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Algorithmic Efficiency Analysis in Innovation-Driven Labor Markets: A Super-SBM and Malmquist Productivity Index Approach

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Abstract: Innovation-driven labor markets play a pivotal role in economic development, yet significant disparities exist in how efficiently countries transform innovation inputs into labor market outcomes. This study addresses the critical gap in benchmarking multi-stage innovation efficiency by developing an integrated framework combining Data Envelopment Analysis (DEA) Super Slack-Based Measure (Super-SBM) for static efficiency evaluation and the Malmquist Productivity Index (MPI) for dynamic productivity decomposition, enhanced with cooperative game theory for robustness testing. Focusing on the top 20 innovative economies over a five-year period, we analyze key inputs (innovation index, GDP, trade openness) and outputs (labor force, unemployment rates), revealing stark efficiency contrasts: China, Luxembourg, and the U.S. demonstrate optimal performance (mean scores >1.9), while Singapore and the Netherlands show significant underutilization (scores <0.4). Our results identify a critical productivity shift period (average MPI = 1.325) driven primarily by technological advancements. The study contributes a replicable, data-driven model for cross-domain efficiency assessment and provides empirical evidence for policymakers to optimize innovation-labor market conversion. The methodological framework offers scalable applications for future research in computational economics and productivity analysis.

Keywords: data envelopment analysis; super slack-based measure; malmquist productivity index; efficiency measurement; computational economics; productivity decomposition; benchmarking

1. Introduction

The transformative power of innovation in shaping economies and labor markets cannot be overstated. In an era characterized by rapid technological progress and intense global competition, the ability of a country to innovate is often seen as a key determinant of its economic success and resilience. Innovation drives growth, creates jobs, and opens new markets, thus playing a pivotal role in national and global economic landscapes. However, the mere presence of innovative activities within a country does not automatically ensure that these benefits will materialize in the form of enhanced labor market outcomes or economic growth. This realization has sparked an interest in understanding the mechanisms through which innovation influences economic variables and the efficiency with which countries convert their innovative inputs into tangible outputs. [1]

This study is motivated by the observation that, despite the recognized importance of innovation, there is a significant variance among countries in how effectively they translate their innovation-related resources into labor market success [2]. Some countries achieve remarkable results with relatively modest innovation inputs, while others struggle to realize the full potential of their substantial innovation investments [3]. This discrepancy raises critical questions about the factors contributing to such differences and the strategies that could be adopted to enhance the efficiency of innovation-led growth [4]. Furthermore, the evolving global economic environment, marked by

fluctuations in trade dynamics, investment patterns, and technological advancements, adds layers of complexity to this issue, making it a ripe area for investigation.

While there is extensive literature on the impact of innovation on economic growth and development, less attention has been paid to the efficiency with which countries utilize their innovation capabilities to achieve favorable labor market outcomes. Specifically, there is a gap in understanding the role of various factors, such as trade openness, capital investment, and high-tech exports, in mediating this process. Additionally, existing studies often fail to employ comprehensive analytical frameworks that can account for the multi-dimensional nature of innovation efficiency. This gap signifies the need for a study that not only examines the efficiency of innovation in a holistic manner but also incorporates the dynamics of global economic conditions and their impact on innovation efficiency.

The primary objective of this study is to analyze the efficiency with which the world's top 20 innovative countries convert their resources into favorable labor market outcomes. This involves a detailed examination of the role played by the innovation index, GDP, trade openness, capital investment, and high-tech exports in shaping these outcomes. To achieve this objective, the study employs a methodological approach that combines Data Envelopment Analysis (DEA) Super SBM and the Malmquist Productivity Index (MPI), offering a nuanced understanding of both static and dynamic aspects of innovation efficiency. Through this analysis, the study aims to highlight the disparities in efficiency among the leading innovative countries and explore the implications of these differences for policy and strategy formulation. Ultimately, this research seeks to contribute to the broader discourse on innovation and economic development by providing insights that could inform the efforts of policymakers and stakeholders to optimize the impact of innovation on labor markets.

This paper is structured as follows: After this introduction, Section 2 provides a review of the relevant literature on innovation and labor market outcomes. Section 3 describes the methodology, including the Super SBM model and the MPI. Section 4 presents the data and the empirical results. Finally, Section 5 concludes the paper with a discussion of the findings and their implications. In examining the impact of the Innovation Index on labor force and unemployment rates in the top 20 innovating countries in a five-year period (Year 1 to Year 5) [5], it is essential to consider the influence of innovation on labor market dynamics. Several studies have shed light on the relationship between innovation and labor force outcomes. Aldieri and Vinci [6] identified a complex interplay of job displacement and compensation forces resulting from labor innovation effects. Moreover, Choi et al. [7] suggested that enhancing technology startup companies could address concerns of unemployment and insecure labor forces due to environmental changes.

To enhance the benchmarking process, this study aligns with Moradi et al. [8] approach of projecting inefficient DMUs onto the efficient frontier with minimal input-output adjustments, ensuring precise efficiency evaluation using advanced DEA methodologies. The integration of DEA with cooperative game theory, as demonstrated by Zhang et al. [9] offer a compelling perspective on resource-sharing and collaborative efficiency enhancement, which is pertinent to analyzing innovation-driven labor market outcomes. Shakouri et al. [10] draw upon the framework of the stochastic p-robust approach to two-stage network DEA models as outlined in prior research, which effectively addresses uncertainties in data and facilitates robust efficiency evaluations in multi-stage processes. Akram et al. [11] incorporate an extended DEA method combined with Fermatean fuzzy sets to evaluate multi-objective performance efficiency, addressing uncertainty and decision-making complexity in resource allocation and performance benchmarking

