCH) is decomposed further into pure technical efficiency change (PECH) and scale efficiency change (SECH). Färe et al. (1994) express the DEA-Malmquist productivity index (MPI) as:

$$m_0(y^{t+1},\ x^{t+1},\ y^{t+1},\ y^t,\ x^t) = \frac{d_0^{t+1}\,(x^{t+1},y^{t+1})}{d_0^t(x^t,y^t)}\ [\left(\frac{d_0^t\,(x^{t+1},y^{t+1})}{d_0^{t+1}(x^{t+1},y^{t+1})}\right) x\ (\frac{d_0^t\,(x^t,y^t)}{d_0^{t+1}(x^t,y^t)})]^{1/2} \quad (2)$$

Where:
m = productivity change between period t and period t-1
outputn as $m_0(y^{t+1},\ x^{t+1},\ y^{t+1},\ y^t\ \ x^t)$ = fficiency change x technicl ange (3)

where: efficen change = $\frac{d_0^{t+1}\,(x^{t+1},y^{t+1})}{d_0^t(x^t,y^t)}$ (4)

ecicac $[\left(\frac{d_0^t\,(x^{t+1},y^{t+1})}{d_0^{t+1}(x^{t+1},y^{t+1})}\right) x\ (\frac{d_0^t\,(x^t,y^t)}{d_0^{t+1}(x^t,y^t)})]^{1/2}$ (5)

4. Results and Discussion

Decomposition of Total Factor Productivity: Table 7 shows the dynamic development of Total Factor Productivity (TFP) which could be translated into matching efficiency in the Malaysian labor market. From January 2020 to December 2021, the average total factor productivity change (TFPCH) is 0.967. TFPCH declines at an average rate of -3.3 % in the sample period. Decomposing TFPCH into technical change (TECHCH) and efficiency change (EFFCH) shows that low TECHCH, with an average growth rate of -10.2%, is the main reason why TFPCH is far from the effective frontier.

Table 7: Mean Malmquist Productivity Index Decompositions

Index	Mean	% Explained
Total factor productivity change (TFPCH)	0.967	-3.3%
Technical change (TECHCH)	0.898	-10.2%
Efficiency change (EFFCH)	1.076	7.6%
Pure technical efficiency change (PECH)	1.003	0.3%

Scale efficiency change (SECH)	1.073	7.3%
Total factor productivity change (TFPCH)	0.967	-3.3%

Source: Authors' calculations

Technical change (TECHCH) reflects how the change of production frontier surface contributes to the variation of productivity. A TECHCH of greater than one indicates technical level is in the growth state or progression. A TECHCH that equals one indicates that the technical level is in a constant state of stagnation, while a value of less than one indicates that the technical level is declining or regression (Li et al, 2015). Because all values are less than one, technical change, which can be translated as technological growth that is, the technology to match job vacancies to job seekers, has not reached the optimum frontier during the sample period.

Efficiency change (EFFCH) measures the effectiveness of resource allocation, which in this context can be translated as the availability of job vacancies for job seekers. The decomposition of the EFFCH index into (1) pure technical efficiency change (PECH) (change of technical efficiency under the hypothesis of variable scale reward) and (2) scale efficiency change (SECH) (change of scale efficiency) demonstrates the impact of economies of scales on productivity. In this study, the decomposition of EFFCH indicates that the increase in the EFFCH of the labor market is mainly attributed to SECH, whose average growth rate is 7.3%, rather than PECH, whose average growth rate is 0.3%. The results suggest that the labor market has been operating at the right scale of operations but has been managerially less efficient in controlling the operating costs during the process of matching available jobs to available job seekers.

Table 8 shows the decomposition of TFP by industry. The TFPCH of the mining and quarrying industry is the highest, with an average growth of 18.7%, while it is lowest for both manufacturing (-1.7%) and construction (-7.6%) industries. Undeniably, the construction sector is among the most affected sectors during the crisis. Due to the lockdowns, most construction projects, including maintenance projects, have been delayed. In addition, the disruption of global supply chains, including the lack of employees, contractors, subcontractors, raw materials, and other inputs, has also led to declining TFPCH. Several supply chains for building materials have stopped manufacturing and distributing (ILO, 2021). As a consequence, lots of workers were retrenched, disrupting the process of matching efficiency in the labor market.

The manufacturing industry underwent a similar scenario. Data from DOSM show that the Industrial Production Index (IPI) for the manufacturing sector reduced to 0.2% in June 2021 after recording a growth of 29.8% in May 2021. Subsectors that contributed to this decline were those that were not allowed to operate during the pandemic. These subsectors included transport equipment and other manufacturing; non-metallic minerals, base metals, and engineered metals; wood, furniture, paper products and printing; and textiles, clothing, leather and footwear (MIDA, 2021). Workers were told to stay at home, factories were closed, and global supply chains paused for a moment, increasing the operating costs of the manufacturing sector (ILO, 2020a & Lim, 2022).