Lyu et al. [12] highlight the crucial role of environmental regulation in driving green technology innovation, emphasizing the importance of a supportive regulatory environment for fostering innovation. Similarly, Yi et al. [13] discuss how government R&D subsidies and environmental regulations affect green innovation efficiency in the manufacturing industry, underscoring the significance of policy interventions in stimulating innovation. Furthermore, Zeng et al. [14] concentrate on assessing technological innovation efficiency in China's strategic emerging industries, providing insights into the effectiveness of innovation processes in key sectors. Bao et al. [15] explore

the green innovation efficiency of cities in the Yangtze River Delta region, demonstrating the application of models like Super-SBM to evaluate innovation outcomes. The relationship between environmental performance and economic performance is explored by Liu et al. [16] indicating a connection between environmental sustainability and economic outcomes. In addition, Chen et al. [17] emphasize the role of environmental regulation in advancing industrial green development, highlighting the interconnected nature of environmental policies and economic performance. Regarding efficiency and productivity evaluations, studies by Tran et al. [18] and Alves and Meza [19] offer methodological insights into utilizing data envelopment analysis (DEA) models for efficiency assessment. To further provide concrete evidence in the field of efficiency assessment research using the Data Envelopment Analysis (DEA), Wang et al. [20] successfully applied an integrated DEA and hybrid ordinal priority approach for multicriteria wave energy locating, focusing on South Africa, thereby offering key insights into renewable energy, [21] expanded the DEA model using prospect theory for wave-wind energy site selection in New Zealand, demonstrating the potential of merging different analytical approaches for decision-making in energy site selection, and [22] mapping sustainable logistics on the 21st-Century Maritime Silk Road, emphasizing the importance of risk considerations in logistics planning for sustainable development. These studies underscore the relevance and versatility of DEA in assessing efficiency across various domains.

Innovations have been found to positively correlate with skill premia in companies, leading to an increased quality of the labor force and company brand. This positive effect of innovation on labor is further supported by Goel et al. [23] who found that both R&D and innovation increased employment growth, indicating strong complementarities between labor and other inputs. Additionally, Asiedu et al. [24] highlighted that innovative firms exhibited higher growth rates in employment and labor productivity compared to non-innovative firms. Furthermore, the impact of innovation on labor productivity and outcomes is evident in various contexts. For instance, Salimova et al. [25] found that paying higher wages to ordinary workers contributes to better innovation outcomes in terms of patent quantity and quality. Additionally, Ou and Zhao [26] emphasized the long-term impact of highly educated workers on technological innovation and economic growth, particularly in innovative firms.

The relevance of the Innovation Index on labor force and unemployment rates is also influenced by factors such as education and digitalization. Formal and non-formal education has been shown to play a significant role in fostering innovation and competitiveness, thereby affecting the labor force. Moreover, Androniceanu et al. [27] highlighted the structural changes required by new economic and social models due to digitalization's impact on the labor force in different countries. Yıldırım et al. [28] specifically focused on the innovation-unemployment nexus in EU countries, aiming to elucidate how innovation influences unemployment rates. Their study contributes significantly to the broader understanding of how innovation impacts labor markets. Furthermore, Lydeka and Karaliūtė [29] examined the effect of technological innovations on unemployment in European Union countries, emphasizing that the level of innovativeness may have diverse effects on unemployment rates. This variability underscores the necessity for a nuanced analysis of the relationship between innovation and unemployment. Moreover, Padi and Musah [30] discussed entrepreneurship as a potential solution to high unemployment, highlighting that entrepreneurship combined with innovation can be a potent force in addressing unemployment conditions. This suggests that a multifaceted approach involving both entrepreneurship and innovation may be crucial in tackling unemployment challenges.

Afzal et al. [31] delved into understanding NIS using Porter's Diamond model in ASEAN-05 countries, shedding light on how innovation plays a pivotal role in shaping the competitiveness of nations. This perspective underscores the significance of innovation in driving economic growth and potentially affecting labor markets. Moreover, the study by Oloruntoba and Oladipo [32] on modelling carbon emissions efficiency in UK higher education institutions using Data Envelopment Analysis (DEA) highlighted the importance of technological innovation in enhancing energy efficiency and productivity. This emphasizes the critical role of innovation in improving overall

efficiency, which could have implications for labor force dynamics and unemployment rates. Additionally, Mavi et al. [33] focused on eco-innovation analysis in OECD countries, emphasizing the link between eco-innovation efficiency and sustainable development. The study's use of the Malmquist productivity index (MPI) to measure eco-innovation efficiency underscores the relevance of innovation in driving sustainable practices, which could have implications for labor force trends and unemployment rates. Furthermore, Aydin [34] discussed benchmarking healthcare systems in OECD countries using a DEA-based Malmquist Productivity Index approach, highlighting the transformative impact of technological innovations on healthcare. This suggests that advancements in technology and innovation play a crucial role in improving productivity and efficiency in various sectors, potentially influencing labor force dynamics.

Studies by Tien et al. [35], Wang et al. [36], and Dakpo et al. [37] emphasize the importance of technological progress and innovation in enhancing productivity and efficiency. These findings suggest that a focus on improving technological innovation can lead to advancements in productivity, which may have implications for labor force dynamics and unemployment rates. Furthermore, the research by Mitropoulos et al. [38] on the impact of the economic crisis on Greek hospitals' productivity highlights the role of reform and technological advancements in achieving productivity gains. This underscores the potential of innovation to drive efficiency improvements even in challenging economic environments, which could positively influence labor force outcomes. Additionally, the study by Bozkurt et al. [39] on the relationship between productivity, digitalization, and the Tobit model based on the Malmquist Index highlights the role of technological advances in driving growth and productivity. This suggests that embracing digitalization and technological advancements can lead to improvements in productivity, potentially impacting labor force trends and unemployment rates.

Research by Pham et al. [40] on statistical inference for the aggregation of Malmquist Productivity Indices emphasizes the importance of robust statistical methods in analyzing productivity trends. This underscores the significance of accurate measurement and analysis techniques in understanding productivity changes, crucial for assessing the impact of innovation on labor force dynamics. Moreover, the study by Sukmaningrum et al. [41] on productivity analysis of family takaful in Indonesia and Malaysia using the Malmquist Productivity Index approach highlights the role of technological change in driving productivity improvements. This underscores the importance of technological advancements in enhancing productivity levels, which could have implications for labor market outcomes.

Chen et al. [42] highlighted the substantial role of environmental regulation in advancing industrial green development. This finding suggests that policies related to environmental factors, often associated with innovation, can impact economic performance, including labor force dynamics and unemployment rates. Moreover, Wang and Chen [43] emphasized the contribution of culture to sustainable development. Understanding how cultural aspects interact with innovation and economic growth is crucial for a comprehensive analysis of the implications of the Innovation Index on labor force and unemployment rates.

Despite the extensive exploration of innovation's impact on labor markets, a significant research gap remains in quantitatively assessing how the world's top innovating countries efficiently convert their innovation inputs into concrete labor market outcomes, such as employment growth and reduced unemployment. The literature largely overlooks a direct, empirical comparison of these countries' performance in leveraging their innovation indices, GDP, trade openness, capital investments, and high-tech exports towards achieving favorable labor market impacts. This gap highlights the need for a focused study employing a unified methodological framework to benchmark and analyze the efficiency with which these nations utilize their resources, filling a crucial void in understanding the specific dynamics at play in optimizing innovation's impact on labor markets.

2. Materials and Methods

2.1. Data Collection

This study focuses on the top 20 countries for the innovation index in the most recent year of the five-year period (Year 5). The innovation index is a composite measure that encapsulates the level of innovation within a country. It is derived from a variety of factors that capture different facets of innovation. These include the number of patents filed, the extent of research and development expenditure, the quality of scientific research institutions, the standard of education and training, the degree of ICT access and use, and the level of business sophistication. The countries selected for this study, which are presented in the subsequent tables, were chosen based on their performance in these areas and aim to be analyzed further by incorporating additional input and output factors for the past 5 years.

Table 1. The DMU designation for the Top 20 Countries by Innovation Index.

Rank	Name of Countries	DMUs
1	Switzerland	SWZ
2	United States of America	USA
3	Sweden	SWD
4	United Kingdom	UNK
5	Netherlands	NDL
6	South Korea	KOR
7	Singapore	SGP
8	Germany	GMN
9	Finland	FNL
10	Denmark	DMK
11	China	CHN
12	France	FRN
13	Japan	JPN
14	Hongkong	HNK
15	Canada	CND
16	Austria	AST
17	Estonia	EST
18	Israel	ISR
19	Luxembourg	LXM
20	Iceland	ICL

According to similar studies, a variety of inputs and outputs are used for an examination related to this. Hence, the research specifically adopts four distinct inputs and two outputs, as demonstrated in the subsequent Table 2. Table 3 below provides a summary of the input and output statistics for the 20 countries from Year 1 to Year 5. It includes the maximum, minimum, average, and standard deviation (SD) for each year.

Table 2. Declaration of input and output variables.

	Variables	Definition
	Innovation Index (II)	Innovation score (0-100).
	Capital Investment (CI)	Calculated new plant and equipment purchases by firms, as a percentage of GDP.
Inputs	Trade Openness (TO)	Sum of exports and imports divided by GDP.
	High Tech Exports (HTE)	Percent of exported manufactured products with high research and development intensity.
	Gross Domestic Product (GDP)	Total monetary value of all final goods and services produced in billion USD.

	Labor Force (LF)	The population 15 years and over who are either employed, unemployed, or seeking employment.
Outputs	Unemployment Rate (UR)	Unemployed individuals in an economy among individuals currently in labor force

Table 3. Five-year summary of statistics for the input and output variables.

Year	Statistics	(I)-II	(I)-CI	(I)-TO	(I)-HTE	(I)-GDP	(O)-LF	(O)-UR
Year 1	**Max**	68.400	43.790	376.890	64.650	20533.060	776.280	9.020
	Min	50.500	17.040	27.610	6.970	26.260	0.220	2.470
	Average	57.075	24.677	124.415	22.672	2854.104	60.536	4.653
	SD	4.496	5.401	102.563	13.899	5086.519	168.350	1.583
Year 2	**Max**	67.200	43.250	382.350	65.560	21380.980	775.320	8.410
	Min	50.000	18.190	26.450	6.570	24.680	0.220	2.350
	Average	57.155	24.310	123.292	23.329	2906.832	60.703	4.474
	SD	4.361	5.326	102.210	14.320	5278.262	168.185	1.483
Year 3	**Max**	66.100	43.370	372.270	69.650	21060.470	751.450	9.660
	Min	48.300	17.350	23.380	5.620	21.570	0.220	2.810
	Average	55.480	24.614	117.805	23.797	2891.527	59.337	5.723
	SD	4.473	5.757	103.607	14.977	5267.564	163.084	1.820
Year 4	**Max**	65.500	43.140	402.510	65.500	23315.080	780.370	8.720
	Min	49.000	16.780	25.480	49.000	25.600	0.220	2.830
	Average	56.225	24.902	127.289	56.225	3273.465	60.878	5.473
	SD	4.285	5.568	110.981	4.285	5998.516	169.227	1.500
Year 5	**Max**	64.600	43.290	388.510	34.810	25439.700	781.830	781.830
	Min	49.500	14.960	27.360	5.870	28.060	0.230	0.230
	Average	55.360	25.238	135.889	19.668	3325.903	61.262	61.262
	SD	4.411	5.921	105.952	7.256	6368.976	169.602	169.602

2.2. DEA Super Efficiency Slacks-Based Measure Model

Tone [44] introduced a method in Data Envelopment Analysis (DEA) known as the slacks-based measure (SBM model). This model is effective in distinguishing between efficient and inefficient Decision-Making Units (DMUs). However, it falls short in differentiating between high-performing DMUs that are fully efficient. To address this, Tone [44] developed the super efficiency slacks-based measure model in DEA (Super-SBM model). This model excludes the efficient DMUs from the efficient frontier of the SBM model and calculates the non-radial distance between the omitted efficient DMUs and the efficient frontier formed by the remaining efficient DMUs. It simultaneously addresses both input and output slacks, making it more suitable for real-world applications.

The model is used to analyze n DMUs with input and output matrices $X = (x_{ij}) \in \mathrm{R}^{mxn}$ and $Y = (y_{ij}) \in \mathrm{R}^{sxn}$, respectively. The production possibility set P is defined as: $P = \{(x,y)|x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\}$ where λ is a nonnegative vector in R^n.

Tone [40] uses the following expression to describe a specific DMU (X_0, Y_0): $x_0 = X\lambda + s^-$ and $y_0 = Y\lambda - s^+$ where $\lambda \geq 0, s^- \geq 0$ and $s^+ \geq 0$. The vectors $s^- \in \mathrm{R}^m$ and $s^+ \in \mathrm{R}^s$ represent the input surplus and output shortfall of this expression, respectively, and are known as slacks. The SBM model is as follows:

$$Minimize\ \alpha^{SE} = \frac{\frac{1}{m}\sum_{i=1}^{m}(\frac{x_{io} + z_{io}^-}{x_{io}})}{\frac{1}{s}\sum_{r=1}^{s}(\frac{y_{ro} - z_{ro}^+}{y_{ro}})}$$

Subject to: $X\lambda \leq x_0 + z_0^-$ and $Y\lambda \geq y_0 - z_0^+, \lambda \geq 0, z^- \geq 0$ and $z^+ \geq 0$.