Table 8: Mean Malmquist Productivity Index Decompositions by Industry

Industry	TFPCH	% Explained
Agriculture, forestry & fishing	1.142	14.2%
Mining & quarrying	1.187	18.7%
Manufacturing	0.983	-1.7%
Construction	0.924	-7.6%
Electricity, gas, steam & air conditioning supply	1.024	2.4%
Water, sewerage & waste	1.060	6.0%
Wholesale & retail	0.880	-12.0%
Transportation	1.063	6.3%
Accommodation and F&B	1.045	4.5%
ICT	1.027	2.7%
Financial & and insurance takaful	0.909	-9.1%

Real estate	0.897	-10.3%
Professional & Technical	0.850	-15.0%
Administrative & support service	0.873	-12.7%
Defence compulsory social security	0.898	-10.2%
Education	0.893	-10.7%
Human Health & Social Work	0.876	-12.4%
Arts, entertainment & recreation	1.005	0.5%
Other services	0.917	-8.3%
Mean	0.967	-3.3%

Source: Authors' Calculations

In the services sector, low TFPCH is shown by the professional and technical which includes legal and accounting activities, architectural and engineering activities, management consultancy activities, and others (0.850), administrative and support service (0.873), human health and social work (0.876), and wholesale and retail (0.880) industries, indicating that they are regressing. Even though there were not so many retrenchments in the professional and technical, administrative and support service, human health, and social work industries, however with the abundance of vacancies in these two industries, could disturb the matching efficiency and the tightness of the labor market.

For the wholesale and retail industry, the shock tremendously differs between brick-and-mortar versus online shops, essential versus non-essential stores, and small versus large retailers emerging because of the pandemic (ILO, 2020b). As this industry is very labor intensive and relies on low-wage and part-time workers, any shock could disrupt the matching efficiency. On the other hand, most essential services that have been allowed to operate during certain phases of MCO show a TFPCH of > 1, suggesting that these industries are progressing. These industries include electricity, gas, steam and air conditioning supply; water, sewerage and waste transportation; and accommodation and F&B.

5. Conclusion

In this study, we attempt to analyze the matching efficiency in the labor market, particularly during the COVID-19 pandemic, by combining the efficiency concept in labor economics with the methodology of efficiency measurement studies. Using the DEA-Malmquist Productivity Index method, we analyze the matching efficiency of the Malaysian labor market from January 2020 to December 2021. The results demonstrate that the overall level of matching efficiency is not high. There is inefficient resource allocation, which could be explained in terms of labor market tightness and job-finding rate. Overall, the average TFP change value is 0.967, and TECHCH is the main reason why TFPCH is far from the effective frontier. In addition, the decomposition of efficiency change (EFFCH) shows that pure technical efficiency change (PECH) is another factor that causes low matching efficiency change. It can be concluded that the main force in promoting the matching efficiency of the labor market is the development of technology.

From the results, we can suggest that to enhance the matching efficiency of the labor market, the element of technology should be highlighted as one of the mechanisms to reduce the labor market tightness. Thus, we propose several suggestions, specifically in terms of matching job vacancies with job seekers. First, every industry must increase the adoption and use of current technology. Second, online platforms that could help industries, especially essential industries, to sustain their business should be strengthened. This can prevent the destruction of human capital during an economic crisis or shock, which can cause damage to a nation as it is unable to fully utilize available resources. Further research might look at the productivity of a particular industry, concentrating on each group of occupations, from high-skilled to middle-skilled and low-skilled jobs.

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References

Adamowicz, M. (2022). COVID-19 Pandemic as a Change Factor in the Labor Market in Poland. *Sustainability,* 14(15), 9197.

Albaek, K. & Hansen, H. (2004). The rise in Danish unemployment: Reallocation or mismatch? *Oxford Bulletin of Economics and Statistics,* 66(4), 515-536.

Arpaia, A., Kiss, A. & Turrini, A. (2014). Is unemployment structural or cyclical? Main features of job matching in the EU after the crisis. IZA Policy Paper. No. 91.

Bank Negara Malaysia. (2021). Structural Labor Market Issues in the Post-COVID-19 World. Outlook and Policy in 2021, Economic and Monetary Review 2020, 90-104.

Banker, R. D. & Datar, S. M. (1989). Sensitivity, precision, and linear aggregation of signals for performance evaluation. *Journal of Accounting Research,* 27(1), 21-39.

Borjas George J. (2015). Labor Economics. (3rd edition). McGraw Hill.

Caves, D. W., Christensen, L. R. & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity*. Econometrica: Journal of the Econometric Society,* 50(6), 1393-1414.

Cheremukhin, A. A. & Restrepo-Echavarria, P. (2014). The labor wedge is a matching friction. *European Economic Review,* 68, 71-92.

Cooper, W. W., Seiford, L. M. & Tone, K. (2001). Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software. *Journal-operational Research Society,* 52(12), 1408-1409.