2.3. DEA Malmquist Productivity Index (MPI)

To measure efficiency not just at a specific point in time but also over duration, the Malmquist Productivity Index (MPI) was introduced by [45]. This extension of the Data Envelopment Analysis (DEA) model allows for the assessment of the change in total factor productivity of a Decision-Making Unit (DMU) across years. MPI provides a means to evaluate the shift in total factor productivity of a DMU between two time periods. By comparing efficiency patterns over time, researchers can gain deeper insights into how efficiency evolves across different periods. Färe [45] identified the total productivity factor derived from DEA as MPI.

This index is acknowledged as one of the most effective techniques for evaluating the shift in productivity of a group of DMUs over time. In this method, each DMU is examined at two distinct periods, t1 and t2, and the change in the combined total factor productivity of that DMU is compared. Given two time periods t1 and t2, MPI is calculated as:

The Malmquist Index assesses the changes in total productivity factor of each DMU by calculating the efficiency score. MPI is defined as the product of the "catch-up" and "frontier-shift" components. The term "catch-up" refers to changes in technical efficiency (given a fixed technology), while "frontier-shift" refers to changes in the technology available to an organization. Total factor efficiency can be enhanced by better utilization of current technologies and economic inputs, a process known as "catch-up". Total factor productivity can also be improved if organizations implement technological innovations or advancements, such as the introduction of new products, processes, and technologies into their operations that lead to improved manufacturing methods, known as "frontier shift".

MPI can be calculated as follows:

MPI = (catch-up) × (frontier-shift).

This equation can then be further transformed into:

$$\text{MPI} = \left[\frac{D^{t_2}((x_o, y_o)^{t_2})}{D^{t_1}((x_o, y_o)^{t_1})}\right] \times \left[\frac{D^{t_1}((x_o, y_o)^{t_1}}{D^{t_2}((x_o, y_o)^{t_1})} \times \frac{D^{t_1}((x_o, y_o)^{t_2})}{D^{t_2}((x_o, y_o)^{t_2})}\right]^{\frac{1}{2}}$$

where D^{t_1} is the distance function at time (t_1) and D^{t_2} is the distance function at time (t_2), efficiency change (catch-up) = $\left[\frac{D^{t_2}((x_o, y_o)^{t_2})}{D^{t_1}((x_o, y_o)^{t_1})}\right]$

and

technological change (frontier-shift) = $\left[\frac{D^{t_1}((x_o, y_o)^{t_1}}{D^{t_2}((x_o, y_o)^{t_1})} \times \frac{D^{t_1}((x_o, y_o)^{t_2})}{D^{t_2}((x_o, y_o)^{t_2})}\right]^{\frac{1}{2}}$

Therefore, an MPI value greater than 1 indicates an increase in productivity from period t1 to t2. As per the definition of MPI, enhancements in productivity are influenced by changes in efficiency and technology.

3. Results

3.1. Efficiency Analysis Using Super-SBM Model

According to Table 4, China (CHN) consistently holds the top rank from Year 1 to Year 5, with a mean score of 4.078, indicating a strong innovation index and labor market outcomes. Luxembourg (LXM) follows as the second most efficient country, with a mean score of 3.209. United States (USA) ranks third with a mean score of 1.905, showing a slight fluctuation but maintaining a top-tier position.

Singapore (SGP) has the lowest mean score of 0.361, indicating room for improvement in innovation-related labor market outcomes. Hong Kong (HNK), despite a significant improvement in Year 5, stays near the bottom with a mean score of 0.601. Netherlands (NDL) also remains towards

the lower end with a mean score of 0.387. Iceland (ICL) shows a remarkable trend with a significant jump to the third position in Year 2 and maintaining high efficiency scores thereafter. Finland (FNL) and Estonia (EST) display consistent performance, staying within the top six throughout the period. Canada (CND) and Austria (AST) show fluctuations but remain in the middle tier.

Table 4. Score and Ranking Using Super-SBM Model (Year 1 – Year 5).

| DMU	Year 1		Year 2		Year 3		Year 4		Year 5		Mean	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
SWZ	0.471	14	0.481	14	0.445	15	0.490	15	0.434	16	0.464	15
USA	1.980	3	1.974	4	2.020	3	1.746	4	1.808	4	1.905	3
SWD	0.700	8	0.818	8	0.880	8	1.025	9	1.037	9	0.892	9
UNK	0.511	13	0.512	13	0.471	14	0.596	11	0.519	14	0.522	14
NDL	0.384	18	0.368	18	0.367	20	0.415	18	0.401	18	0.387	19
KOR	0.406	16	0.444	15	0.380	18	0.383	20	0.376	20	0.398	18
SGP	0.331	19	0.314	20	0.369	19	0.407	19	0.384	19	0.361	20
GMN	0.414	15	0.415	16	0.395	16	0.429	17	0.402	17	0.411	17
FNL	1.577	4	1.336	6	1.288	6	1.254	6	1.372	6	1.365	6
DMK	0.621	9	0.670	10	0.636	10	0.573	13	0.551	12	0.610	11
CHN	4.140	1	4.138	1	3.948	1	4.004	1	4.159	1	4.078	1
FRN	1.349	6	1.307	7	0.737	9	1.053	7	1.152	8	1.120	7
JPN	0.401	17	0.410	17	0.389	17	0.458	16	0.468	15	0.425	16
HNK	0.286	20	0.336	19	0.543	12	0.524	14	1.318	7	0.601	12
CND	0.707	7	0.751	9	1.215	7	1.037	8	0.770	10	0.896	8
AST	0.594	10	0.607	11	0.597	11	0.751	10	0.611	11	0.632	10
EST	1.569	5	1.475	5	1.371	5	1.377	5	1.495	5	1.457	5
ISR	0.513	12	0.532	12	0.510	13	0.584	12	0.526	13	0.533	13
LXM	2.987	2	3.047	2	3.884	2	3.437	2	2.690	2	3.209	2
ICL	0.587	11	2.549	3	1.810	4	2.088	3	2.289	3	1.865	4
Mean	1.026		1.124		1.113		1.132		1.138		1.107	
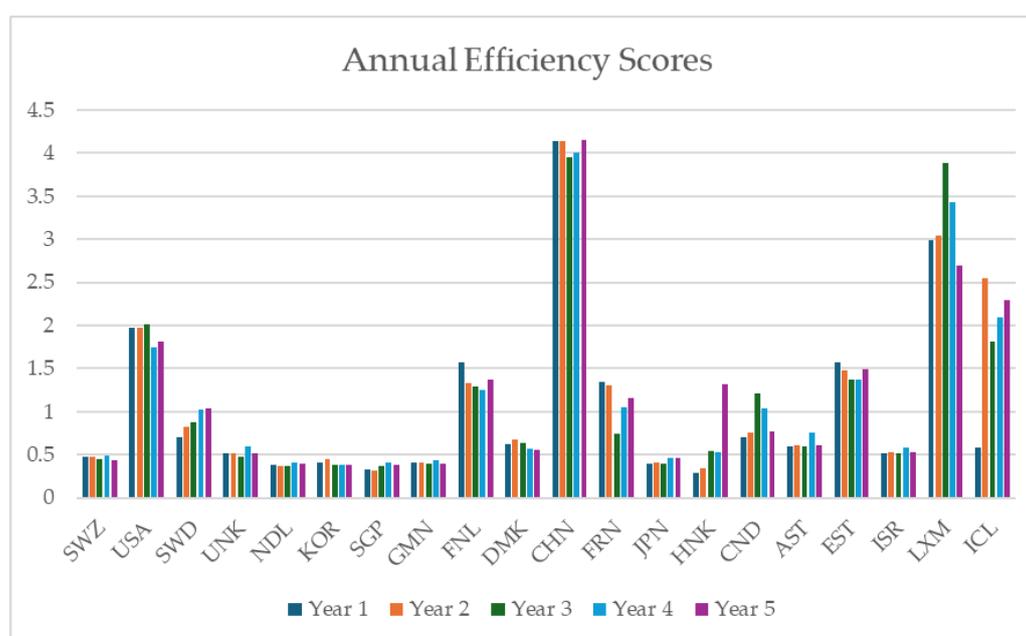
Figure 1. The annual Efficiency scores of each DMU (Year 1 – Year 5).

Top performers like CHN, LXM, USA, and EST, as shown in Figure 1, consistently achieve high ranks, demonstrating their effective use of resources such as GDP, capital investments, trade

openness, and high-tech exports to foster innovation. This effective resource utilization likely contributes to a robust labor force and lower unemployment rates.

Conversely, DMUs such as SGP, NDL, KOR, GMN, and JPN consistently rank lower. Their subpar efficiency scores indicate difficulties in effectively using their resources, particularly in trade openness as depicted in Tables A1 – A5. This could affect their labor markets and potentially lead to an excess input, without yielding the desired impact on the labor force and unemployment rates. It may be necessary for these DMUs to tackle these issues to enhance their labor market results.

On the other hand, in Table A5, HNK demonstrated an effective approach to managing its trade openness in Year 5, as evidenced by a significant increase in efficiency. This suggests promising prospects for its performance in the years ahead.
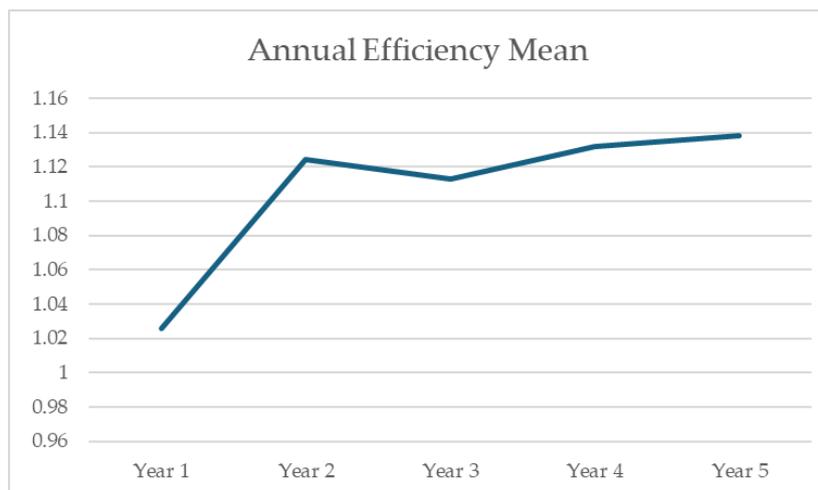

Figure 2. Graph of all the annual efficiency scores of each DMU (Year 1 – Year 5).

From Year 1 to Year 5, the average efficiency score was 1.107, suggesting that these countries generally maintained a high level of efficiency in their innovation activities during this period. However, the yearly scores are fluctuating, as seen in Figure 2, indicating differences in resource utilization efficiency among these countries from one year to the next. This variation could be attributed to a range of factors, including but not limited to the input factors identified in this study, potential policy changes, and differing external economic conditions in each and all the countries.

3.2. Performance Trends Over Time Analysis Using Malmquist Productivity Index (MPI)

3.2.1. Overall Efficiency Analysis

When Decision-Making Units (DMUs) register scores above 1, such as HNK with 1.426 and ICL with 1.211 in Table 5, it reflects a notable improvement in their efficiency over the observed five-year period. Conversely, a score of 1 indicates a steady state of efficiency, exemplified by UNK's average of 1.015, which suggests minimal change. Scores falling below 1, like those of FNL at 0.968 and DMK at 0.972, point to a diminishing efficiency, signaling potential difficulties in capitalizing on innovation for favorable labor market outcomes.

Table 5. Catch-up Efficiency Analysis (Year 1 – Year 5).