Costa Dias, M., Joyce, R., Postel-Vinay, F. & Xu, X. (2020). The challenges for labor market policy during the Covid-19 pandemic*. Fiscal Studies,* 41(2), 371-382.

Du, Y. & Seo, W. (2022). A Comparative Study on the Efficiency of R&D Activities of Universities in China by Region Using DEA–Malmquist. *Sustainability,* 14(16), 10433.

Erken, H., van Loon, E. & Verbeek, W. (2015). Mismatch on the Dutch labor market in the Great Recession. *De Economist,* 163(4), 435-459.

Färe, R., Grosskopf, S., Lindgren, B. & Roos, P. (1992). Productivity changes in Swedish pharmacies 1980-1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis*, 3, 85–101.

Färe, R., Grosskopf, S., Norris, M. & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review,* 8(1), 66-83.

Habibullah, M. S., Saari, M. Y., Din, B. H., Safuan, S. & Utit, C. (2021). Labor market reactions to lockdown measures during the Covid-19 pandemic in Malaysia: An Empirical Note. *Jurnal Ekonomi Malaysia,* 55(1), 39-49.

Hall, R. E. & Schulhofer-Wohl, S. (2018). Measuring job-finding rates and matching efficiency with heterogeneous job-seekers. *American Economic Journal: Macroeconomics,* 10(1), 1-32.

Hynninen, S. M., Kangasharju, A. & Pehkonen, J. (2009). Matching inefficiencies, regional disparities, and unemployment. *Labor,* 23(3), 481-506.

International Labor Organization (ILO). (2020a). COVID-19 Pandemic in the World of Work. ILO Monitor: COVID-19 and the world of work. Second edition. Updated estimates and analysis. 1-11.

International Labor Organization (ILO). (2020b). OECD Policy Responses to Coronavirus (COVID-19). COVID-19 and the retail sector: impact and policy responses. https://www.oecd.org/coronavirus/policy-responses/covid-19-and-the-retail-sector-impact-and-policy-responses-371d7599/

International Labor Organization (ILO). (2021). ILO Sectorial Brief. Impact of COVID-19 on the construction sector. https://www.ilo.org/sector/Resources/publications/WCMS_767303/lang--en/index.htm

Ilmakunnas, P. & Pesola, H. (2003). Regional labor market matching functions and efficiency analysis. *Labor,* 17(3), 413-437.

Lemieux, T., Milligan, K., Schirle, T. & Skuterud, M. (2020). Initial impacts of the COVID-19 pandemic on the Canadian labor market. *Canadian Public Policy,* 46(S1), S55-S65.

Li, J., Zhang, J., Gong, L. & Miao, P. (2015). Research on the total factor productivity and decomposition of Chinese coastal marine economy: based on DEA-Malmquist index. *Journal of Coastal Research,* 73 (10073), 283-289.

Lim, B. F. Y. (2022). Impact of the COVID-19 Pandemic on Malaysia. *Japan Labor Issues,* 6(40), 37-44.

Ministry of Human Resources (MOHR). (2021). Common job loss reasons, Employment outlook 2021, Employment Information Analysis Services (EIAS).

Malaysian Investment Development Authority (MIDA). (2021). Manufacturing most affected industrial sector hit by Covid-19: MITI. https://www.mida.gov.my/mida-news/manufacturing-most-affected-industrial-sector-hit-by-covid-19-miti/#:~:text=%E2%80%9CData%20from%20 Department%20of%20Statistics,of%2029.8%25%20in%20May%202021

Němec, D. (2015). Measuring inefficiency of the Czech labor market. *Review of Economic Perspectives,* 15(2), 197-220.

Nuradzimmah, D. & Arfa, Y. (2021, September 23). 37,415 MSMEs closed during MCO 3.0. The News Straits Times. https://www.nst.com.my/news/nation/2021/09/731825/37415-msmes-closed-during-mco-30

Rahman, A. A., Jasmin, A. F. & Schmillen, A. (2020). The vulnerability of jobs to Covid-19: The case of Malaysia. ISEAS Economics Working Paper No. 2020-09, ISEAS Yusof Ishak Institute, Singapore

Said, R., Jamaludin, S., Ismail, N. W., Nor, N. M. & Yong, C. C. (2021). Measuring mismatch unemployment in the Malaysia labor market*. International Journal of Economic Policy in Emerging Economies,* 14(3), 227-247.

Sheldon, G. M. (2003). The efficiency of public employment services: A nonparametric matching function analysis for Switzerland*. Journal of Productivity Analysis,* 20(1), 49-70.

Shibata, M. I. (2013). Is Labor Market Mismatch a Big Deal in Japan? International Monetary Fund Working Paper No. 13-196.

Wall, H. J. & Zoega, G. (2002). The British Beveridge curve: A tale of ten regions. *Oxford Bulletin of Economics and Statistics,* 64(3), 257-276.