Catch-up	Year 1 - Year 2	Year 2 - Year 3	Year 3 - Year 4	Year 4 - Year 5	Average
SWZ	1.022	0.923	1.101	0.887	0.983
USA	1.002	1.262	0.896	0.910	1.017
SWD	1.164	1.080	1.162	0.980	1.096
UNK	1.000	0.921	1.267	0.871	1.015
NDL	0.957	0.997	1.131	0.967	1.013

KOR	1.081	0.864	1.009	0.982	0.984
SGP	0.951	1.172	1.102	0.943	1.042
GMN	0.998	0.957	1.086	0.936	0.994
FNL	0.851	0.957	0.944	1.121	0.968
DMK	1.076	0.951	0.901	0.961	0.972
CHN	0.995	0.958	1.014	1.039	1.002
FRN	1.008	0.591	1.375	1.102	1.019
JPN	1.022	0.949	1.176	1.023	1.042
HNK	1.176	1.611	0.965	1.950	1.426
CND	1.063	1.617	0.851	0.745	1.069
AST	1.021	0.985	1.258	0.814	1.019
EST	0.867	0.910	0.948	1.305	1.008
ISR	1.053	0.944	1.147	0.901	1.011
LXM	1.084	1.054	0.821	0.968	0.982
ICL	1.823	1.119	1.124	0.778	1.211
Average	1.061	1.041	1.064	1.009	1.044

A closer examination of efficiency trends reveals that HNK has experienced a significant increase, particularly during Year 2 - Year 3 and Year 4 - Year 5 intervals, which underscores a robust advancement in innovation and associated elements. ICL has also seen considerable gains, especially in the initial and concluding years of the timeframe.

On the other end of the spectrum, FNL and DMK are trailing, with their efficiency scores persistently below 1, which may indicate obstacles in harnessing innovation for labor market benefits. The collective efficiency score across all DMUs stands at an average of 1.044, suggesting an overarching trend of amelioration. Year 3 – Year 4 witnessed the highest mean score of 1.064, implying that most countries bolstered their efficiency despite widespread challenges. The subsequent year, Year 4 – Year 5, recorded the lowest average score of 1.009, potentially reflecting stabilization or adaptation to external influences impacting innovation and labor markets.

3.2.2. Frontier Shift Index

The frontier shift index scores, also defined as technological change, are indicative of shifts in the production frontier, reflecting how the adoption of new technologies has redefined best practices. Scores above 1 signify that a DMU has effectively integrated new technologies, moving closer to the frontier, while scores below 1 suggest a lag in adopting new technologies or advancements in the frontier by others.

Table 6. Frontier Shift Analysis (Year 1-Year 5).

Frontier	Year 1 -Year 2	Year 2 - Year 3	Year 3 - Year 4	Year 4 -Year 5	Average
SWZ	0.919	1.157	0.945	0.882	0.976
USA	0.932	1.468	0.741	0.777	0.980
SWD	0.917	1.206	0.883	0.806	0.953
UNK	0.933	1.328	0.812	0.719	0.948
NDL	0.929	1.145	0.946	0.889	0.977
KOR	0.931	1.229	0.865	0.899	0.981
SGP	0.929	1.151	0.948	0.889	0.979
GMN	0.939	1.272	0.839	0.911	0.990
FNL	0.989	1.198	0.966	0.890	1.011
DMK	0.918	1.163	0.943	0.890	0.979
CHN	1.016	1.025	0.966	1.023	1.008
FRN	0.923	1.558	0.695	0.797	0.993
JPN	0.957	1.230	0.816	0.909	0.978
HNK	0.933	1.451	0.952	0.496	0.958
CND	0.911	1.199	0.843	0.860	0.953

AST	0.918	1.159	0.942	0.814	0.958
EST	0.928	1.466	0.888	0.831	1.029
ISR	0.919	1.181	0.932	0.700	0.933
LXM	0.954	1.243	0.804	0.913	0.978
ICL	0.903	1.589	0.932	0.725	1.037
Average	0.935	1.271	0.883	0.831	0.980

In this table, we observe that Decision-Making Units with scores above 1, such as the USA and EST, have shown significant technological advancements, particularly highlighted in the Year 2 – Year 3. A score of 1 would indicate no change in technological capability; however, no DMU hit this mark precisely, though CHN's average score suggests a stable technological landscape throughout the period. Scores below 1, like HNK's notable decline in the Year 4 – Year 5, point to a potential regression in technological efficiency, signaling a need for reassessment or increased investment in technology.

The USA and EST emerge as leaders in technological progress, demonstrating strong improvements that are especially pronounced in the second year of the period. FNL also shows a consistent upward trajectory in technology, maintaining the highest average score over the five years. On the other hand, HNK's significant drop in the last year raises concerns, pulling its average down and indicating a potential area for technological revaluation. ISR's position as the lowest scorer suggests it is an area ripe for technological development.

Looking at the broader picture, the average technological change score across all DMUs is 0.980, hinting at a slight overall decline in technological efficiency. Year 2-Year 3 stands out with the highest average score, suggesting a period where most countries experienced technological improvements. In contrast, the Year 4 – Year 5 reflects the lowest average score, which may be indicative of global challenges impacting technological progress.

3.2.3. Malmquist Productivity Index

The MPI offers an insightful perspective on the evolution of total factor productivity for each Decision-Making Unit over time. A score above 1 denotes enhanced efficiency in transforming inputs into outputs, while a score below 1 reflects a downturn in productivity, suggesting less effective utilization of resources. A score of exactly 1 would imply no change in productivity levels.

Table 7. Total Factor Productivity Change – MPI.

Malmquist	Year 1 -Year 2	Year 2 -Year 3	Year 3 -Year 4	Year 4 -Year 5	Average
SWZ	0.939	1.068	1.041	0.782	0.957
USA	0.934	1.854	0.664	0.707	1.039
SWD	1.067	1.302	1.027	0.790	1.046
UNK	0.933	1.224	1.029	0.626	0.953
NDL	0.889	1.141	1.070	0.859	0.990
KOR	1.007	1.063	0.873	0.884	0.956
SGP	0.883	1.348	1.044	0.838	1.028
GMN	0.937	1.218	0.911	0.852	0.980
FNL	0.841	1.147	0.912	0.998	0.974
DMK	0.988	1.106	0.850	0.856	0.950
CHN	1.011	0.982	0.980	1.063	1.009
FRN	0.930	0.921	0.955	0.879	0.921
JPN	0.978	1.167	0.959	0.929	1.008
HNK	1.098	2.337	0.919	0.966	1.330
CND	0.969	1.938	0.717	0.641	1.066
AST	0.938	1.141	1.185	0.662	0.982
EST	0.804	1.335	0.842	1.085	1.017
ISR	0.967	1.114	1.069	0.630	0.945

LXM	1.034	1.310	0.660	0.883	0.972
ICL	1.647	1.779	1.047	0.564	1.259
Average	0.990	1.325	0.938	0.825	1.019

Highlighting the leaders, HNK emerges with an impressive average score, signaling a robust enhancement in productivity throughout the five-year timeline. ICL follows suit, marking its progress, particularly in the initial years. In contrast, FRN's position at the lower end of the spectrum, along with UNK and DMK, points to a struggle to sustain or elevate productivity levels.

Table 8. Annual Mean of Efficiency Change, Technological Change, and Total Productivity Change.

Year	Efficiency Change	Technological Change	TFP Change
Year 1-Year 2	1.061	0.935	0.99
Year 2-Year 3	1.041	1.271	1.325
Year 3-Year 4	1.064	0.883	0.938
Year 4-Year 5	1.009	0.831	0.825
Average	1.044	0.98	1.019

Table 8 reveals a notable peak in productivity during Year 2-Year 3, with most DMUs reaching their zenith in performance improvements. However, this upward trend seems to go the opposite way by Year 4 -Year 5, where a general dip in productivity is observed. Despite these fluctuations, the overall average score across all DMUs indicates a marginal uptick in productivity, with SGP, EST, and CHN consistently surpassing the threshold of improvement. Meanwhile, DMUs like FNL and LXM display a more erratic pattern, hinting at the complex nature of their productivity dynamics.

4. Discussion

The Malmquist Productivity Index (MPI) results indicate a varied landscape of productivity changes across the top 20 innovative countries between Year 1 and Year 5. On average, there appears to be overall productivity growth, as suggested by the average MPI value over the observed period, being greater than 1 (1.019). This suggests that, collectively, these countries have managed to improve their productivity over the five years in question.

Country-specific trends reveal notable insights. For example, ICL (presumably Iceland), with an impressive average MPI of 1.259, demonstrates robust productivity improvements, suggesting effective utilization of innovation and other resources to enhance labor market outcomes. Conversely, SWZ (presumably Switzerland) shows a modest average MPI of 0.957, hinting at the potential underutilization of resources or other economic factors that may have impeded productivity gains. Several countries, including the USA, SWD (Sweden), and CHN (China), exhibit a fluctuating trend in TFP, with substantial inter-annual variability. The USA, for instance, demonstrates a significant spike in Year 2-Year 3 followed by a drop in the subsequent year, possibly reflecting the impact of external economic shocks or policy changes affecting innovation and productivity. It is striking to note that for many countries, there was a notable dip in productivity in Year 3-Year 4, likely due to external economic shocks or global disruptions. For example, HNK (presumably Hong Kong) shows a high variability with a peak in Year 2 – Year 3 and then a decline. This reflects the broader challenges faced globally during this period, potentially including disruptions in trade, investment, and labor mobility.

Conversely, some countries like CHN show an upward trend in the final year, which may indicate a rapid recovery and adaptation to the post-pandemic economic environment, highlighting the resilience of their innovation systems.

The general trend seems to be a recovery in Year 4 -Year 5, although the extent of this recovery varies significantly across countries. The overall improvement in MPI scores in the last year could be associated with the stabilization of the global economy and the adoption of new technologies and innovative practices in response to the pandemic.

These results also highlight the importance of considering external economic and political factors when interpreting MPI scores. For instance, trade conflicts, policy changes, and environmental

regulations can significantly influence innovation efficiency and, consequently, productivity. The findings underscore the need for tailored policy interventions. For countries with declining productivity, targeted strategies may be necessary to overcome structural challenges and enhance the effectiveness of innovation inputs. For those with improving productivity, it is crucial to understand the contributing factors to sustain and build upon these gains.

5. Conclusions

The primary motivation behind this study was to elucidate the intricate relationship between a country's innovation inputs and its labor market outcomes, focusing specifically on the top 20 innovative nations. Recognizing the need for a deeper mathematical understanding of how innovation influences labor productivity and employment rates underpins the significance of this research. Our objective was to evaluate the efficiency with which these countries convert innovation-related resources into labor market benefits over the five-year period (Year 1 to Year 5), highlighting the leading and lagging nations in this respect.

To achieve this, we employed the Malmquist Productivity Index (MPI), a robust mathematical tool that measures productivity changes over time by considering both technological advancements and efficiency improvements. This method provided a quantitative basis for assessing and comparing the innovation efficiency of each country. Our findings revealed significant inter-country variability, with nations like Iceland showing robust gains in productivity while others, such as Switzerland, struggled to optimize their innovation outputs. The fluctuations in productivity observed through the MPI also captured the impact of external shocks, notably the COVID-19 pandemic, on the innovation-productivity nexus.

This study contributes to the existing literature by highlighting the heterogeneity in innovation efficiency across nations and the importance of temporal dynamics in influencing productivity outcomes. It underscores the utility of the MPI in analyzing productivity trends and extends the discourse on innovation's role in labor market performance.

One limitation of this study is the potential oversimplification of labor market dynamics, which may not be fully captured by the MPI alone. Future research could address this by incorporating additional variables such as quality of education, demographic shifts, and sector-specific innovation trends. Moreover, longitudinal studies could provide insights into the long-term effects of innovation on labor markets. Another direction would be the qualitative examination of policy frameworks across the countries studied to determine how different innovation strategies translate into varying levels of labor market efficiency. By expanding the scope and depth of analysis, subsequent research can offer more nuanced understandings that better inform policymakers and stakeholders.

Conflict of interest: The authors declare that no conflicts of interest exist in this paper.

Appendix

Table A1. Slacks in input and output variables (Year 1).

DMU	GDP	CI	TO	II	HTE	LF	UR
SWZ	492.398	9.439	74.427	30.184	7.439	0	0
USA	0	43.5	27.909	18.668	28.153	981.83	2.469
SWD	263.607	4.06	21.596	11.527	6.263	0	0
UNK	2137.791	3.214	22.395	26.935	16.301	0	0
NDL	630.887	7.515	118.215	32.1	17.529	0	0
KOR	1102.145	17.361	38.695	25.03	30.79	0	0
SGP	204.033	12.286	286.871	30.517	47.064	0	0
GMN	3091.238	8.718	53.065	29.627	10.151	0	0
FNL	367.086	4.83	24.954	13.421	7.366	3.499	0
DMK	145.641	4.946	52.482	16.833	6.027	0	0
CHN	82526.38	55.81	92.084	227.715	55.183	0	14.004
FRN	0	13.637	41.008	29.195	0	6.775	0
JPN	3287.267	16.555	18.43	37.968	8.663	0	0
HNK	203.989	12.231	347.069	31.776	61.106	0	0
CND	1184.654	2.649	4.751	5.282	7.647	0	0
AST	220.707	8.699	55.575	11.312	5.513	0	0
EST	36.966	0	129.618	22.735	5.407	0	0
ISR	183.657	10.283	17.273	24.995	17.648	0	0
LXM	5.051	52.578	0	70.926	38.159	1.429	7.747
ICL	10.864	8.017	15.272	25.809	14.334	0.132	0

Table A2. Slacks in input and output variables (Year 2).

DMU	GDP	CI	TO	II	HTE	LF	UR
SWZ	487.598	10.522	71.965	27.902	6.766	0	0
USA	0	43.437	27.287	20.35	27.476	993.764	3.158
SWD	211.593	0.434	10.217	2.601	5.013	0	0
UNK	2096.97	3.762	20.952	27.267	16.879	0	0
NDL	627.342	9.649	115.24	31.041	18.121	0	0
KOR	1004.007	17.041	31.783	22.585	26.372	0	0
SGP	211.389	13.359	284.864	30.649	47.471	0	0
GMN	2976.968	9.067	51.979	29.349	10.688	0	0
FNL	254.427	0.515	9.946	2.594	4.993	2.588	0
DMK	127.539	3.74	50.506	13.51	5.099	0	0
CHN	84924.71	55.672	86.834	231.479	55.806	0	12.468
FRN	0	10.468	37.939	27.766	0	0.692	0
JPN	3334.989	16.588	17.209	37.529	8.187	0	0
HNK	195.106	7.579	319.059	29.348	61.452	0	0
CND	1120.522	2.127	0	3.375	7.23	0	0
AST	210.933	8.834	53.693	10.089	5.114	0	0
EST	13.598	0	0	15.765	27.455	0	0.282
ISR	205.535	10.029	11.945	24.012	17.873	0	0
LXM	12.777	50.598	0	79.491	38.487	1.542	6.246
ICL	45.186	37.889	240.28	60.897	0	1.354	6.493

Table A3. Slacks in input and output variables (Year 3).

DMU	GDP	CI	TO	II	HTE	LF	UR
SWZ	509.782	14.229	77.428	30.623	6.533	0	0
USA	0	42.819	32.002	20.307	26.515	905.631	0
SWD	75.908	0	10.531	4.093	4.072	0	0
UNK	1462.009	6.188	30.302	34.708	15.114	0	0
NDL	618.249	9.39	111.386	30.561	17.957	0	0
KOR	592.272	21.952	44.009	34.105	28.844	0	0
SGP	164.916	9.589	295.024	26.439	49.919	0	0
GMN	2566.758	11.557	56.511	34.351	8.261	0	0
FNL	200.371	0	13.089	1.221	4.966	2	0
DMK	137.185	4.641	51.809	16.049	5.942	0	0
CHN	80856.15	52.126	71.317	221.621	57.094	0	31.52
FRN	1024.262	5.056	5.896	9.859	10.006	0	0
JPN	3397.928	16.077	13.242	35.256	12.156	0	0
HNK	105.54	0.554	297.175	11.483	62.117	0	0
CND	0	8.096	22.602	17.893	0	0	0
AST	198.706	9.096	51.84	11.842	5.48	0	0
EST	14.144	0	0	25.077	18.229	0	1.509
ISR	216.596	10.788	12.577	22.812	22.75	0	0
LXM	10.637	66.879	0	79.052	49.816	1.562	11.511
ICL	20.967	21.092	119.74	16.293	0	0.729	3.741

Table A4. Slacks in input and output variables (Year 4).

DMU	GDP	CI	TO	II	HTE	LF	UR
SWZ	543.953	9.86	77.41	26.282	7.238	0	0
USA	0	35.341	23.321	10.397	19.308	854.793	0.603
SWD	0	1.876	0	3.245	0	0.865	0
UNK	2084.15	2.414	10.82	23.97	15.222	0	0
NDL	681.748	7.92	113.403	26.085	16.039	0	0
KOR	1055.031	19.809	42.799	30.666	30.369	0	0
SGP	203.815	8.346	285.243	22.148	48.633	0	0
GMN	3183.631	10.158	51.945	28.292	9.172	0	0
FNL	265.53	0	8.027	0	2.826	2.005	0
DMK	181.35	8	58.458	18.591	6.917	0	0
CHN	91658.99	55.938	82.345	233.043	63.436	0	20.572
FRN	0	1.268	8.565	4.247	0	0	0
JPN	2960.941	14.368	13.546	32.739	10.666	0	0
HNK	122.452	0.361	348.919	13.974	63.489	0	0
CND	0	0	8.09	2.836	0	0	0
AST	174.646	7.15	44.016	1.266	2.203	0	0
EST	16.45	0	0	21.003	21.054	0	1.999
ISR	244.972	10.021	5.339	16.424	23.01	0	0
LXM	7.57	57.178	0	75.985	45.602	1.423	10.229
ICL	34.773	26.819	178.103	29.206	0	0.916	4.002

Table A5. Slacks in input and output variables (Year 5).

DMU	GDP	CI	TO	II	HTE	LF	UR
SWZ	564.126	7.619	80.744	28.136	23.567	0	0
USA	0	40.608	26.654	16.517	14.893	938.009	3.403
SWD	0	1.924	5.421	3.987	0	0.787	0
UNK	2183.211	2.983	18.901	27.563	21.286	0	0

NDL	669.795	7.202	128.292	28.054	16.107	0	0
KOR	916.105	21.136	58.037	33.112	12.866	0	0
SGP	270.63	7.815	287.218	26.869	20.623	0	0
GMN	2970.151	11.431	58.094	29.888	11.247	0	0
FNL	251.4	0	4.537	0	7.498	2.211	0
DMK	184.901	6.51	67.626	18.369	10.423	0	0
CHN	99566.35	52.342	88.261	230.211	59.346	0	11.883
FRN	0	3.612	31.163	10.878	0	0	0
JPN	2602.444	14.417	13.373	30.443	8.737	0	0
HNK	0	16.275	0	25.897	0	0	1.399
CND	1120.356	3.92	0	7.325	4.484	0	0
AST	200.127	7.946	54.686	7.903	10.404	0	0
EST	17.862	1.708	0	21.303	26.968	0	0
ISR	305.552	12.428	9.506	18.908	17.304	0	0
LXM	269.048	0	0	5.628	29.602	3.409	0.196
ICL	43.658	34.401	229.385	44.994	0	1.144	6.695

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